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Bias in AI-driven HRM systems: Investigating discrimination risks embedded in AI recruitment tools and HR analytics

M.M. Abdullah Al Mamun Sony^{a,b,**} , Mohammad Bin Amin^{c,d,e,*} , Aysha Ashraf^f, K.M. Anwarul Islam^e, Nitai Chandra Debnath^g, Gouranga Chandra Debnath^h^a Géza Marton Doctoral School of Legal Studies, University of Debrecen, Kassai street, 28, Post Code: 4032, Debrecen, Hungary^b CMN & GKM Program, ChangeMaker Nexus Ltd., Khulna, 9000, Bangladesh^c Doctoral School of Management and Business, Faculty of Economics and Business, University of Debrecen, Böszörményi street 138, Debrecen, 4032, Hungary^d Department of Business Administration, Faculty of Business Studies, Bangladesh Army University of Science and Technology, Saidpur, 5310, Nilphamari, Bangladesh^e Department of Business Studies, State University of Bangladesh, 696 Kendua, Kanchan, Rupganj, Narayanganj, 1461, Dhaka, Bangladesh^f Department of Business Administration, School of Business, Asian University of Bangladesh, Bangabandhu Road, Ashulia, Dhaka, 1341, Bangladesh^g BRAC Business School, BRAC University, Kha 224 Bir Uttam Rafiqul Islam Avenue, Merul Badda, Dhaka, 1212, Bangladesh^h School of Business & Economics, United International University, United City, Madani Avenue, Badda, Dhaka, 1212, Bangladesh

ARTICLE INFO

Keywords:

Ethics in AI
AI-HRM
Recruitment
Algorithmic-bias
Hiring-discrimination
AI-Regulation

ABSTRACT

Artificial Intelligence (AI) has transformed Human Resource Management (HRM), offering efficiency and objectivity in processes like recruitment and performance evaluation. However, AI-driven HRM systems are not without challenges, particularly regarding the biases embedded in their design, which can disproportionately affect marginalized groups—including non-binary individuals, women, racial minorities, and persons with disabilities. This paper investigates the risks of discrimination in AI recruitment tools and HR analytics, focusing on the risks of algorithmic discrimination affecting marginalized groups and the resulting implications for fairness, compliance, and career advancement in the workplace. By employing a doctrinal research methodology, the study examines the legal, ethical, and policy frameworks governing AI in HRM, highlighting the regulatory gaps that allow bias to persist. Through an analysis of legal precedents, AI ethics guidelines, and real-world case studies, the paper proposes actionable solutions for creating more inclusive AI-driven HRM practices. Largely, this study aims to inform policymakers, HR professionals, and AI developers about the importance of ensuring fairness and inclusivity in AI systems, fostering a more equitable work environment for all individuals, regardless of gender identity.

1. Introduction

Over past few years, the integration of AI into HRM has considerably altered workforce analytics, performance evaluation, and recruitment. HRM systems that are AI-driven are expected to improve efficiency, objectivity, and data-driven decision-making (Halid et al., 2024; Mollah et al., 2024). However, these systems also pose significant ethical and legal challenges, particularly in terms of biases that disproportionately affect marginalized groups, such as gender minorities or persons with disabilities (Mendy et al., 2024). A critical evaluation of the implications

for diversity, inclusion, and impartiality in employment practices is required due to the increasing dependence on AI in HRM.

Moreover, diversity and inclusion are essential principles in contemporary business environments, as they contribute to the success of the company, employee satisfaction, and innovation (Elamin et al., 2024; Sony et al., 2025). A more engaged workforce and an enhanced brand reputation are the benefits of companies that adopt inclusive HRM practices (Halid et al., 2024). Nevertheless, the reliance on historical data and algorithmic decision-making in AI-driven HRM tools may inadvertently reinforce existing biases in employee assessments,

* Corresponding author. Doctoral School of Management and Business, Faculty of Economics and Business, University of Debrecen, Böszörményi street 138, Debrecen, 4032, Hungary.

** Corresponding author. Géza Marton Doctoral School of Legal Studies, University of Debrecen, Debrecen, Hungary.

E-mail addresses: abdullahsony.as@gmail.com, abdullahsony.as@mailbox.unideb.hu (M.M.A.M. Sony), binaminbu@gmail.com, binaminbu@mailbox.unideb.hu (M.B. Amin), aysha94@aub.ac.bd (A. Ashraf), anwarul.bs@sub.edu.bd (K.M.A. Islam), nitai.chandra@bracu.ac.bd (N.C. Debnath), gouranga@bus.uui.ac.bd (G.C. Debnath).

<https://doi.org/10.1016/j.ssaho.2025.102082>

Received 20 August 2025; Received in revised form 30 September 2025; Accepted 6 October 2025

Available online 15 October 2025

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promotion, and hiring (Halid et al., 2024; Sony et al., 2025). It is imperative to guarantee equity in these AI systems in order to cultivate a workplace environment that maintains equal opportunities for all individuals (Mendy et al., 2024), irrespective of their gender identity.

The research problem of bias in AI-driven HRM systems is the primary focus of this study, with a particular emphasis on its impact on gender and racial inclusion (Mollah et al., 2024; Rigotti & Fosch-Villaronga, 2024). AI algorithms can perpetuate discrimination through biased data sets, opaque decision-making processes, and exclusionary employment criteria if they are not carefully designed and monitored (Rigotti & Fosch-Villaronga, 2024). The risk of algorithmic discrimination is further exacerbated by the absence of representation of minorities in training data, which can result in disparities in career advancement opportunities and hiring (Rigotti & Fosch-Villaronga, 2024; Sony, Nupur, et al., 2025).

This study treats gender, racial, and disability bias as interconnected manifestations of algorithmic discrimination, since they share common roots in biased data and opaque model design. The scholarships of this study are significant for technology developers, HR professionals, and policymakers who are dedicated to the development of AI systems that are more transparent and equitable in the workplace. Thereafter, this study seeks to (1) examine the extent to which AI-driven HRM systems contribute to bias against marginalized groups, including non-binary individuals, women, racial minorities, and people with disabilities; (2) analyze the legal, ethical, and policy frameworks governing these issues across international and national contexts; and (3) propose actionable policy recommendations to foster more equitable and transparent AI governance. For HR professionals, unchecked AI bias not only undermines fairness in recruitment but also exposes organizations to significant compliance risks under anti-discrimination law. By clarifying these objectives, the paper aims to bridge the gap between technological innovation and legal accountability in employment practices. To guide the analysis, the study is structured around the following research questions:

- What regulatory gaps exist in current AI governance frameworks regarding discrimination in HRM?
- How do existing legal frameworks address algorithmic bias in recruitment and workplace decision-making?
- What policy measures could better protect marginalized groups from discrimination in AI-driven HRM systems?

2. AI in HRM: Opportunities and challenges

Certainly, HRM has experienced a paradigm shift in workforce planning because of the integration of AI. AI applications in HRM, for instance, have introduced tools such as automated resume screening, predictive analytics for employee performance, chatbots for candidate engagement, and workforce analytics for strategic decision-making (Halid et al., 2024; Jia & Hou, 2024). By processing large volumes of data efficiently, these tools allow HR professionals to focus on higher-value tasks, improve workforce planning, and enhance organizational decision-making (Halid et al., 2024; Hasan & Sony, 2022; Mendy et al., 2024).

In addition to operational efficiency, AI can support more objective assessments in recruitment and performance evaluation. Data-driven insights help mitigate human subjectivity, providing standardized evaluations of candidate profiles and employee performance trends (Halid et al., 2024; Hanna et al., 2025; Mollah et al., 2024). This capability also enables organizations to identify attrition risks, optimize workforce allocation, and enhance overall HR strategy.

Despite these advantages, AI adoption in HRM raises significant challenges, particularly concerning bias and fairness. Models trained on historical data can perpetuate existing inequalities, disproportionately affecting women, non-binary individuals, racial minorities, and persons with disabilities (Akter et al., 2021; Rigotti & Fosch-Villaronga, 2024;

Sony, 2025). Algorithmic discrimination can emerge from flawed assumptions or incomplete datasets, leading to misclassification, exclusion, or inequitable opportunities (Chowdhury et al., 2025; Ghasemaghaei & Kordzadeh, 2024).

Moreover, transparency in AI decision-making is another critical concern. The “black box” nature of many algorithms makes it difficult for candidates and HR professionals to understand or challenge decisions (Brožek et al., 2024; Zhou, 2023). Real-world examples underscore these risks: Amazon’s AI hiring tool exhibited gender bias due to historical hiring patterns (Rao & Zhao, 2025; Thakur et al., 2025), and AI healthcare recruitment algorithms underrepresented Black patients, reinforcing systemic disparities (Hasan & Sony, 2022; Thakur et al., 2025).

Addressing these challenges requires a multifaceted approach. Incorporating fairness-aware algorithms, ensuring diverse and representative training datasets, and implementing human oversight are critical strategies for reducing bias and increasing accountability (Madanchian, 2024; Mollah et al., 2024; Rigotti & Fosch-Villaronga, 2024). Coupled with robust legal and ethical frameworks, these measures can guide organizations in deploying AI responsibly, ensuring equitable and transparent HR practices. Organizations must prioritize fairness and accountability in AI deployment to ensure that HRM systems contribute to a more equitable and inclusive workplace environment.

3. Methodology

A doctrinal approach is particularly appropriate because the research problem centers on the adequacy of legal and policy responses rather than on quantifying algorithmic outcomes. While empirical data and technical analyses are vital for assessing the mechanics of bias, this study complements those approaches by examining how laws, regulations, and ethical standards define obligations, accountability, and remedies for discrimination in AI-driven HRM (Novelli et al., 2022; Sony, 2023b). The research is organized around the analysis of primary and secondary legal sources following the study of Huda and Sony (2024), a comparative legal assessment of various jurisdictions, and a critical review of the existing literature on AI bias in HRM. The study endeavors to offer a thorough assessment of the interaction between legal and ethical standards and AI-driven recruitment tools and HR analytics, with a particular emphasis on non-binary individuals, through the integration of these components.

This study is founded on primary sources, which include legislation, international treaties, and case law that pertain to AI governance, workplace discrimination, and gender inclusion in employment. To ensure systematic coverage, the research relied on searches conducted through Westlaw, LexisNexis, HeinOnline, Scopus, and Google Scholar, using keywords such as “AI recruitment,” “algorithmic bias,” “HRM discrimination,” “AI regulation,” and “non-binary employment rights.” The search was limited to the period 2015–2025, reflecting the most significant decade in the development of AI regulation and its integration into HRM practices. Sources were included if they directly addressed AI in HRM, workplace discrimination, or legal and policy frameworks governing AI bias. Excluded were sources that focused on AI ethics in non-employment contexts or opinion pieces lacking legal or regulatory grounding.

Among the primary legal instruments analyzed are the ILO Convention No. 111, which prohibits discrimination in employment, and the United Nations Guiding Principles on Business and Human Rights, which highlight corporate responsibility for inclusivity. Regional frameworks such as the General Data Protection Regulation (GDPR, 2018) and the forthcoming EU AI Act (2025) were examined for their AI transparency and impartiality provisions. In the United States, the study reviewed Equal Employment Opportunity (EEO) laws and the Algorithmic Accountability Act (2025 update), while Finland’s Non-Discrimination Act (1325/2014) and AI Ethics Guidelines (2024) were

analyzed as national-level examples of fairness-focused AI governance. Enforcement challenges and legal precedents were further explored through landmark judicial cases, including Amazon's AI hiring bias case (2018) and more recent litigation from 2024 to 2025.

The study also integrates a comprehensive review of secondary sources, including peer-reviewed journal articles, policy papers, AI ethics guidelines, and regulatory reports. Academic scholarship on algorithmic discrimination, AI governance, and HRM best practices provided theoretical grounding, while reports from the European Commission, the US Federal Trade Commission (FTC), and Finland's AI Task Force offered applied policy perspectives. Corporate AI ethics guidelines issued by major technology firms were analyzed to evaluate the strengths and limitations of self-regulation. By synthesizing these sources, the study bridges legal theory and practice, while also highlighting the limitations of existing governance frameworks in protecting marginalized groups—including women, racial and ethnic minorities, individuals with disabilities, and non-binary employees—from algorithmic discrimination.

A comparative legal analysis was conducted to examine differences and similarities between jurisdictions. The comparison focused on three dimensions: scope of regulation (the breadth of legal coverage addressing AI bias in HRM), enforcement mechanisms (the extent to which oversight was proactive, such as mandatory audits, versus reactive, such as litigation), and coverage of marginalized groups (whether protections extended beyond binary gender definitions to include racial, disability, and non-binary identities). In addition, the study evaluated the influence of international human rights frameworks on national AI and labor policies to determine the extent to which global principles translate into enforceable protections.

For the purposes of analytical clarity, a regulatory gap was defined as either (a) the absence of explicit provisions addressing AI-driven discrimination, (b) inadequate enforcement or monitoring mechanisms, or (c) the exclusion of marginalized groups from coverage under employment law. Each legal framework was reviewed with guiding questions: Does the law explicitly address AI or algorithmic bias? Which groups are protected? What accountability or enforcement mechanisms are specified? Are transparency or audit requirements mandated for AI-driven HRM tools? This process ensured consistency across jurisdictions while making the identification of regulatory gaps systematic and replicable.

In addition to reviewing legal and policy texts, interdisciplinary literature on HRM, AI ethics, and workplace fairness was critically examined to contextualize the legal analysis. Research on algorithmic opacity provided insights into the challenges posed by AI's "black box" nature, while HRM-focused studies emphasized the practical consequences for recruitment and workplace equity. By combining legal, policy, and interdisciplinary perspectives, the study developed a multidisciplinary evaluative framework for assessing AI's impact on workplace discrimination. This framework forms the basis for the study's recommendations to policymakers, HR professionals, and technology developers on how to implement more inclusive and equitable AI-driven HRM practices.

4. Review of legal and policy frameworks: protections against gender-based discrimination in employment

The rapid adoption of AI in HRM has brought unprecedented efficiency but also introduces complex ethical and legal challenges, especially regarding bias and discrimination against marginalized groups, including women, ethnic minorities, and individuals with disabilities. Although national and international legal frameworks strive to foster fairness and inclusion in hiring, regulatory mechanisms have struggled to keep pace with the rapid adoption of AI-driven HRM systems. Consequently, gaps in accountability and enforcement remain, allowing biased AI algorithms to impact employment decisions.

This section explores the interaction between ethical standards,

national legislation, and international protections in shaping equitable AI applications in the workplace (Fig. 1). It examines corporate governance measures that encourage fairness, national laws addressing algorithmic bias in recruitment, and global legal safeguards against gender-based workplace discrimination. By considering these interconnected dimensions, the discussion highlights current regulatory initiatives while pinpointing areas where reforms are needed to ensure AI-driven HRM systems operate transparently and equitably.

4.1. International frameworks on AI bias and workplace discrimination

Legal concepts and agreements that promote gender equality and non-discrimination in work have been created by several international organizations, such as the United Nations (UN) and the International Labor Organization (ILO). Discrimination in hiring and working circumstances based on gender or gender identity is prohibited by the ILO Convention No. 111 on Discrimination (Employment and Occupation) (1958) (Ales et al., 2018). It is imperative to implement current modifications to this standard, but it faces question of directly address AI prejudice, despite its establishment of the foundation for anti-discrimination legislation.

Likewise, the elimination of workplace discrimination is emphasized in the United Nations' Sustainable Development Goals (SDGs), with a particular emphasis on Goal 5 (Gender Equality) and Goal 8 (Decent Work and Economic Growth). The UN Guiding Principles on Business and Human Rights (2011) provide additional guidance on the obligations of corporations to prevent human rights atrocities, which includes algorithmic bias (McGregor et al., 2019). Furthermore, the OECD AI Principles (2019), which upgraded in 2024, encourage governments and corporations to establish safeguards against AI-driven discrimination, thereby advocating for fairness, transparency, and accountability in their AI applications (Lund et al., 2025). Despite these global efforts, many international frameworks lack specific provisions on AI bias in HRM. The absence of standardized AI governance mechanisms means that companies operate under varying degrees of regulatory oversight, often leading to inconsistent implementation of ethical AI principles.

4.2. National-level legal frameworks on AI bias and workplace discrimination

The national legal responses to AI bias in HRM are significantly different across jurisdictions. The European Union (EU), the United States (US), and Finland have each implemented their own strategies for

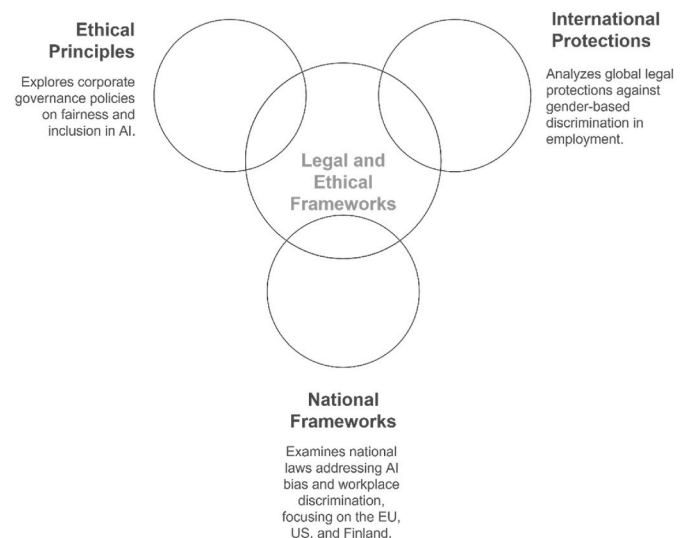


Fig. 1. Global and national strategies for fair AI and employment practices.

addressing algorithmic discrimination and workplace equity. The EU has been a leader in AI governance, as evidenced by regulations such as the General Data Protection Regulation (GDPR) (2018), which requires transparency in automated decision-making processes, including AI-driven recruitment (Papadimitriou & Virvou, 2025). AI in HRM is classified as a high-risk application under the EU AI Act, which is anticipated to be enforced in 2025. This classification necessitates strict adherence to the principles of non-discrimination and fairness. The Equal Treatment Directive (2006/54/EC) also prohibits employment discrimination based on gender identity, a provision that can be expanded to address AI biases (Wörsdörfer, 2024).

Simultaneously, the Equal Employment Opportunity Commission (EEOC) in the US enforces anti-discrimination laws, such as Title VII of the Civil Rights Act (1964), which prohibits gender-based discrimination in employment (Fabris et al., 2025). However, lawsuits against AI-driven recruiting tools for disproportionately rejecting candidates from marginalized groups continue to present a challenge, as evidenced by AI bias (Bose, 2025). The Algorithmic Accountability Act (2022, proposed updates in 2025) is designed to enhance the governance of AI fairness and accountability in employment decisions in response (Lund et al., 2025).

Finland, a pioneer in digital governance, has implemented proactive measures to regulate AI ethics in the workplace. According to International Labour Law Reports Online (2020), employers are mandated to guarantee impartiality in performance evaluations and employment processes pursuant to the Non-Discrimination Act (1325/2014) and the Act on the Protection of Privacy in Working Life (759/2004). The significance of unbiased algorithmic decision-making, particularly in the context of gender and sexual identity in the workplace, is underscored in Finland’s AI Ethics Guidelines (Khan et al., 2025). Enforcement remains a challenge, even though these legal frameworks offer fundamental protections. The detection and correction of algorithmic biases is a challenging task since numerous AI-driven HRM tools operate with minimal external scrutiny.

4.3. Ethical AI principles and corporate governance policies on fairness and inclusion

In addition to legal frameworks, the implementation of ethical AI principles and corporate governance policies is essential for guaranteeing equity in AI-driven HRM. Ethics guidelines have been established by organizations such as the World Economic Forum (WEF), the Partnership on AI, and IEEE, with an emphasis on inclusivity, accountability, and transparency in AI applications (Al-kfairy et al., 2025). To mitigate biases in HR analytics and recruitment, corporate governance policies are increasingly integrating AI fairness guidelines (Rigotti & Fosch-Villaronga, 2024). AI Ethics Boards and Fair AI Audits have been implemented by industry-leading technology companies and multinational corporations to assess algorithmic decision-making processes (Hanna et al., 2025; Li & Goel, 2025; Rigotti & Fosch-Villaronga, 2024).

To enhance the transparency and inclusivity of AI, corporations including IBM, Microsoft, and Google have implemented bias-mitigation tools (O’Connor & Liu, 2024). Conversely, critics contend that self-regulation is inadequate, as numerous organizations neglect to disclose instances of AI bias or implement substantial corrective measures (O’Connor & Liu, 2024). According to earlier scholars (e.g., Halid et al. (2024); Mendy et al. (2024); Mollah et al. (2024); O’Connor and Liu (2024); Rigotti and Fosch-Villaronga (2024); Zhou et al. (2023)), organizations must implement human oversight mechanisms, conduct bias audits, and encourage the development of inclusive AI models to guarantee that AI-driven HRM systems are consistent with ethical and legal standards. Additionally, regulatory enforcement should be strengthened by governments, which should mandate adherence to equity standards and penalize discriminatory AI practices.

5. Case studies and examples of AI-induced discrimination in hiring

Empirical evidence highlights numerous instances where AI recruitment tools have led to discriminatory hiring outcomes. One of the most well-documented cases is Amazon’s now-infamous AI hiring tool, which demonstrated a strong bias against women (Akter et al., 2021; Morabito, 2025). The algorithm systematically downgraded resumes containing indicators of female identity, such as participation in women’s organizations. While this case predominantly concerned gender discrimination against women, similar biases are likely to impact non-binary individuals, particularly when AI models lack inclusive gender markers (Bose, 2025; Jia & Hou, 2024; Madanchian, 2024). When AI systems are trained on historical hiring data that reflect existing gender disparities, they inherently replicate and perpetuate these inequalities, further marginalizing non-binary applicants.

Another example of AI-induced discrimination in hiring involves facial recognition technologies used in video-based AI hiring platforms. Studies (e.g., Chen (2023); Ghasemaghaei and Kordzadeh (2024); Morabito (2025); Tilmes (2022)) indicate that these systems are less accurate in assessing the expressions and emotions of individuals who do not conform to binary gender norms. Many facial recognition algorithms have been trained on datasets primarily composed of cisgender individuals, leading to significant accuracy gaps when evaluating non-binary candidates. As a result, these candidates may receive lower scores in AI-driven personality and competency assessments, resulting in unjustified rejections (Kelan, 2024). The reliance on facial analysis in recruitment raises serious concerns about fairness and the unintended exclusion of gender-diverse individuals from employment opportunities (Table 1).

Additionally, AI-based resume screening tools often prioritize candidates whose profiles align with historical hiring norms. Given that non-binary individuals face systemic barriers to employment, their career trajectories may not align with conventional patterns, causing AI systems to unfairly rank them as less suitable candidates (Kelan, 2024). Many hiring algorithms are designed to optimize for characteristics that

Table 1
Organizes key cases of AI-induced discrimination in hiring, showing the tool types, affected groups, and current mitigation status.

Company/ Platform	AI Tool Type	Discrimination Type	Key Findings/ Outcome	Current Status/ Mitigation
Amazon	Resume screening AI	Gender (against women)	Downgraded resumes with female-associated terms	Tool abandoned; lessons learned applied
IBM	AI hiring tool	Age	Filtered out older candidates	Lawsuit filed; tool modified
Google	AI hiring	Gender	Ranked female applicants lower in technical roles	Algorithm updated internally
Facebook/ LinkedIn	Job ad targeting AI	Gender & racial	STEM ads skewed toward men; lower-wage ads to women/minorities	Ongoing awareness; algorithm adjustments
HireVue	Video interview AI	Non-binary, neurodiverse, non-native English	Penalized facial expressions, speech patterns	Criticism & calls for bias mitigation
Pymetrics	Gamified assessment AI	Neurodiverse	Scored lower due to atypical response patterns	Suggested updates for inclusion

(Source: Author produces, 2025)

have historically led to hiring success, such as uninterrupted career paths or specific educational backgrounds (Tilmes, 2022). Since non-binary individuals may experience employment gaps due to discrimination or lack of inclusive work environments, AI-driven systems may disproportionately penalize them (Jia & Hou, 2024).

Beyond gender-related biases, several real-world cases illustrate how AI recruitment technologies perpetuate broader discrimination. A large multinational financial services company implemented an AI-driven resume screening tool (Bekkum & Zuiderveen Borgesius, 2023; Kelan, 2024; Li & Goel, 2025), only to discover through an internal audit that the system disproportionately downgraded resumes from Black candidates by associating certain word choices and educational backgrounds with lower hiring success rates. The algorithm, trained on biased historical hiring data, systematically ranked highly qualified Black candidates lower, reinforcing existing racial disparities in hiring (Bekkum & Zuiderveen Borgesius, 2023; Bose, 2025; Chen, 2023; Jia & Hou, 2024; Madanchian, 2024; Mendy et al., 2024).

In another instance, AI-driven job advertising algorithms used by Facebook and LinkedIn exhibited gender and racial biases. A 2019 study by researchers at Northeastern University found that AI prioritized men for STEM-related job ads while directing lower-wage job ads toward women and marginalized groups (Test, 2022), reinforcing workplace segregation (Dilmegani, 2025). This bias stemmed not from employers' direct intentions but from AI models optimizing ad placements based on historical engagement patterns, inadvertently mirroring societal inequalities.

Similarly, HireVue's AI-based video interview platform faced criticism for its biased facial and speech analysis tools (Lytton, 2024), which disproportionately disadvantaged non-native English speakers and neurodiverse candidates (Dilmegani, 2025). Investigations found that the AI system rated applicants lower based on accents, facial expressions, and even background noise, often leading to unjustified rejections. Critics argue that such reliance on AI can penalize diversity and exclude well-qualified candidates based on superficial factors rather than genuine competency (Aksoy et al., 2024; Bose, 2025; Ghasemaghahi & Kordzadeh, 2024) (Table 1).

Age-based discrimination has also been identified in AI-driven hiring processes (Rao & Zhao, 2025). In 2018, a lawsuit against IBM revealed that the company's AI hiring tool systematically filtered out older job applicants in favor of younger candidates by prioritizing applicants with recent graduation dates (Gosselin, 2018). A ProPublica investigation further found that IBM intentionally trained AI to reduce the presence of workers over 40, reinforcing age discrimination in recruitment (Gosselin, 2018).

Even well-known tech giants have struggled with biased AI hiring practices. A major tech firm (Google) conducted an internal review and found that its AI ranked female applicants lower for technical roles due to learned biases from historical hiring patterns, which predominantly favored male engineers (Akter et al., 2021; Lytton, 2024). Although Google later modified the algorithm, this case exemplifies how AI can reinforce workplace gender imbalances if not carefully designed and monitored.

AI-assisted screening tools have also raised concerns regarding their impact on candidates with disabilities. Platforms like Pymetrics and HireVue have been found to unintentionally disadvantage neurodiverse individuals, such as those with autism or ADHD, by scoring them lower due to non-traditional response patterns (Akter et al., 2021; Dilmegani, 2025; Lytton, 2024; Rigotti & Fosch-Villaronga, 2024) (Table 1). In some cases, automated voice or facial analysis tools failed to accommodate speech differences or non-standard facial expressions, leading to biased assessments and unjustified exclusions from hiring pools (Dilmegani, 2025). These cases underscore the urgent need for inclusive algorithmic design (Ghasemaghahi & Kordzadeh, 2024; Kelan, 2024), continuous auditing of AI-driven HR technologies (Li & Goel, 2025), and intervention strategies to prevent bias from reinforcing structural inequalities in hiring processes (Fabris et al., 2025; Lytton, 2024). Without

proactive measures, AI-based recruitment tools risk perpetuating the very discrimination they were intended to eliminate.

6. Doctrinal analysis of regulatory gaps

The integration of AI into human resource management has progressed at a pace that far exceeds the development of corresponding legal frameworks designed to mitigate workplace discrimination. While anti-discrimination laws in various jurisdictions provide protections against gender, racial, and disability-based biases, they often fail to address the specific risks associated with AI-driven hiring processes. According to earlier studies (e.g., Chen (2023); Fabris et al. (2025); Kelan (2024); Lytton (2024); Rao and Zhao (2025); Rigotti and Fosch-Villaronga (2024); Thakur et al. (2025)), existing legal provisions generally lack explicit mechanisms for monitoring, auditing, and rectifying algorithmic biases, particularly those affecting non-binary individuals, women, racial minorities, and persons with disabilities. As AI becomes increasingly embedded in recruitment and employment decision-making, these regulatory gaps pose significant challenges in ensuring fairness, transparency, and accountability.

The international and national legal instruments prohibit workplace discrimination, yet their applicability to AI-driven hiring remains ambiguous. For instance, the ILO Convention No. 111 (1958) prohibits employment discrimination based on gender and other factors, but it does not explicitly address how AI-based hiring tools may perpetuate historical biases (Hanna et al., 2025). Similarly, the United Nations Guiding Principles on Business and Human Rights (UNGPs) emphasize corporate responsibility in maintaining fair hiring practices, yet they lack binding requirements for organizations to conduct AI bias audits (Li & Goel, 2025). Some jurisdictions have introduced governance measures targeting algorithmic discrimination, such as the European Union's AI Act (2025), which classifies AI-driven HR tools as high-risk and mandates transparency, fairness audits, and human oversight (Table 2). However, the regulation primarily addresses general AI governance and does not provide specific provisions to combat biases affecting non-binary individuals, racial minorities, or individuals with disabilities (Al-kfairy et al., 2025).

The US's Algorithmic Accountability Act (2025 update) requires organizations to conduct impact assessments for automated decision-making systems (McGregor et al., 2019; Rigotti & Fosch-Villaronga, 2024), but its enforcement remains largely reactive, relying on litigation rather than proactive oversight. Finland's AI Ethics Guidelines (2024) promote non-discrimination in AI governance (Wörsdörfer, 2024); however, they remain largely self-regulatory and lack robust enforcement mechanisms. Despite these regulatory advancements, no universal framework effectively prevents AI-driven hiring discrimination across gender, race, disability, or other marginalized identities. Many legal provisions continue to define gender in binary terms (Sony et al., 2025), neglecting non-binary and gender-diverse individuals, while existing race and disability protections fail to mandate AI-specific audits, making algorithmic discrimination difficult to detect and address (Table 2).

A critical gap in AI governance is the failure to account for diverse gender identities, racial minorities, and individuals with disabilities within algorithmic hiring models (Chen, 2023; Fabris et al., 2025; Ghasemaghahi & Kordzadeh, 2024; Hanna et al., 2025; Kelan, 2024; O'Connor & Liu, 2024). These biases manifest in several ways, including the reinforcement of historical hiring patterns that disadvantage women, non-binary individuals, and transgender applicants. AI recruitment systems are often trained on datasets that reflect cisnormativity and male-dominated hiring trends (Tilmes, 2022), leading to discriminatory outcomes that favor candidates aligning with past employment norms.

Similarly, racial disparities in AI-driven hiring are well documented, with algorithmic screening tools disproportionately downgrading resumes from Black, Indigenous, and other minority candidates (Fabris

Table 2

Summarizes the key legal and policy frameworks relevant to AI-driven HRM, highlighting the scope, enforcement mechanisms, and AI-specific provisions across jurisdictions.

Jurisdiction	Key Legislation/Policy	Coverage Scope	AI-Specific Provisions	Enforcement Mechanism	Penalties/Compliance
European Union	AI Act (2025)	All high-risk AI, including HR	Transparency, fairness audits, human oversight for HR AI	Regulatory oversight (EU authorities)	Compliance mandatory, penalties for non-compliance
United States	Algorithmic Accountability Act (2025 update)	Automated decision-making systems	Impact assessments for AI; no explicit bias enforcement	Litigation-driven enforcement; agencies may investigate	Weak; reactive enforcement
Finland	AI Ethics Guidelines (2024)	AI deployment in organizations	Non-discrimination in AI governance	Self-regulatory; advisory bodies	Non-binding; voluntary compliance
International	ILO Convention No. 111 (1958), UNGPs	Employment discrimination broadly	No AI-specific provisions	National enforcement (ILO monitoring, UN non-binding)	Limited; general compliance only

(Source: Author Produces, 2025)

et al., 2025; Madanchian, 2024; Thakur et al., 2025; Tilmes, 2022). These biases often stem from training datasets that overrepresent dominant racial groups, reinforcing exclusionary hiring practices. Furthermore, individuals with disabilities face additional barriers (Table 3), as AI hiring platforms frequently employ behavioral and facial recognition assessments that disadvantage neurodiverse applicants. Tools such as HireVue, which analyze facial expressions and speech patterns, may unfairly penalize candidates with atypical communication styles, leading to their exclusion from hiring processes (Dilmegani, 2025).

Another major governance gap is the lack of inclusive data representation in AI training models. Many AI-driven hiring systems fail to recognize gender identities outside the male-female binary (Table 3), leading to errors in applicant rankings or the automatic disqualification of candidates who do not fit conventional gender categories (Hanna et al., 2025; Sony, 2023a). Similarly, recruitment algorithms trained on non-diverse datasets may fail to accurately assess the qualifications of candidates from historically underrepresented racial or socioeconomic backgrounds (Li & Goel, 2025; Madanchian, 2024). While corporate AI ethics policies frequently emphasize fairness and inclusion, they are often voluntary rather than legally binding, meaning organizations are not compelled to implement inclusive hiring practices (Table 3). Thereafter, supporting Madanchian (2024) this study also found without stricter regulatory interventions, AI-driven hiring systems are likely to continue reinforcing workplace inequalities rather than mitigating them.

Even in jurisdictions with AI governance frameworks, enforcement mechanisms remain inadequate due to limited oversight capabilities and insufficient compliance incentives. One significant challenge is the absence of AI-specific anti-discrimination bodies. Traditional labor enforcement agencies often lack the technical expertise required to audit AI systems for bias, leading to insufficient regulation of AI-driven hiring tools. Algorithmic opacity further complicates enforcement efforts, as many AI recruitment systems operate as black-box models (Brožek et al., 2024), making it difficult to determine how hiring decisions are made or whether biases are embedded in the algorithms. Usually, companies frequently claim trade secrets over their AI models, limiting external

audits and regulatory scrutiny (Bekku & Zuiderveen Borgesius, 2023; Kelan, 2024; Li & Goel, 2025). This lack of transparency reduces accountability and leaves affected individuals with few avenues for challenging biased hiring decisions.

Additionally, penalties for the use of discriminatory AI hiring tools remain weak. Most of the existing regulatory frameworks generally emphasize self-regulation and voluntary compliance rather than imposing strict legal mandates with enforceable penalties. Organizations are often encouraged—but not required—to conduct AI bias audits and implement corrective measures, resulting in minimal oversight and continued risks of algorithmic discrimination. In the absence of stringent enforcement mechanisms, AI-driven HR systems will likely perpetuate rather than resolve existing inequalities in the workforce.

7. Policy recommendation for inclusive AI-driven HRM practices

The integration of AI in HRM requires a comprehensive approach to mitigate biases and ensure fair outcomes for gender and other marginalized groups. One of the most pressing concerns is the inherent bias in AI recruitment systems due to reliance on historical datasets that often fail to capture diverse gender identities. To counteract this, organizations must actively diversify training datasets by incorporating broader representations of gender and identity. Partnering with advocacy groups and ensuring ethical data collection practices can help build datasets that accurately reflect the workforce’s diversity. Furthermore, regular updates to these datasets are necessary to prevent AI systems from reinforcing outdated biases and to ensure continued alignment with evolving social understandings of gender.

Transparency in AI decision-making is another critical area that demands attention. Many AI-driven hiring systems function as opaque “black boxes,” limiting the ability to scrutinize and address biases. This lack of visibility disproportionately affects marginalized candidates who may be unfairly disadvantaged by algorithmic decisions without clear explanations. Organizations should prioritize the development of AI models that provide understandable and interpretable hiring rationales. Establishing mechanisms that allow candidates to challenge AI-driven decisions further enhances accountability and helps rectify potential

Table 3

Maps specific types of bias against current legal protections across key jurisdictions, highlighting persistent regulatory gaps in AI-driven hiring.

Bias Type	EU AI Act (2025)	US Algorithmic Accountability Act	Finland AI Ethics Guidelines	Gap Analysis/Notes
Gender (women, non-binary)	Covered (high-risk HR AI)	Impact assessment required; reactive	Encouraged, voluntary	Non-binary inclusion limited; enforcement weak
Race/Ethnicity	Covered via anti-discrimination mandates	Partially addressed in impact assessment	Voluntary guidance	Lack of AI-specific auditing; racial bias not systematically enforced
Age	Covered indirectly	Partially addressed	Encouraged	No explicit measures; older workers often unprotected
Disability/ Neurodiversity	Covered under high-risk AI if included	Not explicitly covered	Voluntary guidance	Neurodiverse applicants may be penalized; no binding oversight
Transparency/ Explainability	Required for high-risk HR AI	Encouraged	Voluntary	Black-box AI remains a challenge; enforcement varies

(Source: Author Produces, 2025)

biases. Transparency not only strengthens trust in AI systems but also empowers HR professionals to oversee and intervene when discriminatory patterns emerge.

Legal and corporate accountability frameworks must also evolve to address bias in AI-driven HR practices. Current regulations often lack specificity in addressing AI-related discrimination, particularly concerning non-binary individuals. Governments should implement stringent policies mandating routine bias audits, ensuring that AI systems comply with ethical standards and do not disadvantage certain groups. Within organizations, bias audits should be institutionalized as part of standard HR operations, accompanied by public transparency reports detailing steps taken to mitigate discrimination. Furthermore, holding AI developers and HR professionals accountable for maintaining fair AI practices will reinforce corporate responsibility in this domain.

Inclusive AI policies must explicitly promote equity in recruitment, performance evaluations, and career advancement. Organizations should establish periodic assessments of AI-driven HRM tools to identify and rectify any emerging biases. Importantly, human oversight should remain integral to AI-based decision-making processes, ensuring that final hiring and promotion decisions are not left solely to algorithms. Moreover, AI should be leveraged as a supportive tool rather than as a determinant of employment outcomes, with human evaluators trained to recognize and counteract potential algorithmic discrimination.

Overall, sustained efforts to foster inclusivity in AI-driven HRM require ongoing training and organizational commitment. HR professionals must be equipped with the knowledge and skills to assess AI bias and implement corrective measures effectively. Encouraging open dialogue within organizations about AI fairness and establishing feedback channels for employees and job candidates will further enhance accountability. Promoting a culture of continuous learning and adaptation ensures that AI-driven HRM systems evolve in a manner that upholds fairness, ultimately contributing to a more equitable and inclusive workplace environment.

In sum, Fig. 2 illustrates the relationship between AI-driven hiring risks, regulatory gaps, and policy recommendations. The left column highlights key risks, including gender, racial, disability, and age biases, as well as opaque AI decision-making. The middle column identifies corresponding regulatory gaps, such as incomplete AI-specific

legislation, weak enforcement, lack of inclusive datasets, and limited protections for non-binary and marginalized groups. The right column presents targeted recommendations to address these gaps, including dataset diversification, mandatory bias audits, transparent AI, human oversight, and inclusive legal reforms. The figure visually summarizes how risks in AI recruitment can be mitigated through regulatory and organizational interventions.

8. Limitations and future study direction

This study has several limitations that also suggest directions for future research. First, it relies on a doctrinal and theoretical approach, analyzing legal and policy frameworks without empirical data, and therefore cannot measure the real-world prevalence or impact of AI-driven discrimination in hiring and workforce management. Future studies could incorporate case studies, surveys, or experimental analyses to evaluate actual outcomes and discrimination rates. Second, while legal and regulatory gaps are identified, enforcement challenges were not empirically assessed, highlighting the need for research into practical compliance, oversight mechanisms, and effectiveness of existing laws. Third, the analysis is limited to three jurisdictions (EU, US, and Finland), potentially overlooking alternative regulatory approaches and protections in other countries; comparative studies across more regions could provide broader insights.

Fourth, the study does not include technical evaluation of AI systems, so the feasibility and effectiveness of proposed bias mitigation strategies remain untested, suggesting the need for interdisciplinary collaboration with data science and AI experts. Fifth, rapid AI developments mean findings may become outdated as technologies and regulations evolve, emphasizing the need for continuous monitoring of AI governance. Finally, the focus on general HRM systems limits sector-specific insights; future research could examine industry-specific applications, such as healthcare, finance, or tech, to tailor regulatory and organizational guidance. Together, these limitations indicate avenues for empirical, technical, and comparative research to enhance fairness, transparency, and accountability in AI-driven HRM. And the future empirical research could complement this doctrinal analysis by testing AI systems in real recruitment settings.

9. Conclusion

This research aims to document legal and ethical frameworks addressing AI-driven bias in HRM and to recommend policy interventions for reducing discrimination risks. It highlights how AI systems disproportionately affect marginalized groups, including women, non-binary individuals, and racial minorities. While AI offers efficiency and objectivity in recruitment and workforce analytics, biases in training data and algorithms can disadvantage underrepresented groups. Such biases may create barriers in hiring and career progression for gender, racial, and ethnic minorities. Current legal and ethical frameworks often fall short, as many still rely on binary conceptions of identity and fail to protect all groups. To address these gaps, stronger legal protections, inclusive HRM practices, transparency, bias audits, and human oversight are needed to ensure fairness in AI-driven decision-making. These measures have practical implications for HR professionals and policymakers, including managing compliance risks, implementing regular audits, and providing training on AI oversight to mitigate bias in recruitment and workforce management.

However, this study follows a doctrinal approach, relying on legal and theoretical analysis rather than empirical data. While this methodology provides a strong conceptual foundation for understanding AI biases in HRM, the absence of primary data limits its ability to measure the real-world impact of algorithmic discrimination. Future research could incorporate empirical investigations, such as case studies, surveys, or experimental analyses, to explore how some AI-driven HRM systems may introduce biases in hiring and workforce management.

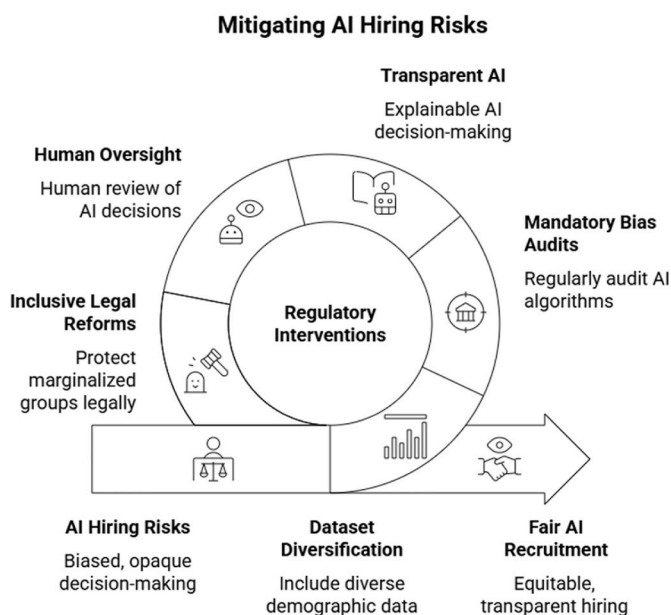


Fig. 2. AI-driven hiring risks, regulatory gaps, and recommended interventions, highlighting biases, enforcement gaps, and solutions such as diverse datasets, bias audits, transparency, human oversight, and inclusive legal reforms.

Additionally, examining intersectional perspectives—considering how AI may affect individuals belonging to multiple marginalized groups—could provide a more nuanced understanding of potential discrimination in AI-driven HRM systems.

Moving forward, research and policy initiatives should focus on developing standardized guidelines for ethical AI implementation, strengthening enforcement mechanisms, and fostering international collaboration on AI governance. Comparative studies across different regulatory environments can provide insights into best practices for mitigating algorithmic discrimination. Moreover, interdisciplinary approaches that integrate insights from law, social sciences, and data science will be essential in designing AI-driven HRM systems that prioritize fairness, accountability, and inclusivity. By addressing regulatory gaps, improving data representation, and fostering transparency, organizations can create HRM systems that promote diversity and equal opportunities for historically marginalized groups, ensuring AI-driven HRM contributes to a truly equitable workplace.

CRedit authorship contribution statement

M.M. Abdullah Al Mamun Sony: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Conceptualization. **Mohammad Bin Amin:** Writing – original draft, Visualization, Investigation. **Aysha Ashraf:** Writing – original draft, Visualization, Resources, Data curation. **K.M. Anwarul Islam:** Writing – original draft, Validation, Supervision, Project administration, Investigation. **Nitai Chandra Debnath:** Writing – review & editing, Supervision, Methodology. **Gouranga Chandra Debnath:** Writing – review & editing, Software, Resources.

Informed consent and participant details

Not applicable.

Ethical approval

Not applicable.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Quillbot in order to improve the Academic English since the Authors are not native speaker. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Funding

This research was funded by Institute for Advanced Research Publication Grant of United International University, Ref. No.: IAR-2025-Pub-077.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research was supported by the University of Debrecen Program for Scientific Publication.

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