

MAPPING IDEA & LITERATURE FORMAT | RESEARCH ARTICLE

Digital Human Resource Management for Inclusive and Sustainable Workplaces: A Systematic Review of Diversity, Equity, Inclusion, and Algorithmic Fairness

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ABSTRACT

The integration of artificial intelligence (AI) into human resource management (HRM) creates opportunities for efficiency while raising concerns about algorithmic bias, discrimination, and workplace inequality. This study systematically reviews literature on digital HRM, diversity, equity, and inclusion (DEI), and algorithmic fairness to examine their implications for inclusive and sustainable workplaces. Guided by PRISMA 2020 and informed by PRISMA-S, the review synthesizes conceptual and empirical research on AI-enabled HRM, workplace inclusion, and sustainable human resource practices. The findings indicate that algorithmic systems may reproduce existing inequalities through biased training data, proxy variables, and design assumptions. Although AI can improve recruitment and operational efficiency, fair outcomes require transparency, accountability, human oversight, and continuous evaluation. The review also identifies limited integrated empirical evidence connecting algorithmic fairness, DEI, and sustainable HRM, particularly regarding long-term employee well-being and organizational outcomes. These findings emphasize the importance of embedding fairness and inclusion into digital HRM governance. Future research should prioritize real-world evaluations, intersectional fairness, and longitudinal investigations of employee autonomy and workplace sustainability.

Keywords: Digital Human Resource Management, Artificial Intelligence, Diversity, Equity, Inclusion.

I. Introduction

Digital transformation has reshaped human resource management (HRM), changing how organizations recruit employees, evaluate performance, develop competencies, and make workforce decisions. The integration of information technology into HRM initially emphasized administrative efficiency and service delivery, but its development has increasingly expanded toward data-driven and AI-supported decision-making (Bondarouk & Ruël, 2009; Strohmeier, 2020). Artificial intelligence (AI) now offers organizations opportunities to process large volumes of workforce data, standardize personnel decisions, and improve operational efficiency. However, these benefits do not necessarily translate into fair, inclusive, or sustainable employment practices. The growing use of AI in recruitment, selection, and employee management has intensified concerns about algorithmic bias and discrimination. Although automated systems may reduce some forms of subjective human judgment, they can reproduce existing inequalities

when trained on historically biased data or designed around inappropriate performance criteria. Köchling and Wehner (2020) demonstrate that algorithmic decision-making in recruitment and employee development raises substantial concerns about discrimination and perceived unfairness. Similarly, research on AI applications across HRM functions highlights the expanding technological capabilities of workforce management alongside the need to examine their organizational and ethical implications (Votto et al., 2021). These concerns indicate that technological efficiency alone is an inadequate measure of successful digital HRM.

Algorithmic fairness presents an additional challenge because fairness cannot always be reduced to a single technical criterion. Different definitions and evaluation objectives may produce conflicting assessments of whether an algorithm treats individuals equitably (Mitchell et al., 2020). Furthermore, algorithmic management can reshape workplace relationships through automated monitoring, performance evaluation, and managerial control, affecting employee autonomy and organizational power structures (Benlian et al., 2022). Consequently, diversity, equity, and inclusion (DEI) should not be treated as separate organizational initiatives but as essential considerations in the design and governance of digital HRM systems. Fairness also requires attention to transparency, accountability, meaningful human oversight, and the circumstances of employees affected by automated decisions (Hunkenschroer & Luetge, 2022; Rigotti & Fosch-Villaronga, 2024). These issues become particularly important when digital HRM is examined through the perspective of sustainable human resource management. Organizational sustainability extends beyond financial and operational performance to encompass social and environmental considerations over time (Lu et al., 2022). Nevertheless, the relationship between algorithmic fairness, workplace inclusion, and sustainable HRM remains insufficiently integrated across the literature. Existing research has examined AI applications, algorithmic discrimination, and fairness principles, but important questions remain concerning how these dimensions interact and whether responsible digital HRM produces demonstrable improvements in employee well-being, equitable opportunities, and long-term workplace sustainability (Fabris et al., 2025).

To address this gap, this study systematically reviews conceptual and empirical literature at the intersection of digital HRM, DEI, algorithmic fairness, and sustainable workplaces. Following the PRISMA 2020 reporting framework (Page et al., 2021), the review examines how AI-enabled HRM creates opportunities and risks for workplace inclusion, identifies the mechanisms through which algorithmic systems may reproduce or mitigate inequality, and maps priorities for future research. By integrating technological, organizational, and ethical perspectives, this study positions fairness and inclusion as central dimensions of responsible digital HRM rather than secondary considerations. It contributes an integrated understanding of the conditions under which digital HRM may support inclusive and sustainable workplaces and identifies empirical gaps requiring further investigation.

II. Literature Review and Hypothesis Development

2.1. Framing the Field: Digital HRM, Inclusion and Algorithmic Fairness

a. The Significance of AI-Enabled People Management

Human resource management has changed radically over the past two decades under the combined pressure of market and technological forces, becoming more cross-functional and data-driven (Fenwick, Molnár, & Frangos, Revisiting the role of HR in the age of AI: bringing humans and machines closer together in the workplace, 2024). Artificial intelligence — understood broadly as "the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks" (Bujold et al., 2023) — has moved from the margins to the operational core of people management. Digitization within HRM has made AI increasingly prevalent in Human Resource Management Systems and HR Information Systems, with growth documented across recruitment, employee performance evaluation and satisfaction, compensation and benefit analysis, best practice analysis, discipline management, and employee training and development (Votto et al., 2021). The same diffusion is visible in adjacent managerial domains: online labour platforms alone have attracted over 180 million independent workers and freelancers in Europe and the United States, and the practices used

to orchestrate and control them foreshadow how algorithmic management may transform classical management and the future of work as a whole (Benlian, et al., Algorithmic Management, 2022, p. 825).

b. Core Concepts and Their Relationships

The literature on technology-mediated people management is terminologically heterogeneous, and the concepts it uses are frequently implicit and proliferating rather than clearly defined (Strohmeier, Digital human resource management: A conceptual clarification, 2020). This review therefore adopts an explicit working vocabulary.

Table 1. Core Concepts and Their Relationships

Concept	Working definition adopted in this review	Source
e-HRM	An umbrella term covering all possible integration mechanisms and contents between HRM and information technologies, aiming at creating value within and across organizations for targeted employees and management; it encompasses the content of e-HRM, its implementation, and the targeted employees and managers	(Bondarouk & Ruël, 2009)
Digital HRM	A conceptually clarified successor concept, developed through a terminology and typology that uncovers digital HRM as an evolutionary advancement of previous conceptualizations of technology-based HRM	(Strohmeier, Digital human resource management: A conceptual clarification, 2020)
AI in HRM	Technologies that mimic human intelligence (computer vision, natural language processing, machine learning, deep learning), defined here as the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks	(Bujold et al., 2023)
AI-augmented HRM	The current stage of maturity, in which "weak" AI provides solutions for delimited processes such as recruiting or selection and HR practitioners use algorithmic recommendations for decisions	(Böhmer & Schinnenburg, Critical exploration of AI-driven HRM to build up organizational capabilities, 2023, p. 1062)
Algorithmic management	The large-scale collection and use of data on a platform to develop and improve learning algorithms that carry out coordination and control functions traditionally performed by managers	(Benlian, et al., Algorithmic Management, 2022, p. 825)
Algorithmic fairness	A body of research attempting to define fairness quantitatively for decisions based on the predictions of statistical and machine learning models, characterized by inconsistent motivations, terminology and notation	(Mitchell et al., 2020)
DEI	Diversity, equity and inclusion initiatives whose positive workplace impact is documented in empirical work, alongside the historical movements that produced them and the resistance and backlash they have attracted	(Nitttrouer et al., 2024)
Sustainable HRM	The adoption of HRM strategies, policies and practices that enable the achievement of financial, social and ecological goals, with an impact inside and outside the organization and over a long-term time horizon	(Lu, Zhang, Yang, & Wang, Sustainable human resource management practices, employee resilience, and employee outcomes: Toward common good values, 2022, p. 333)

These concepts are nested rather than parallel. e-HRM supplies the foundational, technology-based precursor: it already extended HRM support beyond the HR department to line management and employees by the turn of the century (Bondarouk & Ruël, 2009). Digital HRM reframes that inheritance as an evolutionary advancement rather than a rupture (Strohmeier, Digital human resource management: A conceptual clarification, 2020). The research field's own disorder compounds the difficulty: the rapid growth of quantitative fairness research has produced wildly inconsistent motivations, terminology and notation, presenting a serious challenge for cataloguing and comparing definitions (Mitchell et al., 2020).

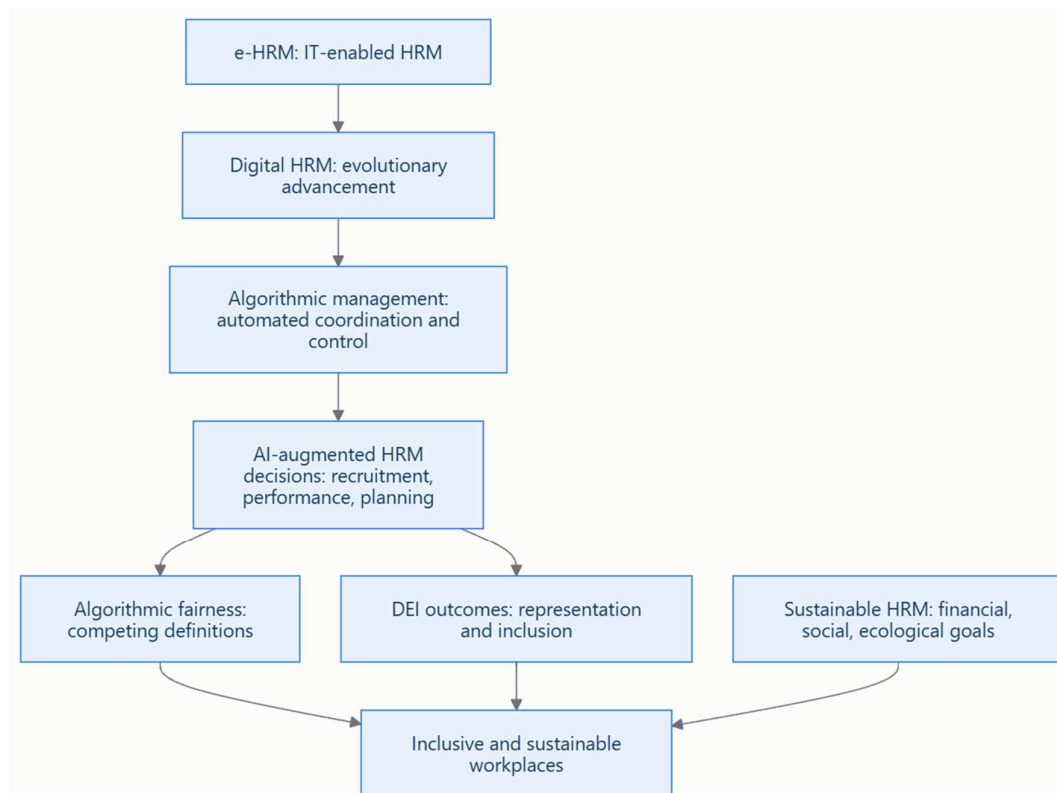


Figure 1. Conceptual Framework of Digital HRM, Algorithmic Fairness, DEI, and Sustainable Workplaces

c. Aim, Scope and Boundaries

This review synthesizes the empirical and conceptual literature at the intersection of digital HRM, DEI and algorithmic fairness. Its aim is to map how AI-enabled people management is theorized and studied in relation to inclusive and sustainable work, and to identify where evidence is thin or contradictory. Three boundaries delimit the scope. First, the review addresses applied, decision-support systems rather than speculative general intelligence: technological maturity has not reached "strong" AI, so the relevant object is weak AI applied to delimited HRM processes and the AI-augmented HRM arrangements it produces (Böhmer & Schinnenburg, Critical exploration of AI-driven HRM to build up organizational capabilities, 2023, p. 1062). Second, the review covers algorithmic management as it extends into standard work settings, not only platform-mediated gig work, because that is where its implications for power and social structures within organizations become salient (Jarrahi et al., 2021). Third, the review treats fairness as a contested, stakeholder-dependent construct rather than a settled technical criterion (Rigotti & Fosch-Villaronga, 2024), and it is deliberately balanced between the optimistic and pessimistic narratives that have constrained prior work on algorithmic hiring (Fabris et al., 2024).

d. Search and Selection Procedure

The review follows the PRISMA 2020 statement, which was designed to help systematic reviewers transparently report why the review was done, what the authors did, and what they found, and which updated the 2009 guideline in light of advances in systematic review methodology and terminology (Page et al., 2021).

Because the literature search is the underlying process that establishes the data available for analysis — and because search components in systematic reviews are often poorly reported — the search itself is documented in line with the PRISMA-S extension, whose final checklist comprises 16 reporting items, each detailed with exemplar reporting and rationale, so that every component of the search is completely reported and reproducible (Rethlefsen et al., 2021). The review retains a maximum of roughly thirty unique sources, prioritising works that define the field's core constructs, that report empirical evidence on AI in HRM, or that advance fairness and inclusion analysis. No sources beyond this set are introduced.

2.2. Conceptual and Empirical Foundations of Digital and Algorithmic HRM

a. Defining e-HRM and Its Conceptual Boundaries

The scholarly foundations of what is now called digital human resource management were laid in the literature on electronic HRM (e-HRM), and the definitions advanced there continue to anchor the field. The contrast is between a channel-based conception centred on web technology and a network-based conception centred on shared, multi-actor performance of HR activities.

Table 2. Defining e-HRM and Its Conceptual Boundaries

Definitional anchor	Core formulation	Distinctive emphasis
Bondarouk and Ruël	Umbrella term for all integration mechanisms and contents between HRM and IT, aiming at value creation for targeted employees and management (Bondarouk & Ruël, 2009)	Value creation; content, implementation, and target users as constituent aspects
Ruel, Bondarouk and Looise	Implementing HRM strategies, policies and practices through the conscious and directed support of web-technology-based channels (Marler & Fisher, 2012)	Web-technology channels
Strohmeier	Application of IT for networking and supporting at least two actors in their shared performing of HR activities (Marler & Fisher, 2012)	Networking and shared performance across actors

b. From e-HRM to AI-Augmented and AI-Driven HRM

The terminological succession linking HRM and information technology is itself a record of the field's evolution. Prikshat and colleagues catalogue the concepts scholars have coined — "web-based HRM," "e-HRM," "HRIS," "HRM cloud computing," "HR analytics," "Online HRM," "Digital HRM," "Smart HRM," and the ad-hoc and strategic use of artificial intelligence-enabled HRM applications — noting that research on the application of IT in HRM is rapidly increasing and that these labels have accumulated over time (Prikshat, Malik, & Budhwar, AI-augmented HRM: Antecedents, assimilation and multilevel consequences, 2021, p. 100860). The trajectory runs from administrative and web-delivered HRM through analytics and digital/smart HRM to AI-enabled applications, with each label signalling a change in the sophistication of the technology and in the ambition of its use.

c. Goals and Consequences: From Efficiency to Relational and Transformational Outcomes

The most systematic account of how the goals and consequences of technology-based HRM have shifted comes from Bondarouk, Parry and Furtmueller's review of four decades of research. Dividing the factors affecting adoption into technology, organization, and people — the "TOP" framework — they divide consequences into operational, relational, and transformational, and find a dual shift: in the goals for e-HRM, from efficiency to improved HR service provision and the strategic reorientation of HR departments, and in the type of consequences the literature focuses on, from operational effects to relational and then transformational outcomes (Bondarouk et al., 2016). This double movement — in intentions and in measured effects — is the central narrative of the field's maturation. Empirical work supports both the shift and its limits. Parry and Tyson's qualitative study of the goals organizations state for e-HRM and the outcomes they actually realize found evidence for each of the goals identified in the literature and added the goal and outcome of "organisational image"; efficiency and service-delivery goals were stated and achieved by most organizations, supporting previous work in the area, and service-delivery improvements were generally achieved, supporting improved effectiveness of the HR function as an outcome of e-HRM (Parry & Tyson, 2010). The

same study records an important qualification: interviewees suggested that older workers or those not familiar with the internet may not obtain the same benefits from e-HRM systems, and it is not clear whether this finding generalizes to other organizations (Parry & Tyson, 2010) — an early indication that the benefits of digital HRM are unevenly distributed across the workforce.

d. The Technology–Organization–People Framing of Adoption

The TOP framework is the most influential organizing device for adoption research in this literature. Bondarouk, Parry and Furtmueller derived it from their review of four decades of work, finding that the factors affecting the adoption of e-HRM can be divided into three areas — technology, organization, and people (Bondarouk et al., 2016). The pairing of a TOP-based antecedent structure with an operational–relational–transformational consequence typology shows that the two conceptual innovations of the e-HRM era have become the standard scaffolding for studying AI in HRM.

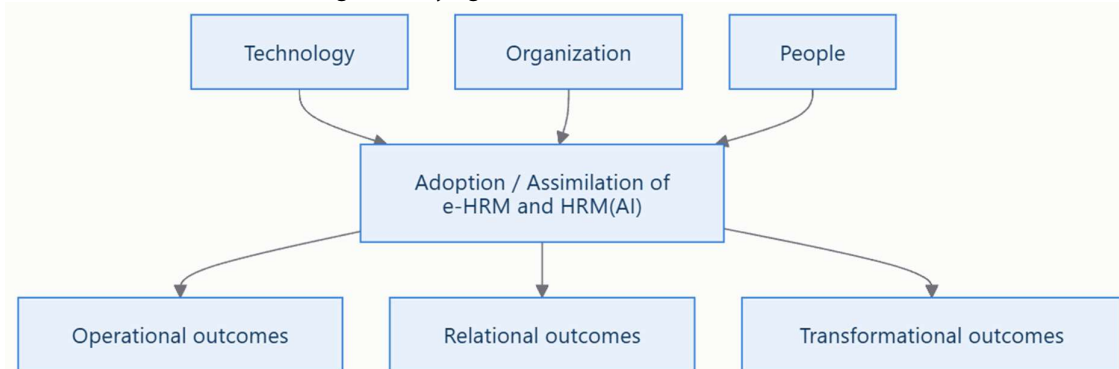


Figure 2. Technology–Organization–People (TOP) Framework for e-HRM and AI-Enabled HRM Adoption and Outcomes

2.3. Algorithmic Fairness, Bias, and Discrimination in Digital HR Decision-Making

a. The Objectivity Claim and Its Critics

The commercial case for algorithmic screening rests on a claim of superior consistency. Providers of recruitment algorithms promise that "when using an automated process, all candidates are screened against the same criteria consistently," and vendors of HR tools promise that algorithmic results are fairer and less biased than human judgment; most prominently, technology firms propose that algorithm-based HR decision-making is evidence-based, bias-free, and superior to human intuition (Leicht-Deobald et al., 2019). That promise has been directly challenged. Recent literature questions the objectivity of algorithms, and O'Neil — drawing on her own experience as a mathematician in finance — suggests that algorithms used for HR processes such as recruitment, evaluation, or performance appraisal remain impaired by racial and gender biases (Leicht-Deobald et al., 2019).

b. Where the Bias Enters

The literature converges on a structured account of bias origins rather than a single cause. Barocas and Selbst, as summarized by Simon, Wong and Rieder, describe four entry points: problem specification, where the definition of target variables rests on subjective choices that may systematically disadvantage certain populations; training data, where biased datasets lead to discriminatory models and harmful results; feature selection, where the reductive representation of real-world phenomena may result in inaccurate determinations and adverse effects; and proxy variables, where specific data points are highly correlated with class membership, facilitating disparate treatment and potentially implicating less favorable outcomes for members of disadvantaged groups (Simon et al., 2020).

Table 3. Bias Enters

Locus of bias	Mechanism	Illustrative evidence
Problem specification	Target variables defined through subjective choices that may systematically disadvantage populations	(Simon et al., 2020)

Training data	Models learn from historical records that encode past exclusion	Algorithms derived from information about current employees unintentionally discriminate when incumbents are not proportionately representative (Hunkenschroer & Luetge, 2022); an algorithm trained on historic employment data assumes women are less interested in management (Leicht-Deobald et al., 2019)
Feature selection	Reductive representation of real-world phenomena produces inaccurate determinations and adverse effects	(Simon et al., 2020)
Proxy variables	Data points correlated with class membership stand in for protected attributes	Zip code used as legitimate grounds for discriminating against a protected group (Hunkenschroer & Luetge, 2022); "regional labor market" as a proxy for historic socioeconomic disadvantage (Allhutter et al., 2020)
Designer and organizational assumptions	Designers' backgrounds and the exclusion of domain specialists from design	Homogeneity of the specialists creating AI systems (Yarger et al., 2019); biases unknowingly introduced through developers' background and upbringing (Spiekermann et al., 2022); HR algorithms designed without HR specialists and treated as beyond scrutiny (Vassilopoulou et al., 2022)
Optimization and delivery	Cost and relevance optimization skews who sees an opportunity	Gender-neutral STEM ad seen by fewer women due to crowding out (Lambrecht & Tucker, 2019); employment and housing ads skewed along gender and racial lines despite neutral targeting (Ali et al., 2019)

c. Biased and Unrepresentative Training Data

Training data is the most extensively documented mechanism. Machine-learning biases can stem from the data with which the algorithm was trained (Leicht-Deobald et al., 2019), and critics are concerned that algorithms derived from information about current employees will unintentionally discriminate against underrepresented groups if existing employees are not proportionately representative of the broader application pool, constituting a case of biased training data (Hunkenschroer & Luetge, 2022). The mechanism is illustrated with a hypothetical that reads as a description of routine practice: an algorithm trained on historic employment data would integrate that most managers are male, thereby assuming that women are less interested in management positions, and would consequently not show an employment advertisement for a management position via social media to women — the advertisement would in fact be invisible to women, who would have no opportunity to apply. In this case the recruitment algorithm actively reifies the original gender bias, based on the data with which it was trained (Leicht-Deobald et al., 2019). As these data may be biased according to an external reference point, the training has the great capacity to be faulty (Leicht-Deobald et al., 2019).

d. Designer Bias and the Social Production of Data

A second strand locates bias in the people and organizations that build systems. Yarger and colleagues emphasize that the potential for propagating inequity and harm is far more significant and widespread due to the homogeneity of the specialists creating artificial intelligence systems (Yarger et al., 2019). Information systems researchers make the complementary point that biased data is itself the result of real-world discrimination: it reflects how humans design organizational processes, and biases in algorithms may be unknowingly introduced through the developers' background and upbringing (Spiekermann et al., 2022). The organizational-design variant of this argument holds that biases become entrenched in HR algorithms precisely because those algorithms are often designed without consultation with HR specialists, are assumed to operate with scientific objectivity, and are viewed as instruments beyond scrutiny (Vassilopoulou et al., 2022). Spiekermann and colleagues summarize the cumulative evidence that the broad use of algorithms can lead to inferior treatment of already disadvantaged parts of society, contributing to societal tensions — a phenomenon frequently referred to as algorithmic discrimination — with reported examples including autonomous recruitment systems with a gender bias and jurisdictional decision support systems suffering from a racial bias (Spiekermann et al., 2022).

e. Proxy Variables and the Indirect Route to Disadvantage

Bias need not travel through a protected attribute at all. The discrimination occurring in algorithmic hiring may be direct or indirect via proxy attributes; in the latter case, a protected group is discriminated against but based on legitimate grounds, such as a zip code (Hunkenschroer & Luetge, 2022). The Austrian Public Employment Service profiling system offers a detailed empirical illustration. Its "regional labor market" variable models the situation of the labor market in a given office's region based on the calculated ratio of "new job seekers registered" to "job seekers taking up employment," which in practice carries the danger of becoming a proxy variable for historic socioeconomic disadvantages predominant in that region, implicitly representing a marginalized group associated with cumulative disadvantage, such as minority ethnic groups (Allhutter et al., 2020). A second implicit route is the separation of populations with incomplete data into three subpopulations: job seekers with an incomplete or "fragmented" employment history, those with a "migration background," and young adults (Allhutter et al., 2020). Proxy-variable bias is thus not an edge case but a structural feature of how employment data is assembled.

f. Optimization: Discrimination Without Discriminatory Intent

A distinct and empirically well-evidenced source of disparity lies in delivery optimization rather than in the scoring of candidates. In a field test of an algorithm delivering advertisements for STEM job opportunities, the ad was explicitly intended to be gender-neutral in its delivery, yet empirically fewer women saw the ad than men; this happened because younger women are a prized demographic and are more expensive to show ads to, so an algorithm that simply optimizes cost-effectiveness will deliver ads intended to be gender-neutral in an apparently discriminatory way, due to crowding out — a regularity the authors show extends to other major digital platforms (Lambrecht & Tucker, 2019). On Facebook, skewed delivery occurs due to market and financial optimization effects as well as the platform's own predictions about the "relevance" of ads to different groups of users; both the advertiser's budget and the content of the ad each significantly contribute to the skew, and significant skew is observed along gender and racial lines for real ads for employment and housing opportunities despite neutral targeting parameters (Ali et al., 2019). The implication drawn is that policymakers and platforms must consider the role of the ad delivery optimization run by platforms themselves, and not just the targeting choices of advertisers, in preventing discrimination in digital advertising (Ali et al., 2019). This is a mechanism in which no actor holds discriminatory intent and no protected attribute is used as an input, yet access to employment opportunity is unequally distributed.

Algorithmic human resource management (HRM) creates governance challenges because its decision-making processes may be opaque to employees, employers, developers, and regulators. Langer and König (2021) identify technical solutions, education and training, and regulation as complementary approaches to improving transparency. However, transparency may have both beneficial and adverse consequences, making a multi-stakeholder perspective essential. Effective governance therefore requires explainability, independent auditing, and enforceable regulation.

2.4. Governance, Explainability, Auditing and Regulation as Responses to Algorithmic HRM Risks

a. Explainability, Transparency and Contestability

Explainability and transparency are related but distinct. Explainable artificial intelligence (XAI) concerns how a model communicates its internal processes, whereas transparency concerns stakeholders' awareness and understanding of how the system operates (Bujold et al., 2023). Interpretable models and explanations of algorithmic decisions can help identify potential bias, although they do not guarantee fair outcomes (Hunkenschroer & Luetge, 2022). Explainability can also influence trust in AI-assisted recruitment. In an experiment involving 194 participants, Hofeditz et al. (2022) found that AI recommendations reduced discrimination against older and female candidates but could disadvantage foreign-race candidates. The effects of explainability varied by context, demonstrating that transparency alone cannot ensure equitable selection.

Counterfactual explanations offer another approach by showing how changing particular input characteristics could alter a decision (Verma et al., 2024). In algorithmic management, such explanations could help workers understand how performance ratings influence assignments or compensation (Benlian et al., 2022). However, explanations must identify changes that individuals can realistically make. Guidotti (2022) argues that recommendations based on uncontrollable characteristics, such as age, do not provide meaningful recourse. Ferrario and Loi (2022) further show that model retraining can invalidate previously actionable recommendations, limiting the reliability of algorithmic recourse over time. Contestability extends explanation beyond disclosure. Individuals affected by algorithmic decisions need sufficient information to

challenge both how a decision was made and why it was justified. Human oversight is insufficient when affected individuals cannot engage in meaningful dialogue with decision-makers (Alfrink et al., 2022). Explainability is also relevant to legal compliance, particularly for high-impact employment decisions subject to data-protection requirements (Henckaerts et al., 2022).

b. Auditing Approaches: Bias, Stability and Ethics-Based Audits

Auditing helps determine whether algorithmic systems meet their stated fairness and accountability commitments. Mökander and Floridi (2021) distinguish three principal approaches: functionality audits examine the rationale behind decisions, code audits inspect source code, and impact audits assess the consequences of algorithmic outputs. Credible auditing requires independence from routine management. Organizations may establish internal auditing teams, engage external specialists, and conduct random checks of recruitment recommendations (Hunkenschroer & Luetge, 2022). Automated tools can also support systematic auditing. Rhea et al. (2022) developed a stability audit to evaluate personality-prediction systems used in hiring. Their assessment of Humantic AI and Crystal found insufficient reliability across key measurement dimensions, highlighting the need for further evidence of validity before these systems are used in employment decisions.

Ethics-based auditing examines the normative values embedded in algorithmic systems. Nevertheless, its effectiveness is constrained by competing definitions of fairness, including individual fairness, demographic parity, and equality of opportunity, which may conflict with one another (Mökander et al., 2021). Auditing practices also face practical challenges. Interviews with 34 participants across seven countries revealed limited stakeholder participation, inconsistent success measures, inadequate external reporting, and resource and regulatory constraints (Schiff et al., 2024).

Table 4. Audit Approaches Relevant to Algorithmic HRM

Audit approach	Object of scrutiny	Source
Functionality audit	Rationale behind the decision	Mökander & Floridi (2021)
Code audit	Source code	Mökander & Floridi (2021)
Impact audit	Effects of algorithmic outputs	Mökander & Floridi (2021)
Bias audit	Potential discriminatory effects of automated employment decision tools	Mökander (2023)
Stability audit	Reliability of black-box personality-prediction algorithms	Rhea et al. (2022)
Ethics-based auditing	Normative values embedded in a system	Mökander & Floridi (2021)

c. Regulatory Frameworks: The EU AI Act and New York City Audit Law

Regulation provides enforceable requirements for algorithmic accountability. Yam and Skorburg (2021) discuss three frameworks: the European Union's General Data Protection Regulation (GDPR), the proposed US Algorithmic Accountability Act, and Canada's proposed Consumer Privacy Protection Act. These instruments address data protection, impact assessment, and the evaluation of algorithmic risks. Subnational initiatives have introduced additional requirements. California's Privacy Rights Act provides for risk assessments involving personal information, while Illinois' Artificial Intelligence Video Interview Act requires disclosure of AI use in video interviews and information about the characteristics used to evaluate candidates (Drage & Mackereth, 2022; Yam & Skorburg, 2021). The EU AI Act identifies certain employment and worker-management systems as high-risk because their decisions can affect career opportunities and livelihoods. These systems are subject to oversight and conformity requirements, while the Act also prohibits specified harmful AI practices (Álvarez et al., 2024; Rhea et al., 2022). New York City's Local Law 144 requires independent bias audits of covered automated employment decision tools before use and disclosure to job seekers. Compared with the EU's conformity-assessment approach, this law emphasizes periodic independent verification (Mökander, 2023; Rhea et al., 2022).

Table 2. Regulatory Instruments Bearing on Algorithmic HRM

Instrument	Jurisdiction	Core requirement	Source
GDPR	European Union	Data-protection impact assessment	Yam & Skorburg (2021)
Algorithmic Accountability Act (proposed)	United States	Assessment of accuracy, fairness, bias, discrimination, privacy, and security	Yam & Skorburg (2021)
Consumer Privacy Protection Act (proposed)	Canada	Privacy impact assessments	Yam & Skorburg (2021)
California Privacy Rights Act	California	Risk assessment of personal-information processing	Yam & Skorburg (2021)
Artificial Intelligence Video Interview Act	Illinois	Disclosure of AI-based video interviews and general evaluation characteristics	Drage & Mackereth (2022); Yam & Skorburg (2021)
Local Law 144	New York City	Independent bias auditing and disclosure to job seekers	Mökander (2023); Rhea et al. (2022)
AI Act	European Union	High-risk classification, conformity assessment, and prohibitions on specified harmful practices	Álvarez et al. (2024); Mökander (2023); Rhea et al. (2022)

d. Limitations of Current Ethics Tools and the Turn to External Verification

Ethical principles and voluntary self-assessment are insufficient without clear accountability mechanisms. Mittelstadt (2019) argues for enforceable requirements, transparent ethical review, documentation of models and datasets, and independent auditing. General principles should also be complemented by case-specific investigations of AI systems in practice. Similarly, Ayling and Chapman (2021) emphasize external verification, accessible mechanisms for contesting decisions, and accountability to stakeholders beyond system developers and purchasers. Malgieri and Pasquale (2023) caution that conformity assessments may leave some potentially harmful lower-risk systems outside stringent oversight. They also identify insufficient attention to fairness, privacy, power imbalances, nondiscrimination, and vulnerable groups. Overall, the literature indicates that explainability is necessary but insufficient, auditing should be independent and repeated, and regulation must address both technical risks and the experiences of affected individuals. Evidence also reveals persistent gaps concerning the practical effectiveness of governance measures. Future research should evaluate whether audits and regulatory requirements improve recruitment and workplace outcomes over time, particularly in relation to fairness, inclusion, and accountability.

2.5. Diversity, Equity and Inclusion in Inclusive Workplaces

a. Conceptual Foundations: From Diversity Climate to Inclusion Climate

Diversity climate refers to employees' perceptions that organizational practices are fair and support the social integration of all employees (McKay & Avery, 2015). However, diversity does not automatically improve organizational effectiveness. A meta-analysis of 109 independent samples from 94 studies found that diversity climate predicts employee attitudes and behaviors, with stronger associations for inclusion climate and attitudinal outcomes. These relationships also depend on demographic diversity, climate strength, and measurement methods (Holmes et al., 2020). Drawing on optimal distinctiveness theory, inclusion requires satisfying employees' needs for both belongingness and uniqueness (Shore et al., 2010). An inclusion climate therefore extends beyond diversity representation by ensuring that employees feel valued, respected, empowered, and encouraged to contribute (Guillaume et al., 2013). Fair treatment, interpersonal integration, and the consideration of diverse perspectives can strengthen employee satisfaction and retention (Guillaume et al., 2013).

Table 5. Core Concepts of Diversity and Inclusion

Construct	Core definition	Key reference
Diversity climate	Employees view the organization as using fair personnel practices and socially integrating all personnel	(McKay & Avery, 2015)

Inclusion climate	Broader than diversity climate; dissimilar employees feel valued, respected and empowered	(Guillaume et al., 2013)
Employee inclusion	Satisfaction of needs for both belongingness and uniqueness	(Shore et al., 2010)
Diversity climate (meta-analytic)	Predicts attitudes/behaviors; moderated by climate measure, outcome type, demographic diversity, climate strength, source	(Holmes et al., 2020)

b. Diversity and Inclusion Initiatives and Organizational Outcomes

Diversity and inclusion initiatives may support innovation, decision-making, engagement, and employee satisfaction, particularly when leadership commitment and accountability are strong (Okatta et al., 2024; Stamarski & Hing, 2015). Nevertheless, diversity does not guarantee better performance. A meta-analysis covering 615 reports and 2,638 effect sizes found that the average relationship between demographic, job-related, and cognitive diversity and team performance was positive but small ($|r| < .1$). Benefits were more evident in complex, creative, and innovation-oriented tasks (Wallrich et al., 2024). Evidence concerning financial performance is also mixed. Carter et al. (2010) found no significant relationship between board diversity and financial performance measured by return on assets and Tobin's Q. Conversely, Foster et al. (2022) found that corporate equality ratings and ESG scores were associated with higher Tobin's Q, with evidence suggesting that diversity initiatives preceded improved market performance. These findings indicate that outcomes depend on how diversity is measured, the organizational context, and the performance indicators used.

c. Leadership Commitment and the Institutionalization of Inclusion

Leadership commitment is essential to effective inclusion initiatives. Leaders influence whether HR policies are implemented consistently and whether organizational structures and practices support diversity (Stamarski & Hing, 2015). Inclusion is more likely to become institutionalized when leadership role modelling, organizational rewards, and shared goals reinforce inclusive behavior (Boekhorst, 2014). Leadership must therefore translate inclusion principles into everyday organizational practices rather than relying on formal statements alone.

d. Intersectionality: Multiple Identities and Distinct Experiences of Marginalization

Intersectionality is defined as the intertwined and multiplicative effects of multiple identity groups, considering how various combinations of individuals' social identities (for example gender, race/ethnicity, age) and their embedded meanings impact their lives, their employment, and the organizations where they work (Thatcher et al., 2023). A review synthesizing findings from 153 articles examines how different levels of power perpetuate, amplify, or attenuate experiences associated with intersectionality, providing insight into which identity combinations have been studied, the outcomes associated with intersectionality experiences, and the variety of organizational and individual responses that occur when intersectionality is experienced (Thatcher et al., 2023). The multilevel power lens highlights intersectionality trends relevant for DEI research and practice alike, with identity representation, contextual and analytical considerations, and theoretical extensions identified as fruitful avenues for future research (Thatcher et al., 2023).

e. Double Jeopardy Versus Intersectional Invisibility

Intersectionality examines how multiple social identities, such as gender, race, and age, interact with organizational power and shape employment experiences (Thatcher et al., 2023). Two perspectives are particularly relevant. The double-jeopardy perspective suggests that multiple marginalized identities may compound disadvantage, whereas intersectional invisibility explains how people whose identities do not fit conventional group prototypes may be overlooked or insufficiently recognized (Chrobot-Mason et al., 2018). Research on 59 Black women in senior organizational positions illustrates how intersectional invisibility can create both opportunities and constraints, requiring strategies to establish professional credibility and visibility (Smith et al., 2019). These findings show why experiences of marginalized groups should not be inferred from research examining gender or race independently.

f. Inclusive Leadership Behaviors and Their Outcomes

A systematic review of 107 papers identifies four dimensions of inclusive leadership: fostering employee uniqueness, strengthening belongingness, appreciating employee contributions, and supporting organizational inclusion efforts (Korkmaz et al., 2022). However, the integrated model requires further

empirical testing. Psychological safety is an important mechanism connecting inclusive leadership with employee outcomes. Studies indicate that inclusive leadership, characterized by openness, accessibility, and availability, supports psychological safety and employee creativity (Carmeli et al., 2010). Evidence from 356 employees across 90 teams further shows that psychological safety mediates the relationship between inclusive leadership and innovative performance at individual and team levels (Li & Tang, 2022). Supportive team climates may also strengthen employee resilience by reducing identity-related bias and improving perceptions of belonging (Li & Peng, 2023).

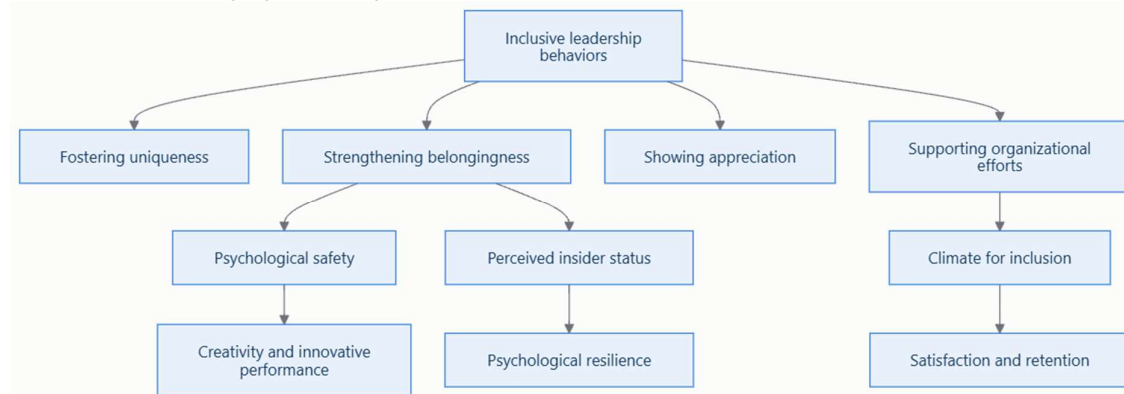


Figure 3. Inclusive Leadership Behaviors and Their Employee and Organizational Outcomes

g. Synthesis and Gaps

Three conclusions follow from this body of work. First, the field has converged on a two-dimensional conception of inclusion — belongingness and uniqueness (Shore et al., 2010) — that is conceptually broader than diversity climate and empirically more strongly related to attitudinal outcomes (Guillaume et al., 2013; Holmes et al., 2020). Second, inclusive leadership has a reasonably well-specified behavioral repertoire of four dimensions (Korkmaz et al., 2022) with replicated mediation through psychological safety for creativity and innovative performance at individual and team levels (Carmeli et al., 2010; Li & Tang, 2022), and emerging evidence for resilience via insider status and supportive climate (Li & Peng, 2023). Third, the outcome case for diversity itself is conditional: effects on team performance are positive but insubstantial on average and emerge mainly for complex, creativity-demanding tasks in lower-collectivism, lower-power-distance contexts (Wallrich et al., 2024), and financial-performance findings diverge depending on the diversity measure and outcome used (Carter et al., 2010; Foster et al., 2022). Several gaps are visible in the sources reviewed here. The inclusive leadership review explicitly calls for empirical testing of its multi-level model and for assessment of predictive value on employee and organizational outcomes (Korkmaz et al., 2022), indicating that the four-dimension framework remains largely untested as an integrated model. The research on inclusive leadership and resilience similarly notes the absence of prior work testing the role of supportive organizational climate in that process (Li & Peng, 2023). The intersectionality review identifies identity representation and contextual and analytical considerations as areas requiring further development (Thatcher et al., 2023), and the qualitative work on executive Black women shows how much of the intersectional experience is accessible only through longitudinal, in-depth methods (Smith et al., 2019). What the reviewed literature does not provide is direct evidence on how digital HR systems, algorithmic decision tools, or technology-mediated work arrangements shape these DEI processes; the constructs of diversity climate, inclusion climate, inclusive leadership and intersectionality are theorized and measured largely in conventional organizational settings, leaving the digital mediation of inclusion an open empirical question rather than a settled finding.

2.6. Sustainable HRM, Employee Wellbeing and the Algorithmic Management of Work

a. Sustainable and Green HRM: Conceptual Foundations

Sustainable human resource management (SHRM) connects people management with economic, social, and environmental sustainability. Socially responsible HRM seeks to create social value, although its practices may remain primarily directed toward organizational benefits, such as reputation, risk reduction, and profitability. Green HRM focuses more directly on environmental outcomes through practices such as green recruitment, environmental training, and green rewards (Lu et al., 2022). Green HRM also includes green performance management, compensation, and goal setting. These practices can improve resource efficiency,

reduce costs, and encourage environmentally responsible employee behavior (Gyensare et al., 2023). The social dimension of sustainable HRM additionally encompasses employee well-being, job security, and organizational justice, including fair decisions, allocation processes, information, and interpersonal treatment (Stahl et al., 2019).

Table 6. Sustainable HRM Approaches and Their Main

SHRM strand	Primary value created	Illustrative practices	Dominant logic
Socially responsible HRM	Social value (e.g. organisational social reputation)	Awareness-raising of business influence on employees, customers and suppliers	Economic objective remains underlying; subsumed for economic purposes (Lu, Zhang, Yang, & Wang, Sustainable human resource management practices, employee resilience, and employee outcomes: Toward common good values, 2022, p. 333)
Green HRM	Ecological value	Green recruitment (virtual interviews), green awareness training, green rewards (car-pooling, electronic filing); green performance management, green reward and compensation, green goal setting (Lu, Zhang, Yang, & Wang, Sustainable human resource management practices, employee resilience, and employee outcomes: Toward common good values, 2022; Gyensare, Adomako, & Amankwah-Amoah, Green HRM practices, employee well-being, and sustainable work behavior: Examining the moderating role of resource commitment, 2023, p. 333)	Economic and environmental outcomes (Lu, Zhang, Yang, & Wang, Sustainable human resource management practices, employee resilience, and employee outcomes: Toward common good values, 2022, p. 333)

b. Sustainable HRM and Employee Wellbeing: The Evidence Base

Empirical evidence suggests that sustainable HRM can support both employee well-being and organizational performance. A multilevel study in China found that sustainable HRM practices positively influenced employee resilience and work engagement, while resilience indirectly contributed to performance through engagement (Lu et al., 2022). A systematic review of 30 studies published between 2008 and 2022 also associated sustainable workplace practices with improved employee well-being, reduced pollution, and organizational viability (Madero et al., 2023). However, SHRM remains largely employer-driven, often prioritizing productivity. An employee-centred approach would give greater consideration to worker voice, trade unions, and self-organized employees (Richards, 2020). This perspective is particularly relevant when digital systems influence working conditions and managerial decisions.

c. The Human-Centred HRM Agenda for Sustainable Workforces

A human-centred approach places employees and broader social outcomes at the centre of sustainable HRM (Cooke et al., 2022). Digitalization and remote work do not affect all workers equally; their benefits and costs may differ according to socioeconomic circumstances and employment conditions. Research should therefore examine how digital technologies reshape workplace power, access, and exclusion, rather than assuming that technological adoption automatically supports sustainability (Cooke et al., 2022).

d. Algorithmic Management: Definition and Mechanisms of Control

Algorithmic management refers to software algorithms that perform managerial functions alongside the institutional arrangements supporting their use (Noponen et al., 2023). It is increasingly used in platform work and conventional employment to monitor performance, allocate tasks, and automate decisions. Its main characteristics include continuous behavioral tracking, performance evaluation, automatic decision implementation, system-mediated interaction, and limited transparency (Félix et al., 2023). Kellogg et al. (2019) identify six mechanisms, known as the **6 Rs**, through which algorithms direct, evaluate, and discipline workers: restricting, recommending, recording, rating, replacing, and rewarding. These mechanisms can increase managerial control while also generating opportunities for workers to adapt to or resist algorithmic systems.

e. Job Autonomy and the Autonomy Paradox

Algorithmic management presents an autonomy paradox. Digital platforms may provide scheduling flexibility while simultaneously increasing surveillance and managerial control (Benlian et al., 2022). Similar concerns arise outside platform work, including among truck drivers and bank employees whose discretion may be reduced by monitoring and algorithmic decision tools (Noponen et al., 2023). Evidence from 21,869 European organizations indicates that algorithmic management affects workplace well-being partly through reduced job autonomy and changes in total rewards (Kinowska & Sienkiewicz, 2022). In gig work, intensive monitoring and algorithmic control may also increase stress and undermine the balance between worker discretion and organizational supervision (Lang et al., 2023).

f. Well-Being, Psychological Needs and Dehumanization

Algorithmic management can affect autonomy, relatedness, motivation, and workplace relationships. Continuous system instructions, performance rankings, and communication monitoring may generate helplessness, competition, and reduced interpersonal connection (Benlian et al., 2022). Five preregistered studies involving 3,153 participants found that algorithmic rather than human management reduced prosocial motivation through increased objectification of employees (Granulo et al., 2023). Although algorithmic systems may improve efficiency and data-driven decision-making, they also raise concerns about fairness, accountability, opacity, anxiety, and the loss of empathy in people management (Kinowska & Sienkiewicz, 2022). People analytics can further reduce complex employee performance to numerical indicators, while monitoring technologies may undermine privacy, autonomy, satisfaction, and access to development opportunities (Giermendl et al., 2021; Tursunbayeva et al., 2021).

g. Gig Work, Worker Voice and Collective Organizing

Gig work exposes tensions between flexibility and employment insecurity. While platform work can provide income and scheduling options, algorithmic control may weaken worker security, voice, and collective power (Félix et al., 2023). Workers nevertheless develop individual and collective responses, including algorithmic activism, digital tools for protecting workers, union organizing, and worker-owned platforms (Kellogg et al., 2019; Burrell & Fourcade, 2021). Collective bargaining can also support responsible AI implementation. A case involving H&M workers represented by the German union ver.di showed that worker representation helped delay the introduction of technology pending negotiations over risk mitigation (Cole et al., 2022). Such examples demonstrate that worker participation can influence how algorithmic systems are introduced and governed.

h. Inclusive Design: Neurodivergent and Disabled Workers

Digital inclusion must account for employees whose employment opportunities are already constrained. Research using a UK sample of more than 25,000 people found that neurodivergent individuals were more likely to experience precarious and temporary employment, underemployment, and shorter job tenure (Branicki et al., 2024). A review of workplace neurodiversity also identified limited integration between neurodiversity research and human capital management (Rollnik-Sadowska & Grabińska, 2024). For disabled gig workers, platforms can offer access to income while introducing new challenges related to algorithmic control, performance evaluation, accessibility, and discrimination. Interviews with 24 disabled gig workers highlighted the need for platform designs that improve task accessibility and reduce discriminatory interactions (Sannon & Cosley, 2022). These findings connect inclusive design directly to sustainable HRM.

i. Synthesis and Research Gaps

The literature links sustainable HRM with employee resilience, engagement, well-being, and environmental responsibility. However, employee-centred approaches remain underdeveloped, and the evidence comes from a limited number of empirical contexts (Lu et al., 2022; Madero et al., 2023; Richards, 2020). Algorithmic management research identifies pathways through which digital control affects autonomy, rewards, psychological needs, and well-being (Benlian et al., 2022; Kinowska & Sienkiewicz, 2022). Workers also respond through activism and collective organizing (Burrell & Fourcade, 2021; Cole et al., 2022). Yet evidence on algorithmic management outside platform work remains limited, while research connecting inclusive design with algorithmic management is still emerging. Future studies should examine sustainable HRM, worker voice, and inclusive algorithmic design as interconnected issues.

2.7. Synthesis: Convergent Findings, Persistent Tensions, and a Research Agenda

The literature broadly agrees that algorithmic technologies are reshaping HRM activities, work structures, and workforce management, while algorithmic bias can reinforce existing inequalities (Kim et al., 2024; Kordzadeh & Ghasemaghahi, 2021). However, scholars disagree about whether algorithmic HRM primarily reduces or reproduces exclusion and whether technical or organizational interventions are the most effective responses.

a. The Optimistic–Critical Divide Over Algorithmic HRM

The optimistic perspective argues that AI-supported recruitment can reduce subjective human bias, accelerate screening, lower costs, and improve candidate experience (Chen, 2023). A review of 17 screening studies reported that algorithms performed better than human decision-making in identifying above-average employees under high-volume screening conditions. Interviews with HR professionals also suggested that AI could reduce opportunities for bias and improve recruitment diversity (Hofeditz et al., 2022). The critical perspective warns that algorithms can reproduce systematic bias and make organizations more homogeneous. Systems that inadequately account for language and cultural differences may disadvantage particular racial or ethnic groups (Hunkenschroer & Luetge, 2022). Algorithmic management can also create information and power asymmetries when employers can monitor workers extensively while workers have limited knowledge of how systems operate (Noponen et al., 2023). These perspectives are not necessarily contradictory. Algorithmic systems may simultaneously enable and constrain worker autonomy, depending on their design, implementation, and use (Meijerink & Bondarouk, 2021). Research must therefore examine the conditions under which the benefits and harms of algorithmic HRM emerge. Existing theoretical assumptions that prioritize algorithms as independent agents or management as economic control may also obscure questions of inclusion and sustainability (Lamers et al., 2024).

Table 7. Competing Perspectives on Algorithmic HRM

Dimension	Optimistic account	Critical account
Bias in selection	AI may reduce subjective human bias and improve screening (Chen, 2023; Hofeditz et al., 2022)	Systematic algorithmic bias may increase homogeneity and reduce workforce diversity (Hunkenschroer & Luetge, 2022)
Worker experience	Greater efficiency, improved candidate experience, and lower costs (Chen, 2023)	One-way transparency and increased information and power asymmetries (Noponen et al., 2023)
Reconciliatory position	Algorithms can support autonomy and value creation	Algorithms can also restrict autonomy; outcomes depend on design and use (Meijerink & Bondarouk, 2021)

b. Technical Versus Managerial Responses to Bias

Technical responses include fairness assessment tools, bias mitigation methods, and algorithmic auditing. However, their effectiveness may be limited by computational constraints and differences between legal jurisdictions (Hunkenschroer & Luetge, 2022). Organizational responses emphasize HR professionals' collaboration with data scientists, control over training data, clear human responsibility, and context-sensitive auditing (Köchling et al., 2020). Governance must also extend beyond organizational self-regulation. External oversight, third-party testing, and regulatory requirements can strengthen transparency and accountability (Chen, 2023). Risk-management frameworks should address organizational structures, leadership,

documentation, compliance, and monitoring in addition to model-level risks (Daniel et al., 2025). An unresolved question is whether technical, managerial, and regulatory mechanisms reinforce one another or substitute for one another under cost pressures.

c. Gaps in the Literature

1) Intersectionality Remains Marginal in Digital HRM

Fairness assessments based on a single attribute may overlook discrimination affecting groups defined by intersecting identities. A system can appear fair across gender and race separately while disadvantaging a subgroup such as Black women (Yang et al., 2021). Existing approaches also face limitations involving small intersectional groups, incomplete representation, and restricted implementation of multi-attribute fairness measures (Lett & Cava, 2023). Intersectional fairness methods have been proposed, but recruitment research still insufficiently incorporates the perspectives of marginalized communities (Roche et al., 2022; Drage & Mackereth, 2022).

2) The Disconnect Between Fairness Principles and Practice

Ethical principles do not automatically produce changes in system design or organizational behavior. Abstract guidelines often provide limited practical guidance, while voluntary commitments may create an appearance of responsibility without substantive change, a problem described as *ethics washing* (Morley et al., 2019; Munn, 2022). Empirical research on AI responsibility in HRM remains limited, particularly in real-world settings examining fairness perceptions, trust, and actual decision outcomes (Bujold et al., 2023; Kordzadeh & Ghasemaghahi, 2021).

3) Algorithmic Fairness and Sustainability: An Underexplored Link

Evidence suggests that digitalization may support organizational sustainability, including environmental efficiency and workplace inclusion, but existing findings are limited and context-specific (Kuzior et al., 2021). More broadly, AI may contribute to sustainable development while also increasing inequality when access to data and technological resources is uneven (Vinuesa et al., 2020). Research has yet to establish empirically whether fairer algorithmic HRM improves decent-work outcomes, reduces inequality, or strengthens social and environmental sustainability.

4) A Future Research Agenda

- a) Methodological priorities. Future studies should clearly define the AI systems and responsibility principles under investigation, provide detailed descriptions of algorithms, and combine technical and HRM expertise. Research should move beyond hypothetical scenarios toward real-world and longitudinal evaluations, including the role of human oversight, employee autonomy, and accountability (Bujold et al., 2023).
- b) Theoretical reframing. Research should move from single-axis to intersectional fairness assessments and examine how algorithmic systems interact with organizational power and worker agency (Roche et al., 2022; Yang et al., 2021; Lett & Cava, 2023). The duality perspective on algorithmic management and the distinction between technology as a tool, proxy, and ensemble offer ways to examine how outcomes are shaped by design, human action, and institutional context (Meijerink & Bondarouk, 2021; Kim et al., 2024). Further work should also test the mechanisms linking algorithmic bias to fairness perceptions and technology-related behavior (Kordzadeh & Ghasemaghahi, 2021).
- c) Governance and policy. Research should evaluate whether risk audits, third-party certification, and external oversight improve actual HRM outcomes. It should also examine how audit documentation, role-based accountability, and integration with existing governance systems support compliance with frameworks such as the EU AI Act and ISO 42001:2023 (Daniel et al., 2025; Chen, 2023). Workforce diversity among AI developers is another relevant concern because the perspectives represented in system design can influence the risks and biases embedded in algorithms (Chen, 2023).

d. Implications for Practice and Policy

For organizations, three priorities emerge. First, assign clear human responsibility for algorithmic decisions, including data quality, system implementation, and regular auditing (Köchling et al., 2020). Second, strengthen HR professionals' algorithmic literacy through collaboration with data scientists so that decision

criteria and outcomes can be meaningfully explained (Bujold et al., 2023; Köchling et al., 2020). Third, make worker participation part of system design and implementation, including consultation about working conditions, autonomy, and the potential for discrimination (Graziani et al., 2022). For policymakers, voluntary commitments should be complemented by enforceable oversight, independent testing, and effective mechanisms for contesting harmful decisions (Chen, 2023). Organizational governance must address leadership, documentation, and internal decision-making, rather than focusing exclusively on technical model performance (Daniel et al., 2025). Closing the gap between ethical principles and practice requires practical implementation resources and accountability mechanisms that prevent ethics commitments from becoming merely symbolic (Morley et al., 2019; Munn, 2022).

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