

The Algorithm-Mediated Inequality Regime in Hiring: A Systematic Review and Integrative Framework

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Abstract

AI-driven hiring has become widespread, yet concerns about fairness persist. Technical and behavioral research have evolved in largely disconnected streams. This paper conducts a systematic review following the PRISMA 2020 guidelines, synthesizing 50 studies to propose an “algorithm-mediated inequality regime” framework that integrates technical analyses of bias, applicant fairness perceptions, and ethical critiques. The framework captures how algorithmic hiring systems actively produce and legitimize inequality. Our findings reveal that data bias, algorithmic bias and human-in-loop bias map respectively onto Acker’s mechanisms of invisibility, legitimation, and control, forming a self-reinforcing cycle. Existing governance strategies, including technical fixes, organizational oversight, and legal-institutional mandates, operate within the prevailing inequality regime and fail to address underlying power asymmetries. The study extends organizational inequality theory into algorithmic contexts and offers practitioners a systemic diagnostic tool for auditing and reforming AI-enabled hiring.

Keywords

algorithmic bias, algorithmic fairness, AI hiring, inequality regime, systematic review

1. Introduction

Artificial intelligence now pervades hiring. Automated resume screening, video interviews, and algorithmic candidate scoring have become routine, yet they have triggered fairness concerns. Amazon’s experimental screening tool, which systematically downgraded female applicants, remains a landmark illustration [1]. Research on algorithmic fairness in hiring has since developed in largely disconnected streams. The technical stream focuses on detecting and measuring algorithmic bias. Chen et al. [2] show that model outputs may look fair even when the training data contain structural discrimination. The behavioral stream looks at perceived fairness. Lavanchy et al. [3] find that higher objective accuracy does not necessarily improve applicants’ perceptions of justice. A systematic review by Mori et al. [4] points to a broader ethical imbalance: most studies center utilitarian efficiency, while justice-based concerns and individual rights receive less attention.

Taken together, these separate streams leave an obvious gap. Neither explains how algorithmic hiring systems themselves produce and normalize inequality. This systematic review addresses that problem by proposing the concept of an algorithm-mediated inequality regime. The framework identifies how bias is produced, follows how it moves through the hiring pipeline, and shows how these systems affect both measurable outcomes and applicants’ subjective evaluations of fairness.

The algorithm-mediated inequality regime lens has three main advantages over existing approaches. First, it brings together technical, behavioral, and ethical perspectives within one framework, so researchers can connect the origin of bias to its later effects across the hiring process. Second, by linking algorithmic bias to Acker's [5] mechanisms of invisibility, legitimation, and control, it makes clearer how hiring inequalities can reproduce themselves over time. A single disciplinary lens misses that. Third, the framework makes it easier to compare proposed governance responses against the full process through which inequality is produced, rather than against isolated outputs alone.

To build this integrative framework, the review is guided by three research questions:

Research Question 1: What are the sources of algorithmic bias in AI-enabled hiring, and how do they map onto the core components of an inequality regime?

Research Question 2: How does algorithmic discrimination shape objective hiring outcomes and applicants' subjective fairness perceptions?

Research Question 3: What governance strategies have been proposed to counter algorithmic discrimination in hiring, and what are their limitations when evaluated against the inequality regime lens?

The study makes both theoretical and practical contributions. On the theoretical side, it brings technical studies, research on applicant perceptions, and ethical critiques into a single analytical frame, the algorithm-mediated inequality regime, and in doing so extends organizational inequality theory [5] into algorithmic settings. On the practical side, the framework gives human resource professionals a way to move past narrow technical metrics and examine hiring as a process that can generate inequality at several points. It also gives policymakers and auditors a broader basis for evaluation. Rather than checking algorithmic outputs alone, they can assess the structural processes that keep unequal outcomes in place. This review therefore answers the growing demand for socially responsible artificial intelligence with a diagnostic tool that is both theoretically grounded and usable in practice.

2. Theoretical Background

2.1 Algorithmic Bias, Fairness, and Perceived Justice

Algorithmic bias means systematic and unwanted discrimination that is built into, or produced by, computational systems. Friedman and Nissenbaum [6] divide it into three types. Preexisting bias comes from social institutions and cultural attitudes that existed before the system. Technical bias comes from design limits and from turning human choices into code. Emergent bias appears when a system is used in settings, or by groups of users, that were not part of the original design assumptions. Taken together, this framework suggests that algorithmic unfairness is not only a technical problem. It develops through the interaction between social inequality and engineering decisions.

The legal literature makes this point more precise. Barocas and Selbst [7] show that data mining can lead to discriminatory outcomes even when there is no discriminatory intent. They link this to the U.S. doctrine of disparate impact. In practice, bias can enter through technical steps that look neutral at first glance. These include choosing a target variable that correlates with protected class membership, training on labels shaped by past discrimination, and relying on proxy features instead of directly protected attributes. A model built this way may systematically disadvantage historically marginalized groups. Even so, it may survive legal challenge because its predictive accuracy meets the business-necessity defense. That matters for the present study. It suggests that algorithmic hiring tools can reproduce inequality while still appearing procedurally legitimate.

Attempts to define “fairness” in these systems run into a deeper problem. Binns [8] argues that the different fairness metrics used in machine learning are mathematical versions of competing philosophical theories of justice. Metrics based on demographic parity rely on egalitarian assumptions. Metrics that equalize error rates across groups draw on equality of opportunity. Metrics that give priority to the worst-off group reflect Rawlsian contractarianism. These starting points do not fit neatly together. As a result, choosing a fairness metric is not just a technical matter of optimization. It is also an ethical and political choice. For that reason, algorithmic fairness cannot be treated as a simple question of which metric appears on a dashboard. It needs to be addressed within a wider institutional framework.

Table 1: Dimensions of Organizational Justice

Dimension	Core Question	Key Predictor
Distributive Justice	Is the outcome proportionate to my contribution?	Outcome satisfaction
Procedural Justice	Was the decision-making process fair and consistent?	Organizational commitment
Interpersonal Justice	Was I treated with dignity and respect?	Evaluation of the decision-maker
Informational Justice	Were the explanations candid, timely, and personalized?	Trust and collective esteem

As shown in Table 1, organizational justice theory distinguishes four dimensions: distributive, procedural, interpersonal, and informational justice, each answering a different fairness question. Distributive justice asks whether outcomes proportionate to contributions, while procedural justice concerns the consistency and neutrality of the decision process. Interpersonal and informational justice capture the relational aspects: whether applicants are treated with dignity and receive candid, timely expectations. This multidimensional structure explains why technical accuracy and perceived fairness often diverge. An algorithmically “correct” decision may still be perceived as unjust if the process is opaque or the communication is impersonal. The four dimensions thus provide the conceptual vocabulary for analyzing the subjective side of the algorithm-mediated inequality regime developed in later chapters.

2.2 The Inequality Regime Lens

Organizations are not neutral sites where hiring happens. They actively produce and reproduce social inequality. Acker [9] indicates that seemingly abstract job and the disembodied worker assumed by organizational theory are gendered constructs. The ideal worker is implicitly modeled on a male body free from caregiving responsibilities. Job evaluation systems that treat positions as empty slots conceal this assumption. Gendered division of labor was embedded into the very definition of job requirements.

Acker [5] formalizes this insight into the concept of an inequality regime, and defines it as the interrelated practices and processes that sustain systematic disparities. All organizations manifest such regimes. The bases include class, gender and race. Routine process such as recruitment, hiring, and wage setting reproduce these disparities. The regime’s durability, however, rests on three mutually reinforcing mechanisms: invisibility, where privileged groups tend not to perceive their own privilege; legitimation, where narratives of natural difference render inequality legitimate; and control, where gendered and racialized assumptions become embedded in rules, surveillance and internalized beliefs.

Amrute [10] extends this framework into digital labor contexts, and argues that algorithmic systems re-encode organizational inequality processes in code. Algorithmic filtering can render certain bodies invisible, as illustrated by migrant programmers who must constantly attune to the risk of exclusion in order to approximate the ideal worker. These outcomes are algorithmic expression of inequality regime. The recursive loops of algorithmic bias and the systematic exclusion produced by hiring algorithms are precisely the organizational processes that Acker described, operating at the level of code.

2.3 The Socio-technical Nature of Algorithmic Systems

The separation between technology and organization is a persistent but untenable assumption. A survey of top-tier management journals reveals that more than 95 percent of published articles neglect the presence of technology in organizational life [11]. This omission grows out of a deeply rooted assumption that technology, work, and organization belong to separate domains. The concept of sociomateriality [11] challenges that view directly. From this perspective, social practices are always materially constituted. Technology and human actors do not carry fixed properties that exist before they meet. Instead, their form and meaning emerge through constitutive entanglement. Organizational practices are therefore sociomaterial by nature. Technology does not enter as an outside force at isolated moments. It is part of the ongoing enactment of organizational reality [11].

Applied to algorithms, this view suggests that they are situated within wider sociotechnical assemblages that include hardware, training data, legal frameworks, organizational cultures, and the everyday practices of programming teams [12]. Algorithmic design is shaped by judgments and constraints. It is not neutral. Algorithms are also ontogenetic, evolving through continued interaction with data. At the same time, they are performative. They do not just process representations of the world, but help produce effects in it through

classification, ranking, scoring, and regulation of populations. In that sense, algorithms carry particular epistemologies and power logics, rather than functioning as neutral cognitive tools [12].

This has direct implications for algorithmic fairness. Five abstraction traps have been identified as key reasons technical fairness solutions often fail [13]. The framing trap treats the technical subsystem in isolation and ignores the social actors who shape outcomes in practice. The portability trap assumes that a fairness metric from one setting can be transferred to another without adjustment. The formalism trap turns fairness into a mathematical definition and removes its procedural, contextual, and contestable aspects. The ripple effect trap overlooks how the introduction of a technical system changes surrounding incentives and power relations. The solutionism trap assumes technology is the answer without asking whether the technology should be built in the first place.

Taken together, these traps point to a basic problem: fairness is a feature of social and legal systems, and it cannot be fully encoded as a computational metric [13]. These three arguments form a clear theoretical sequence. At the ontological level, sociomateriality defines technology and society as constitutively entangled. At the epistemological level, the socio-technical assemblage lens treats algorithms as performative actors. From there, the abstraction traps show why attempts to address algorithmic fairness apart from institutions, history, and context are not just incomplete, but mistaken at a more basic level. Algorithmic hiring systems are therefore not external tools applied to an existing inequality regime but active mediators within it. This insight provides the theoretical foundation for the concept of an algorithm-mediated inequality regime developed in this review.

3. Research Methodology

3.1 Research Design

This study employs a systematic literature review method. It follows the guidelines of the PRISMA 2020 statement [14]. A systematic review is appropriate for this research because the literature on algorithmic fairness in hiring is fragmented across multiple disciplines. The objective is to identify, evaluate and integrate studies that examine algorithmic bias, applicant fairness perceptions, and governance approaches. The synthesized findings serve as the empirical basis for constructing the algorithm-mediated inequality regime framework.

3.2 Search Strategy

A systematic search was conducted across four electronic databases: Scopus, Web of Science, ACM Digital Library and IEEE Xplore

The search combined terms from three conceptual blocks. The first block covered AI and algorithms. The second blocks covered hiring and recruitment. The third block covered bias, fairness, discrimination, and governance. Within each block, synonyms were connected with the OR operator. The three blocks connected with the AND operator. The complete search strings are provided in the Appendix.

All searches were limited to English language publications. The time frame spanned from January 2010 to December 2025. This time frame applied to the systematic search. Foundational works published before 2010 were consulted for the conceptual background but were not eligible for inclusion in the reviewed sample.

3.3 Inclusion and Exclusion Criteria

Eligibility criteria were defined based on the research questions. The complete criteria are summarized in Table 2.

3.4 Screening Process

A total of 2,615 records were identified across the four databases (Scopus: 1,842; Web of Science: 524; IEEE Xplore: 191; ACM Digital Library: 58). After removing 481 duplicates (by DOI or normalized title), 2,134 unique records proceeded to title and abstract screening.

Screening applied the four assessable criteria (topic focus, core issue, publication type and time frame) to all 2,134 unique records. Of these, 1,247 were excluded: 713 for topic focus (studies outside hiring contexts), 447 for time frame (of which 423 were dated 2026 due to search timing), 10 for publication type, 19 for lacking bias or fairness content, and 58 because abstracts were unavailable in the exported metadata. Exclusions based on topic focus are provisional and subjective to verification during full-text review, as keyword-based judgments carry higher error risk.

Table 3 details the reasons for exclusion at the title and abstract screening stage. The largest single category was studies falling outside the AI-in-hiring/personnel selection topic focus (33.4% of records screened), followed by 20.9% removed for being outside the 2010–2025 time window. Mostly papers dated 2026 inadvertently captured during the search. Together, these two categories accounted for over half of all exclusions, confirming that a substantial portion of the initially retrieved literature was tangentially related or fell outside the intended temporal scope.

Table 2: Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Topic focus	AI or algorithmic systems in hiring or personnel selection	AI in HRM without hiring focus; fairness in non-employment contexts
Core issue	Bias, fairness, discrimination, perceived justice, or governance	Technical papers without organizational or social implications
Publication type	Peer-reviewed journal articles or conference proceedings	Book chapters, editorials, non-peer-reviewed reports
Language	English	Non-English
Time frame	2010–2025	Outside this range
Availability	Full text accessible	Full text not accessible
Analytical relevance	Addresses at least one of the three RQ foci: (1) sources of algorithmic bias, (2) applicant fairness perceptions, or (3) governance strategies	Engages with hiring-related topics but does not substantively address any of the three RQ foci

Table 3: Reasons for Exclusion at Title/Abstract Screening

Exclusion reason	n	% of records screened
Topic focus (not AI-in-hiring / personnel selection)	713	33.4%
Outside 2010-2025 time frame (of which 423 dated 2026)	447	20.9%
No bias / fairness / justice / governance angle	19	0.9%
Publication type (book / book chapter)	10	0.5%
No abstract available (unable to screen)	58	2.7%
Total excluded	1,247	58.4%

887 records exceeded solo full-text screening capacity. Only journal articles with “hiring” and “bias” in titles were retained, eliminating 830 sources and yielding 57 articles for full-text assessment (selection workflow in Figure 1). This title-based filtering strategy was adopted as a pragmatic response to the volume of records exceeding the capacity of a single reviewer. Requiring both terms “hiring” and “bias” in the title served as a high-precision filter to rapidly isolate studies most directly relevant to the review’s core focus on bias in AI-driven hiring. I acknowledge that this step may have excluded relevant articles that address bias and algorithmic fairness in hiring contexts without featuring both keywords in their titles, and therefore the resulting sample of 57 full-text articles may not exhaust the literature. However, given the resource constraints of a solo systematic review, this trade-off between comprehensiveness and feasibility was considered necessary and transparent. To mitigate this limitation, I supplemented the systematic search with backward reference tracking of the included studies and foundational theoretical works, a procedure that allowed me to capture additional key sources that were not retrieved by the title-based filter and thus partially compensate for potential omissions.

57 papers were evaluated against Table 2 criteria, which demanded relevance to bias origins, applicant fairness perceptions or governance tactics. 7 articles were excluded for irrelevant foci (HRM, non-algorithmic discrimination, recruitment technical optimization). Ultimately, 50 studies qualified for final synthesis.

Table 4 presents the distribution of the 50 included studies across 3 analytical foci. The remaining 2 studies are systematic reviews or broad overviews that span multiple foci, and retained as contextual sources. Figure 1 presents the complete PRISMA 2020 flow diagram.

Figure 1: PRISMA 2020 Flow Diagram

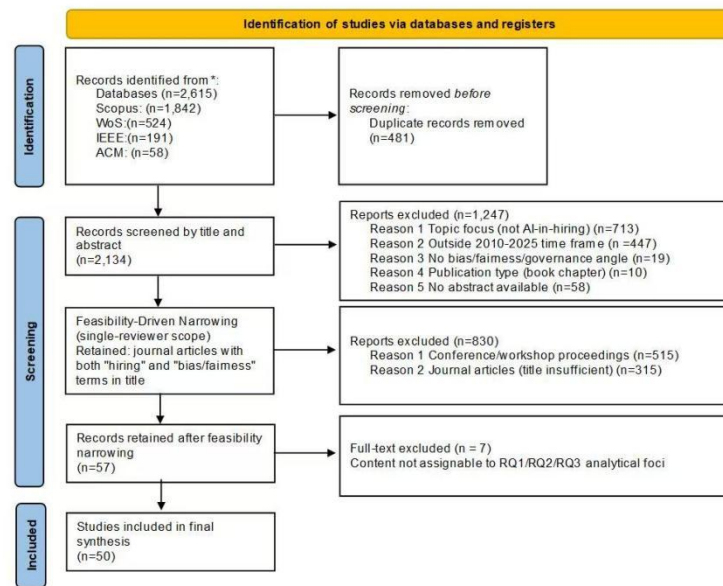


Table 4: Distribution of Included Studies by Analytical Focus

Focus	Corresponding RQ	n
Sources and mechanisms of algorithmic bias	RQ1	12
Fairness perceptions and subjective impacts	RQ2	10
Governance, mitigation, and legal/ethical frameworks	RQ3	26
Reviews and multi-focus conceptual overviews		2
Total		50

In addition to the systematic search, a small number of foundational or conceptual works were identified through backward reference tracking and targeting retrieval. These sources are used exclusively to support the theoretical framework and do not form part of the 50 studies included in systematic synthesis.

4. Findings: The Algorithm-Mediated Inequality Regime in Action

4.1 Sources of Algorithmic Bias and Their Mapping onto the Inequality Regime

This section answers Research Question 1 regarding sources of algorithmic bias in AI hiring and the connections to inequality regime components. The thematic analysis of 50 eligible papers identified three interconnected biases: data bias, algorithmic bias, and human-in-the-loop bias. These biases interact as a sequential chain embedding historical inequities, amplifying them via computation and validating them socially. Using Acker's [5] inequality regime theory, this study links three biases to invisibility, legitimation and control mechanisms, expanding organizational inequality research to algorithmic hiring scenarios.

4.1.1 A Typology of Bias Sources in AI Hiring

Data bias originates from structural and historical inequalities embedded in training data, manifesting in three key mechanisms. First, the systemic operation of proxy variables enables algorithms to discriminate without directly accessing protected attributes. Barocas and Selbst [7] showed that seemingly neutral features (zip codes, linguistic patterns, or educational institutions) can function as reliable statistical proxies for race, gender or socioeconomic status. Parviainen [15] further demonstrated that proxy-based discrimination could constitute direct discrimination under EU law when the proxy is "inextricably linked" to a protected ground, though this doctrinal extension remains contested. Second, the structural absence and medicalized framing of disability data constitute a distinct representational harm. Tilmes [16] argued that training datasets not only underrepresent disabled populations but also draw disability data predominantly from medical contexts, reducing disability to a biological dysfunction while erasing its social and relational dimensions. Third, the self-reinforcing feedback loop amplifies initial biases through iterative retraining: algorithmic outputs that disadvantages certain groups shape future user behavior and data generation, turning statistical noise into structural exclusion [17].

Complementary evidence from freelancing platforms confirms that opaque ranking mechanisms systematically disadvantage certain worker groups [18], while analyses of AI-driven HRM systems in developing economies reveal that discrimination risks are compounded by weak regulatory environments [19].

Algorithmic bias originates from model design choices, optimization objectives and inherent opacity. Two mechanisms are particularly salient. First, the conflation of correlation with causation pervades current machine learning practice. Recruitment algorithms prioritize predictive accuracy rather than causal modelling, assigning decision weight to all variables correlated with job performance regardless of genuine causal connections. When such correlations involve proxy variables for protected groups, the algorithm systematically disadvantages those groups while appearing merely to “follow the data” [17]. Second, fairness metrics embody irreconcilable normative commitments. Binns [8] demonstrated that different mathematical formulations of fairness, including demographic parity, equalized odds and individual fairness, stem from conflicting philosophical foundations and cannot be achieved simultaneously. Tilmes [16] extended this critique by arguing that any single operationalization of fairness necessarily flattens variance within and across disadvantaged groups. The choice of fairness metric is thus not a technical optimization problem but an inherently political decision, yet it is routinely presented as neutral. These concerns are not confined to Western contexts, Zheng et al. [20] found that AI adoption in Chinese recruitment reduced some forms of human bias while simultaneously introducing new algorithmic distortions. Third, algorithmic opacity compounded by trade secrecy claims, prevents external auditing and frustrates candidates’ attempts to establish *prima facie* discrimination cases under EU equality directives [15, 17].

Human-in-loop bias emerges from how decision-makers selectively interpret, accept, or reject algorithmic recommendations based on their own cognitive dispositions. Selective adherence describes the tendency to accept algorithmic advice when it aligns with pre-existing stereotypes and to discount it when it contradicts those stereotypes [21, 22]. This transforms algorithms from bias-reduction tools into bias legitimization devices. Moral buffering and responsibility drift further attenuate human oversight: decision-makers experience reduced moral accountability when adverse decisions can be attributed to algorithmic recommendations, diffusing responsibility across human and machine actors [22]. Finally unaware reliance operates at a more fundamental level. A majority of recruiters who extensively use platforms like LinkedIn do not perceive themselves as using AI. Algorithmic mediation is rendered invisible by integration into routine workflows.

4.1.2 Mapping to the Inequality Regime and the Algorithm-Mediated Framework

Acker’s [5] inequality regime framework identifies three linked mechanisms through which organizations produce and maintain inequality: invisibility, legitimization, and control. The literature reviewed here suggests that sources of algorithmic bias map closely onto these mechanisms. In this sense, AI does not reduce organizational inequality. It often carries existing patterns forward and, in some cases, makes them harder to see and challenge.

Invisibility works through three added layers that go beyond more familiar forms of privilege blindness. One is technical invisibility, which comes from the black-box character of deep learning models and from proxy-based discrimination, where the source of bias cannot easily be traced [15,17]. Another is pipeline invisibility. Here, standard legal metrics can miss discrimination at the sourcing stage. Adverse impact ratios remain statistically unchanged even when biased algorithms substantially reduce minority hiring, because the metric only applies to actual applicants [23]. There is also cognitive invisibility, which appears through unaware reliance. If recruiters do not recognize platform recommendations as algorithmic outputs, they are less likely to question them as biased in the first place [24].

Legitimation also works at several levels. At the discursive level, the language of “data-driven objectivity” presents algorithmic outputs as better than human judgement and depends on a disputed idea of rationality and bias [25]. At the technical level, formal fairness metrics can offer a kind of quasi-legal legitimization. A system may satisfy a mathematical criterion and still produce outcomes that systematically disadvantage disabled or neurodiverse candidates [16]. The gap matters. At the cognitive level, selective adherence can turn personal prejudice into something that appears algorithmically confirmed. This reduces cognitive dissonance and makes discriminatory decisions seem acceptable, even reasonable, to the decision-maker [22].

Control appears in three main dimensions. Information dominance places decisional power with platform owners and employers, while trade secrecy claims block disclosure of algorithmic details [15,17]. Behavioral

shaping follows when candidates adjust their applications to what they expect algorithmic screening will reward. This can homogenize profiles and encourage compliance with unstated algorithmic norms before any human review takes place. Lifecycle extension pushes algorithmic governance beyond hiring and into performance evaluation, promotion, and turnover prediction. As a result, an early disadvantage can carry through later assessments and narrow future opportunities over time [26].

Table 5 synthesizes the mapping between bias sources, entry points and inequality regime mechanisms, while Figure 4.1 provides a visual representation of the full casual chain from bias sources to regime outcomes.

Table 5: Mapping Bias Sources to Inequality Regime Mechanisms

Bias Source	Key Mechanism	Primary Entry Point	Inequality Regime Mechanism
Data Bias	Historical inequality encoded as statistical pattern	Information distribution, Application screening	Invisibility (proxy logic), Control (definitional power)
Algorithmic Bias	Correlation treated as causation; fairness as formal compliance	Application screening, Assessment	Invisibility (black-box), Legitimation (metrics)
Human-in-the-Loop Bias	Personal bias selectively confirmed by algorithmic outputs	Final decision, Post-hire evaluation	Legitimation (objective confirmation), Control (diffused responsibility)

Figure 2 provides a visual synthesis of the algorithm-mediated inequality regime. The left column maps the three bias sources identified in 4.1.1; the middle column shows their instantiation through Acker's mechanisms; the right column captures the regime-level outcomes. The arrows indicate the recursive, self-reinforcing nature of the regime (see Figure 2).

This analysis builds the integrated framework of algorithm-mediated inequality regime. The concept contains two core traits. Mediation means algorithms reshape social relations by embedding magnifying and legitimating inequality beyond mere reflection. Regime refers to systematic, long-term and institutionalized inequality instead of occasional incidents. Algorithmic bias is accordingly a systemic property of AI recruitment rather than isolated technical faults. This framework supports follow-up analyses of hiring outcomes, applicants' fairness perceptions (RQ2) and relevant governance suggestions (RQ3).

4.2 Algorithmic Discrimination in Hiring: Objective Outcomes and Subjective Fairness Perceptions

This section addresses Research Question 2 by examining algorithmic discrimination at two interconnected levels: objective hiring outcomes and applicants' subjective fairness perceptions. The reviewed literature reveals a persistent gap that reflects the constitutive entanglement of technical systems with organizational inequality processes between the promise of algorithmic objectivity and its actual effects [5, 11].

4.2.1 Objective Hiring Outcomes

Large-scale evidence shows that AI screening systems produce significant racial and gender disparities. Alexander III et al. [23] found that when each job position was examined separately, as required by U.S. discrimination standards, adverse impact against Black and Asian applicants emerged in many roles, yet this effect became invisible when data were aggregated across positions. This "pipeline invisibility" means organizations may believe the processes are fair while algorithms systematically exclude certain groups before reaching formal evaluation.

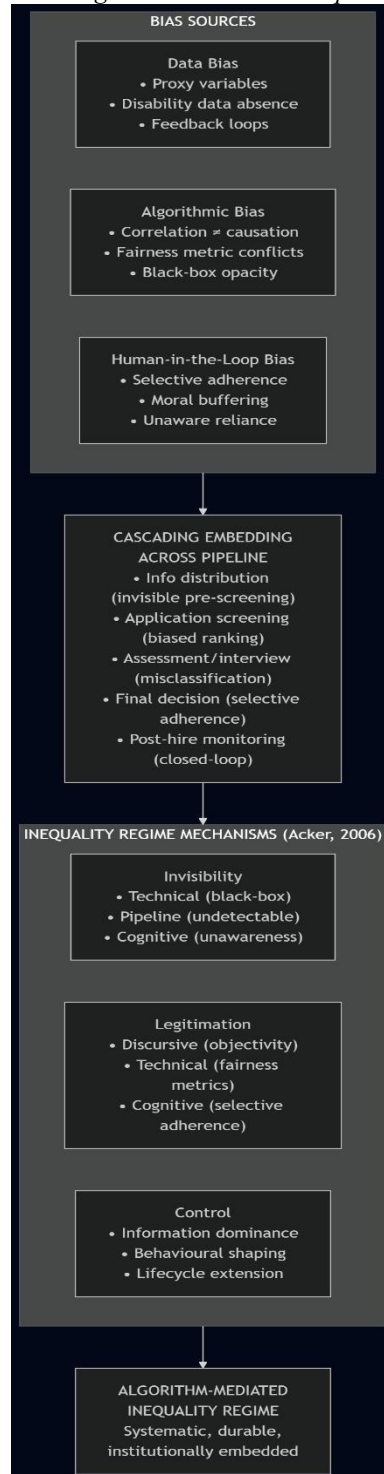
Objective outcomes are further shaped by unintended human-algorithmic interactions. Koch-Bayram et al. [27] indicates that algorithm-based digital interviews generally lower fairness perceptions, but human recruiters exercising discretionary judgment over algorithmic shortlists can amplify bias, transforming algorithms from bias-reduction tools into legitimation devices [22]. Thus, algorithmic hiring does not simply reflect existing inequality. Instead reshapes decision-making conditions, creating new pathways for discrimination.

4.2.2 Subjective Fairness Perceptions

Applicants' perceptions of algorithmic hiring are multidimensional. Drawing on organizational justice theory, Ochmann et al. [28] validated that four justice dimensions: procedural, distributive, interpersonal, and informational. These are equally predictive for algorithmic decision-makers as for humans. However,

applicants aconsistently rate AI-driven processes as less fair, less trustworthy, and less attractive than human-led ones [3, 29].

Figure 2: *The Algorithm-Mediated Inequality Regime*



Trust and procedural justice act as key mediating mechanisms. Babaei and Shank [29] demonstrated that the negative effects of AI hiring on organizational attraction and application intentions are fully mediated by reduced trust, two-way communication and perceived chance to perform.

Cultural and individual differences moderate these perceptions. Park and Jung [30] found that American applicants view AI interviews as less fair than human ones across multiple dimensions, whereas Korean applicants show little difference or even perceive AI as fairer in some respects. Critically, prior discrimination

experience weakens algorithms aversion: Koch-Bayram et al. [27] showed that applicants who had experienced workplace discrimination rated algorithmic and human decision-makers as equally fair, suggesting that for historically disadvantaged groups, AI may represent a neutral alternative.

Beyond these findings, Feldkamp et al. [31] demonstrated that trust and moral judgments jointly mediate reactions to algorithm-supported selection, while Hosain et al. [32] confirmed that procedural justice concerns dominate applicants' evaluation of AI-driven hiring in South Asia contexts. Yu et al. [33] further showed that the effects of AI-based hiring decisions on justice perceptions and organisational commitment depend on configurational interactions among multiple design features rather than on any single factor.

4.2.3 The Gap and Its Implications for the Inequality Regime

The reviewed literature reveals three consequences of the gap between objective outcomes and subjective perceptions. First, objective fairness does not guarantee perceived fairness. This means applicants may reject technically fair processes due to lack of opacity or lack of interpersonal treatment [28, 34]. Second, perceived unfairness can arise even without measurable discrimination, driven by concerns about reductionism and loss of human judgement [3]. Third, objective discrimination can remain undetected when fairness metrics are applied at the wrong level of aggregation [23].

These findings confirm algorithm-mediated inequality regime. AI hiring system actively mediate inequality through biased sourcing, human-algorithmic interactions, fairness perceptions, and flawed metric. Closing this gap requires governance that integrates technical design, organizational context, and applicant experiences, as discussed next.

4.3 Governance Strategies to Counter Algorithmic Discrimination: A Critical Evaluation

Addressing algorithmic discrimination in hiring has prompted a wide array of governance strategies spanning technical fixes, organizational interventions and legal-institutional reforms. This section critically synthesizes these approaches through the algorithm-mediated inequality regime lens to answer Research Question 3. Table 6. below summarizes the core logic and representative approaches of each paradigm before the subsequent subsections critically examine their limitations.

Table 6: Governance Strategies and Representatives

Paradigm	Core Logic	Representative Approaches
Technical	Correct biased outputs via mathematical intervention	Fairness metrics, debiasing algorithms, XAI, algorithmic auditing [35, 36, 37]
Organizational	Reform human decision-making contexts	Human oversight, recruiter training, participatory design, accountability structures [38, 39, 40]
Legal-Institutional	Mandate compliance through external regulation	Anti-discrimination law, impact assessments, AI Act, audit mandates [41, 42, 43]

4.3.1 Technical Governance

Technical strategies apply fairness metrics, bias detection algorithms, explainable AI, and auditing to correct discriminatory outputs directly within the system [35, 36, 37]. Alongside these mainstream approaches, a range of complementary technical interventions has been proposed: fair-by-design matching algorithms [44], debiasing-assisted generative models with gender-weighted sampling [45], and personality-based algorithms aimed at reducing gender disparities [46]. Researchers have also developed algorithmic equity framework for underrepresented groups [47] and evaluated the inclusivity of AI tools for candidates with disabilities [48, 49]. Experimental evidence further shows that biased algorithms impair applicant pool quality and diversity, and that debiasing methods differ markedly in their effectiveness [50]. Proponents argue these tools can detect inadvertent proxy discrimination and render decisions more interpretable [28]. Yet when evaluated through the inequality regime lens, technical governance demonstrates profound limitation across all three mechanisms.

Invisibility arises because technical solutions narrow discrimination to what can be mathematically operationalized, rendering structural and historical sources invisible. Fairness metrics that scrutinize outcome distributions fail to capture how biased job advertisements, exclusionary networks, or ableist assumptions shape the applicant pool before any algorithm processes a resume [23, 16]. Auditing may find no adverse impact while remaining blind to “pipeline bias”, which is the systematic exclusion of candidates with non-

traditional career paths [51]. The choice of which demographic attributes to monitor can obscure intersectional discrimination, as systems fair across single axes may still disadvantage multiply-marginalized groups [37].

Legitimation occurs when mathematical fairness actively legitimates discriminatory systems. An algorithm satisfying a chosen metrics can be presented as “debiased” even when optimizing a fundamentally inequitable construct, such as cultural fit” as a proxy for racial or class homogeneity [52, 53, 54]. This “fairness washing” [43] shields organisations from deeper scrutiny.

Control remains with employers and vendors who define metrics and interpret audits, leaving applicants without meaningful say [40, 55, 56]. In sum, technical governance treats algorithmic discrimination as model mis-specification rather than systemic inequality, inadvertently reinforcing the very dynamics it claims to correct.

4.3.2 Organizational Governance

Organizational strategies emphasize human oversight, recruiter training, participatory design, and cultural reform [38, 39]. The theory of change holds that bias resides not solely in code but in the practices and mental models of human decision-makers [57]. Yet these strategies rely upon the very judgment they were meant to improve, without necessarily reforming the organizational conditions that make the judgment biased.

Invisibility tends to emerges when oversight become perfunctory. Research on automation bias shows that human reviewers often rubber-stamp algorithmic recommendations under time pressure, leading to “check-the-box” behaviour that gives a false sense of control while biased outputs go unchecked [38, 58]. The diffusion of responsibility between human and machine can also create a “moral crumple zone” where no single actor feels accountable [24, 26].

Legitimation occurs when recruiters selectively accept algorithmic advice that matches their stereotypes, which reduces cognitive dissonance because prejudice seems to have been confirmed objectively [22, 25].

On the issue of control, training programs often leave organizational cultures, including definitions of merit, incentive systems, and hierarchies, untouched. Participatory design has similar limits. It often includes only management-selected stakeholders and leaves out affected communities [59,57,40].

Rao and Zhao [60] offered a case study of ethical AI implementation in tech hiring and showed the practical obstacles of operating fairness principles within existing organizational structures. Gupta and Mishra [61] catalogued the range of ethical concerns arising across the recruitment workflow, which points to the need for governance mechanisms that cover the full hiring pipeline rather than isolated stages.

4.3.3 Legal-Institutional Governance

Legal strategies extend anti-discrimination law, mandated impact assessments and require audits through frameworks like the EU AI Act and NYC Local Law 144 [41, 42, 43]. These frameworks aim to reduce opacity and enable enforcement, but confront structural barriers that limit their transformative potential.

Invisibility is the central limitation: trade secrecy and model complexity mean that regulators and plaintiffs cannot access source code or training data, making it nearly impossible to prove causation [62, 17, 15]. Audits can become formalistic exercises that verify documentation rather than investigate the socio-technical system generating outcomes [51].

Legitimation follows when compliance grants an official seal of approval: an “audit culture” that produces due process paperwork while altering little for marginalized groups [43, 63].

Regarding control, vendors frame systems as technical products, excluding questions about whether hiring constructs embed discriminatory norms, while applicants lack collective bargaining rights over these technologies [40, 62]. Legal governance thus often ends up refereeing a system whose basic rules are written by one side.

5. Discussion

5.1 Synthesis of Findings: The Algorithm-Mediated Inequality Regime in Action

This review confirms algorithmic hiring is an active mediator of inequality. ata bias (proxy variables [15, 17, 16]), algorithmic bias (conflating correlation with causation [17]), and human-in-the-loop bias (selective

adherence, Rosenthal-von der [22, 26]) map onto Acker's [5] mechanisms of invisibility, legitimation, and control, forming a self-reinforcing feedback loop that perpetuates inequality. A persistent gap separates objective outcomes from perceived fairness: algorithms produce adverse impact invisible in aggregate metrics [23], while applicants rate AI processes as less fair, trustworthy, and interpersonally just [3, 29]. Even technically "fair" algorithms are perceived as unjust when they eliminate voice and respectful treatment [28, 34] and this legitimacy deficit can be strategically exploited. Governance strategies that target outputs including technical fairness trapped by formalism [51, 37], organizational oversight subverted by automation bias [38, 59], and legal frameworks struggling with trade secrecy and proof [62, 43]. All inadvertently reinforce the regime by providing a veneer of fairness without redistributing power. The regime is thus sustained by bias generation and amplification (RQ1), objective exclusion and subjective delegitimation (RQ2), and governance that fails to restructure underlying power asymmetries (RQ3). These conclusions extend and update earlier systematic reviews that first mapped the landscape of algorithmic discrimination in HR recruitment and development [64].

5.2 Towards a Multi-Level Governance Architecture for Transformative Fairness

Countering algorithmic discrimination requires a regime-oriented architecture addressing invisibility, legitimation, and control through four-cross cutting principles:

1. Redefine the object of regulation. Scrutiny must cover the whole hiring pipeline through causal fairness frameworks [17], including job advertisements [65], platform design [23], and "ideal candidate" constructs, with mandatory audits of upstream processes.
2. Redistribute epistemic and decision-making power. Participatory governance should be built into institutions with worker representatives and marginalized communities [40,55,53], including collective bargaining over algorithmic management [62], with real veto power over how fairness is defined.
3. Pierce the legitimacy veil. Mandate radical transparency beyond technical explainability [56], including public disclosure of validity evidence, intersectional adverse impact, and accessible data-processing explanation [42], supported by public algorithmic registries.
4. Close the accountability gap. Clear legal responsibility should be assigned at each stage to counter the "moral crumple zone" [26], alongside mandatory algorithmic literacy [39] and protections against "check-the-box" automation bias [38].

Taken together, these principles move governance away from a narrow technical focus on bias mitigation and toward a political question of how power is distributed.

5.3 Implications for Theory and Practice

This review extends Acker's [5] inequality regime theory to digital hiring by showing that invisibility, legitimation, and control are intensified through algorithmic systems. It also connects technical fairness research with organizational justice and critical algorithm studies. One tension stands out. Interventions aimed only at outputs can make systems look more credible without changing the structures that produce inequality in the first place. For practitioners, the framework works as a diagnostic tool. Developers need to avoid the solutionism trap [13] and engage with the organizational sociology of inequality as seriously as they engage with loss functions.

5.4 Limitations of the Review

This review has several limits. Pragmatic title screening may have missed adjacent terminology, and the restriction to English-language publications narrows the range of studies included. The evidence is also weighted toward Western high-income contexts. In addition, there is interpretive judgment in linking different forms of bias to Acker's [5] mechanisms.

5.5 Future Research Directions

Several areas should be prioritized in future research: longitudinal studies of cascading career outcomes (the lifecycle extension hypothesis; [26]), intersectional auditing methods, comparative governance analyses

(e.g., NYC Local Law 144 vs. EU AI Act), participatory research centering applicants' voices, and work on how bias changes with generative AI in hiring.

6. Conclusion

This systematic review has argued that algorithmic discrimination in hiring is neither a set of technical glitches nor a problem that can be solved by better metrics alone. Through the lens of the algorithms-mediated inequality regime, the evidence shows that data bias, algorithmic design choices and human-in-loop dynamics interact to produce systematic disadvantages that map precisely onto Acker's mechanisms of invisibility, legitimation, and control. Proxy-driven discrimination and the flattening of disability data render structural exclusions invisible; fairness metrics and claims of data-driven objectivity lend these exclusions an aura of legitimacy; and trade secrecy, automation bias, and responsibility diffusion keep control firmly in the hands of employers and platform owners. Consequently, outputs that are technically "fair" may still produce adverse impact that disappears into aggregate statistics, while applicants consistently rate algorithm-driven processes as less just, less trustworthy, and interpersonally impoverished.

This study makes two primary theoretical contributions. First, it extends Acker's inequality regime theory into algorithmic contexts, demonstrating how the mechanisms of invisibility, legitimation, and control are not merely replicated but actively amplified by AI-enabled hiring systems. Second, it exposes a fundamental governance paradox: technical fixes, organizational oversight, and legal-institutional mandates each operate within the very inequality regime they seek to correct. Technical interventions are trapped by formalism and fairness washing, organizational solutions are subverted by selective adherence and perfunctory oversight, and legal frameworks struggle against opacity and trade secrecy. Together, these approaches provide a veneer of fairness without redistributing the underlying structures of power.

Dismantling the algorithm-mediated inequality regime therefore requires a transformative shift from retrospective output checks to prospective regulation of the entire hiring pipeline. Meaningful reform requires institutionalizing genuine worker and community participation in defining fairness, mandating transparency that goes beyond technical explainability, and closing the accountability gap that currently diffuses responsibility across human and machine actors. Future research should prioritize longitudinal studies tracing how initial algorithmic disadvantages cascade across entire career trajectories, develop intersectional auditing methods capable of detecting discrimination across multiple axes of marginalization, and conduct comparative analyses of emerging regulatory frameworks to identify governance designs that substantively redistribute power rather than merely certify compliance.

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Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgment

This paper is an output of the science project.

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