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Organizational Blindness in AI-Based Human Resource Management: A Conceptual Framework from a Feminist Data Ethics Perspective

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Abstract

Background. Artificial intelligence (AI)-based decision mechanisms are increasingly assuming a central role in human resource management (HRM) processes under often unquestioned claims of efficiency and neutrality. Existing approaches treat algorithmic bias as a system-specific property, overlooking the organizational-level mechanism (organizational blindness) that leads to the exclusion of certain contributions before any algorithm is even built.

Aim. This study examines how organizational blindness toward care, emotional, and relational labor becomes institutionalized through AI-based HRM, distinguishing it from algorithmic bias, organizational myopia, and invisible work.

Method. Using a conceptual development approach, the study synthesizes feminist labor theory, feminist data ethics, and organizational-blindness research with algorithmic management and AI-based HRM literature to build a stage-based conceptual model with explicit propositions. No empirical data were collected.

Findings. Organizational blindness is conceptualized as a six-stage, self-reinforcing cycle spanning performance definitions, datafication choices, AI-HRM decision rules, and resulting HRM decisions that institutionalize the exclusion of care and relational labor across HRM functions.

Conclusion. Feminist data ethics, translated into governance mechanisms, impact assessment, disparate-capture auditing, human oversight, and participatory redefinition of performance, offers a route for interrupting this cycle and establishes testable propositions for future research on AI, organizational blindness, and gender equity in HRM.

Keywords: Feminist Data Ethics, Algorithmic Management, Organizational Blindness, Artificial Intelligence, HRM.

Yapay Zeka Tabanlı İnsan Kaynakları Yönetiminde Örgütsel Körlük: Feminist Veri Etiği Perspektifinden Kavramsal Bir Çerçeve

Öz

Arka plan. Yapay zeka temelli karar mekanizmaları, verimlilik ve tarafsızlık iddialarıyla İKY süreçlerinde giderek merkezi bir rol üstlenmektedir. Mevcut yaklaşımlar algoritmik yanlılığı sistemlere özgü bir özellik olarak ele almakta; herhangi bir algoritma kurulmadan önce belirli katkıların dışlanmasını sağlayan örgütsel düzeydeki mekanizmayı (örgütsel körlük) göz ardı etmektedir.

Amaç. Bu çalışma, bakım, duygusal ve ilişkisel emeğe yönelik örgütsel körlüğün yapay zeka temelli İKY uygulamalarıyla nasıl kurumsallaştığını; bunu algoritmik yanlılıktan, örgütsel miyopiden ve görünmez emekten ayırt ederek incelemektedir.

Yöntem. Kavramsal geliştirme yaklaşımını benimseyen çalışma; feminist emek kuramını, feminist veri etiğini ve örgütsel körlük yazınını, algoritmik yönetim ve yapay zeka temelli İKY literatürüyle sentezleyerek, açık önermeler içeren aşamalı bir model inşa etmektedir. Ampirik veri toplanmamıştır.

Bulgular. Örgütsel körlük; performans tanımları, datafikasyon tercihleri, yapay zeka-İKY karar kuralları ve İKY kararlarından oluşan, kendini pekiştiren altı aşamalı bir döngü olarak kavramsallaştırılmakta; bu döngü bakım ve ilişkisel emeğin İKY işlevlerinde dışlanmasını kurumsallaştırmaktadır.

Sonuç. Yönetişim mekanizmalarına -etki değerlendirmesi, asimetrik veri yakalama denetimi, insan gözetimi ve performansın katılımcı yeniden tanımlanması- dönüştürülen feminist veri etiği, bu döngüyü kesintiye uğratma yolu sunmakta; yapay zeka, örgütsel körlük ve İKY'de toplumsal cinsiyet eşitliği için gelecek araştırmalara sınanabilir önermeler ortaya koymaktadır.

Anahtar Kelimeler: Feminist Veri Etiği, Algoritmik Yönetim, Örgütsel Körlük, Yapay Zeka, İKY.

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1. Introduction

In recent years, artificial intelligence (AI)-based automation technologies have gained an increasingly central position in organizations' management and human resource practices. Algorithmic systems used in core human resource management (HRM) processes such as performance evaluation, recruitment, promotion, job design, and workforce planning are largely legitimized through claims of efficiency, objectivity, and freedom from bias (Basu et al., 2023; França et al., 2023). However, alongside the technical restructuring of work processes, this technological transformation also brings about the construction of a new and often implicit normative framework regarding which forms of labor are considered valuable within organizations (Khan et al., 2025).

The critical management and feminist organization studies literature has long discussed how value is defined in organizations, which forms of labor are deemed visible and rewardable, and how these processes are intertwined with gender regimes (Altan-Olcay & Bergeron, 2024). A common emphasis in this literature is that modern organizations are built upon structural assumptions that take male experience as the norm (Bell et al., 2020).

In this context, care labor, emotional labor, relational coordination, and the invisible activities that sustain organizational ties are systematically positioned as secondary or peripheral activities (Anderson, 2023). These forms of labor are routinely excluded from organizational performance regimes not because they resist quantification, but because prevailing definitions of performance were never built to register them as data-worthy, and they are largely undertaken by women employees (Malhotra, 2022).

It is often assumed that the incorporation of AI and automation technologies into the organizational context will, in itself, eliminate these historical inequalities. On the contrary, critical algorithm studies and data feminism scholarship demonstrate that technology is not independent of its social context. It has been observed that technology reproduces existing power relations, norms, and biases at the level of code and data (Lau, 2025). The prevailing discourse that algorithms are neutral can be regarded as a contemporary manifestation of the male-centered modes of knowledge production that feminist epistemology has long criticized (Weinberg, 2022). In this respect, AI functions not merely as a technical tool but also as a valuation mechanism that privileges certain types of knowledge and forms of labor (Sciannamblo, 2024). From an organizational standpoint, one of the most notable effects of AI-based automation is that it places the logic of measurability at the center of management practices (Basu et al., 2023). Algorithmic systems operate, by their very nature, on inputs that can be quantified, standardized, and compared (Boussoussa & Ali, 2025). This leads to the systematic exclusion of context-sensitive, process-oriented, and relational forms of labor such as care and emotional labor. The devaluation of care labor, long emphasized in the feminist literature, is taking on a new dimension in the age of AI. Invisibility is no longer merely a cultural or organizational preference but is becoming an algorithmic outcome (Malhotra, 2022). This argument, however, risks repeating positions already well established in adjacent literatures.

Data feminism and critical algorithm studies have shown in detail how algorithmic systems encode historical power relations and produce discriminatory outcomes (D'Ignazio & Klein, 2020; Noble, 2018), and the sociology of work has long documented how certain forms of labor remain invisible to formal accounting systems regardless of the technology involved (Star & Strauss, 1999). Recent HRM-specific work has likewise identified algorithmic bias as a strategic and ethical problem for

organizations (Bandara et al., 2025) and has proposed a feminist data ethics of care for machine learning in general terms (Gray & Witt, 2021). The present study does not restate these positions; it departs from them at three specific points. First, it separates organizational blindness from algorithmic bias as distinct constructs operating at different levels—the former concerning which categories of contribution are specified as data-worthy in the first place, the latter concerning how fairly a system treats the categories it already includes. Second, it specifies the mechanism by which this blindness becomes institutionalized as a six-stage, self-reinforcing cycle specific to AI-HRM processes, rather than treating the technological reproduction of inequality as a general, undifferentiated claim (developed as a conceptual model in Section 2.7). Third, it distinguishes two parallel and potentially co-occurring failure modes—algorithmic invisibility and algorithmic hypervisibility—that existing accounts of algorithmic bias do not differentiate, and that carry different implications for intervention. The research gap this study addresses, accordingly, is not whether AI-based HRM can reproduce gender inequality, which prior literature has already established, but how organizational blindness toward care, emotional, and relational labor becomes specifically and cumulatively institutionalized across the sequence of HRM data and decision practices, and through which distinguishable mechanisms this occurs.

At this point, human resource management plays a critical role. HRM performs a central function in organizations in determining job descriptions, competency frameworks, performance metrics, and career paths (Vrontis et al., 2022). The integration of AI-based systems into HRM processes renders visible not only this unit's technical decisions but also its normative assumptions (Khan et al., 2025). Yet the existing literature largely approaches HRM's role in this transformation process from the perspectives of efficiency, strategic alignment, or digitalization, treating gender-based effects as a secondary matter (Akter, 2025). When evaluated from a feminist perspective, this very approach itself produces a form of organizational blindness.

Organizational blindness refers to the systematic failure or refusal of organizational actors to see certain facts, relationships, or problems (Seymen et al., 2016). The exclusion of care and emotional labor in AI-based automation processes can be conceptualized not as a lack of individual awareness but as an institutionalized form of organizational blindness (Porter et al., 2025). This blindness, reproduced through HRM policies and algorithmic designs, leads to the further marginalization of women's labor within the organizational value hierarchy. This concept is defined more precisely, and distinguished from algorithmic bias, organizational myopia, invisible work, and gendered organizational processes, in Section 2.1.

Within this framework, the study is positioned less around the general question of how AI and automation are transforming women's labor in organizations, and more around the specific question of how organizational blindness toward care and emotional labor becomes institutionalized through AI-based HRM practices, and which mechanisms distinguish this process from algorithmic bias considered in isolation. Accordingly, the following theoretical questions are addressed: (1) How does organizational blindness, as distinct from algorithmic bias and organizational myopia, operate within AI-based HRM processes? (2) Through which stage-specific mechanisms—spanning the definition of performance, data representation, and algorithmic decision rules—do HRM's measurability-oriented approaches institutionalize gender-based labor inequalities? (3) How can algorithmic invisibility and algorithmic hypervisibility be conceptually distinguished as parallel outcomes of this process, and what are their respective implications for feminist data ethics interventions in HRM?

The aim of the study is to theoretically analyze how organizational blindness toward care and emotional labor becomes institutionalized in AI-based human resource management, developing feminist labor theory and the concept of organizational blindness into an explicit conceptual model with testable theoretical propositions. Rather than presenting an empirical investigation, the article critically synthesizes the existing international literature—while explicitly identifying where it departs from that literature—and proposes a new, gender-sensitive conceptual framework for HRM, formalized as a stage-based model rather than left as a general claim. In this scope, the study offers an interdisciplinary contribution by bringing together the literatures on AI, automation, care labor, and HRM, and it questions the widespread acceptance of AI as a neutral technology within organizations. It conceptualizes the invisibilization of women's labor not as a technical side effect but as a gender-based organizational outcome produced through an identifiable and self-reinforcing cycle. In this respect, the study aims to bring an HRM-centered opening to feminist discussions of AI and to establish a theoretical foundation, including explicit propositions, for future empirical research.

This study's conceptual synthesis integrates four bodies of literature, each addressing a different link in the sequence it traces: feminist labor theory, which supplies the substantive category of care, emotional, and relational labor whose exclusion is being explained; feminist data ethics, which supplies the normative and design vocabulary for addressing that exclusion; the organizational-blindness construct, which supplies the mechanism-level claim distinguishing this exclusion from algorithmic bias and organizational myopia; and empirical research on algorithmic management and AI-based HRM, which supplies the operational detail of how AI-HRM systems function in practice. These literatures were read critically against one another, rather than catalogued independently, to identify where each one's claims created a testable implication about organizational blindness specifically. The six-stage model and its four propositions were derived from this targeted synthesis rather than from an exhaustive or systematic search of any single field, and the study should accordingly be read as theory-building through conceptual integration, not as a systematic literature review.

2. Conceptual Framework

2.1. Organizational Blindness: Conceptual Foundations and Boundaries

Organizational blindness is the central explanatory concept of this study, and it requires a definition precise enough to carry that weight. Seymen et al. (2016) use the term primarily to describe routine-based *organizational myopia*: a tendency of organizational actors to repeat established patterns of action without reassessing them against changing conditions. The present study retains the core insight of that formulation—that certain facts, relationships, or problems become systematically unavailable to organizational decision-making—but extends it beyond routine and habit to the structural and technological conditions under which certain forms of contribution are rendered unrecognizable in the first place. Organizational blindness, as used here, refers to a patterned failure of an organization's formal evaluation, recognition, and reward systems to register a form of labor as labor, independent of whether any individual actor is aware of that omission.

This definition requires organizational blindness to be distinguished from four related but non-equivalent concepts. First, organizational myopia (Levinthal & March, 1993; Seymen et al., 2016) concerns a bounded temporal and informational horizon—organizations privilege the near term, the local, and the already-successful. Organizational blindness, by contrast, concerns a bounded category

of recognition: certain contributions fall outside what counts as organizational knowledge regardless of time horizon. Second, *algorithmic bias* denotes a systematic distortion in a model's outputs relative to a defined fairness criterion—for instance, a hiring algorithm that scores otherwise comparable male and female candidates differently. Algorithmic bias is a property of a specific system that can in principle be measured, audited, and corrected within the existing categories of data the system uses. Organizational blindness operates one level upstream: it concerns which categories of contribution are specified as data-worthy in the first place, prior to any question of how fairly a model treats the categories it does include. A system can be statistically unbiased with respect to the variables it models and still be blind to a form of contribution it never represents.

Third, *invisible work* (Daniels, 1987; Star & Strauss, 1999) describes labor that is unseen because it occurs outside formal accounting systems—a well-established empirical phenomenon in the sociology of work. Organizational blindness names the organizational-level mechanism that produces and sustains this invisibility; invisible work is its observable consequence. Fourth, *gendered organizational processes* (Acker, 1990) describe how organizational structures encode assumptions about an idealized, unencumbered worker. Gendering explains why certain forms of invisibility fall disproportionately on women; organizational blindness explains the cognitive and institutional mechanism—the failure of recognition itself—through which that gendered exclusion is enacted and reproduced. Building on this distinction, Section 2.5 below introduces algorithmic blindness as a conceptually distinct, technologically mediated variant of organizational blindness, rather than a synonym for algorithmic bias. The relation among these concepts is developed further, and formalized as part of the conceptual model, in Section 2.7.

2.2. Care and Emotional Labor in Feminist Labor Theory

Feminist labor theory argues that the concept of labor has historically been defined within a narrow framework and that this definition is built upon a gendered knowledge regime. Classical economic and organizational approaches treat labor in a manner limited to activities that are waged, measurable, and directly contributing to the production process. Feminist theory, by contrast, reveals that this restriction systematically excludes forms of labor undertaken primarily by women (Folbre, 2001). In this context, care labor and emotional labor are conceptualized in the feminist literature not merely as alternative types of labor but as fundamental elements that enable the continuity of modern organizations and capitalist production systems (Park, 2024).

In its most general sense, *care labor* refers to activities directed toward meeting individuals' physical, emotional, and social needs (Tronto, 2020). This form of labor has historically been associated with the private sphere, the family, and femininity. For this reason, it has been rendered invisible under the assumption that it does not produce economic value (Nussbaum, 2002). The feminist economics literature emphasizes that this confinement of care labor to the private sphere is a fundamental mechanism securing the reproduction of the capitalist system (Dronkers, 2022). The continuity of waged labor rests largely on unpaid or low-paid care labor. Accordingly, the exclusion of care labor is the result of a structural choice rather than a mere oversight (Folbre, 2001).

The concept of *emotional labor* gained a central place in the literature through Hochschild's (1983) pioneering work. Hochschild defines emotional labor as an organizationally regulated form of labor in which individuals are directed to feel and express particular emotions. This approach demonstrated that emotions are not merely individual experiences but also elements that are organizationally

managed and commodified (Hochschild, 1983). Although emotional labor, particularly concentrated in the service sector, is critically important for outcomes such as customer satisfaction, team cohesion, and organizational climate, it is often not valued to the same extent as technical skills. This study's use of emotional labor requires an important qualification. Emotional labor in Hochschild's original sense is typically a formal, organizationally specified requirement of customer-facing occupations, and it is frequently already monitored through customer-satisfaction scores, call-center quality metrics, or service scripts (Hochschild, 1983). It is, in this sense, often highly visible to organizational measurement rather than excluded from it. The exclusion this study is primarily concerned with involves a related but distinct category: informal care, relational, and coordinative contributions that are not part of any formal job description or service script—helping a struggling colleague, absorbing team conflict, informally onboarding a new hire, or sustaining morale during a difficult period. Unlike Hochschild's emotional labor, these informal contributions are rarely specified as a role requirement and are consequently rarely captured by any existing measurement system, formal or algorithmic. For the remainder of this study, "emotional labor" is retained only where the Hochschildian, service-script sense is intended; "care labor" and "relational labor" are used for the broader, informal category that is this study's central concern, and the two should not be read as interchangeable.

Rather than treating care and relational labor as inherently feminine activities, feminist labor theory argues that their uneven distribution, differential expectation, and systematic undervaluation are produced at the intersection of gender norms and organizational structures (Acker, 1990)—that is, these forms of labor are gendered in how they are distributed, expected, and valued within organizations, rather than being a fixed property of who performs them. The identification of women with traits such as empathy, patience, and communication skills leads to the perception that these forms of labor occur naturally or spontaneously when performed by women. This, in turn, makes it more difficult for such activities to be recognized as labor (Acker, 1992), and it is compounded by other axes of differentiation: occupational segregation channels much of this work into formally recognized care occupations—nursing, eldercare, early-childhood education—where it is paid but still undervalued relative to comparably skilled technical work, while class and ethnicity shape which women are assigned informal relational tasks within mixed-gender workplaces and which are not (Acker, 2006; Babcock et al., 2017; Heilman & Chen, 2005). As Fletcher (1999) notes in her analysis of relational practice, such labor is often regarded not as the work itself but as a by-product of the work, regardless of the gender, class position, or occupational category of the person performing it. This situation causes care and relational labor to be positioned toward the lower end of the organizational value hierarchy.

A common characteristic of care and emotional labor in the feminist literature is that they are process-oriented and context-sensitive (Brake, 2020). These forms of labor focus not on outcomes but on sustaining relationships, strengthening organizational ties, and softening conflicts. However, modern organizations, and human resource management practices in particular, are built upon a rationality based on outputs, individual performance, and quantitative indicators (Subramony, 2006). This rationality tends to systematically exclude forms of labor that prevailing performance definitions were never built to register, independent of whether such labor could in principle be measured or standardized. Feminist labor theory regards this exclusion not merely as a technical mismatch but as a gendered valuation mechanism.

At this point, feminist epistemology offers an important contribution. Feminist epistemology argues that knowledge is socially situated and that which knowledge is accepted as valid is determined by power relations (Harding, 1986). The exclusion of care and emotional labor from knowledge production processes also causes the experiences related to these forms of labor to remain outside the academic and managerial knowledge pool. Organizational decision-making processes, performance criteria, and competency models are considered to be constructed upon this limited knowledge framework.

An important emphasis of feminist labor theory is that care labor is not merely an interpersonal relationship but also a political matter. Fraser (2016) defines care labor as a background condition of capitalism and argues that its systematic erosion leads to social crises. Viewed within the organizational context, the devaluation of care and emotional labor does not merely produce inequality for women employees but also threatens organizational sustainability. Nevertheless, these forms of labor are rarely rendered visible in narratives of organizational success.

2.3. Care Labor and Gendered Division of Labor in Organizations

The conceptualizations of care and emotional labor developed within feminist labor theory offer a strong challenge to the widespread assumption that organizations are gender-neutral structures independent of social context (Husso & Hirvonen, 2012). Organizations are not viewed merely as rational systems operating through technical divisions of labor. Rather, organizations are among the foremost structures through which gender norms are produced, redistributed, and institutionalized. Acker's (1990) gendered organizations approach reveals that organizational processes—job descriptions, hierarchies, career paths, and performance metrics—are built upon assumptions that take male experience as the norm. Within this framework, care and emotional labor are systematically marginalized within the organizational division of labor, giving rise to a gender-based division of labor. This gendered division of labor should not be understood merely as women being concentrated in certain positions; it also concerns the failure to recognize certain forms of labor as real work. Activities such as ensuring coordination, softening intra-team conflicts, contributing to the socialization of new employees, providing emotional support, and sustaining relational ties are often absent from formal job descriptions (Frögéli et al., 2023). Although these activities are critically important for organizational outcomes, they are coded as personal traits, voluntary contributions, or natural aptitudes (Fletcher, 1999). This leads to care labor remaining invisible within the organizational division of labor.

This positioning of care labor in the organizational literature becomes directly linked with gender norms through a pattern of expectation rather than through any inherent property of the labor itself. Employees read as women—whether in formally recognized care occupations such as nursing, where this dynamic has been documented directly (Aca et al., 2025), or in informal relational roles embedded within otherwise unrelated jobs, such as international assignments (Strzelec & Krysińska-Kościańska, 2021)—are disproportionately expected to display empathy, patience, self-sacrifice, and communication skills, and these displays are then evaluated as personality characteristics rather than professional competencies. This expectation pattern should be distinguished from the formally compensated and occupationally bounded care work studied in the nursing and eldercare literatures: the present study's concern is primarily with the latter, informal case, in which relational labor is not part of any job description and therefore has no occupational category to anchor its recognition or its

compensation. Such framing makes it difficult for the care and relational labor performed under this expectation to be recognized as an organizational contribution, and even renders it invisible. Behaviors that are coded as leadership or managerial skill when displayed by employees read as men often become mere expectations—unremarkable, uncompensated baseline behavior—when displayed by employees read as women (Eagly & Karau, 2002).

In this context, care labor faces a double exclusion within the organizational division of labor. Not only are these forms of labor excluded from formal job descriptions, but employees who undertake this labor are also not rewarded for these contributions in career advancement processes. On the contrary, employees who become identified with care labor may be pushed into a disadvantaged position on the grounds that they are not sufficiently focused on their "real" work (Johnson, 2015), which plays a significant role in sustaining horizontal and vertical gender inequalities within organizations. The specific HRM tools and practices through which this division of labor becomes institutionalized—competency models, performance evaluation systems, and promotion criteria—are examined in Section 2.4.

Feminist organization theory treats this situation not as a lack of awareness on the part of individual managers but as a structural problem. The gendered division of labor is embedded in the everyday functioning of organizations and is often reproduced without being questioned. The invisibility of care and emotional labor is related less to the question of who does what in organizations than to the question of which activities are recognized as work. The problem, therefore, is not simply that women undertake more care labor; it is that this labor is systematically excluded by organizational valuation mechanisms. In this context, although organizations benefit intensively from care labor, they leave this labor outside the scope of institutional responsibility. Care activities that reduce employee burnout, strengthen team cohesion, and ensure organizational stability are often carried out through individual self-sacrifice. This situation points to a structural tension that the feminist literature identifies as the care labor gap (Stranz, 2021). Organizations need care labor, yet they avoid recognizing and institutionalizing this need.

2.4. The Institutional Exclusion of Care Labor in the HRM Literature

The human resource management literature has historically been built upon a normative and instrumental perspective that treats organizations primarily through the axes of efficiency, performance, and competitive advantage (Birdi et al., 2008). This approach positions the employee predominantly as a rational actor producing measurable outputs, treating the emotional, relational, and care-related dimensions of the labor process as secondary or peripheral elements—a structural tendency that leads to the systematic exclusion of care labor within the HRM literature. While mainstream HRM scholarship often addresses care and emotional labor under categories such as "soft skills," personal qualities, or organizational citizenship behaviors (Güler, 2020; Lamri & Lubart, 2023), it removes these forms of labor from the center of the organizational production process. In particular, the organizational citizenship behavior (OCB) literature presents employees' contributions that go beyond their formal role definitions within a positive normative framework, while largely neglecting the question of why these contributions are undertaken more intensively by certain groups of employees (Bolino et al., 2004). This neglect causes care labor to be rendered invisible under the guise of voluntarism.

The exclusion of care labor in the HRM literature stands out not only as a conceptual gap but also as a methodological problem. The research tradition based on quantitative measurement tools systematically leaves out of analysis those forms of labor that are not measurable or that are difficult to standardize. Studies on performance management, competency modeling, and compensation systems largely focus on outputs and individual achievement indicators. This causes the indirect effects of care labor on organizational sustainability to be overlooked. Care labor is excluded, in other words, not because it resists measurement but because HRM's prevailing definition of performance was never built to include it—a claim developed more precisely, and distinguished from the separate question of biased historical data, in Section 2.5. This exclusion is legitimized through the discourse that HRM is a neutral and technical field of management, but critical HRM literature demonstrates that this discourse serves an ideological function: as tools that reflect and reproduce organizational power relations, HRM practices determine which forms of labor are recognized, rewarded, or neglected as a direct consequence of organizational value hierarchies (Benschop & Doorewaard, 2012; Mandel et al., 2024).

The feminist HRM approach offers an important critique of the literature at this point. The marginalization of care labor in the HRM literature contributes to the reproduction of gender regimes at the organizational level. The care and emotional labor undertaken by women employees not only fails to contribute to career advancement but is also often not even taken into account in performance evaluations. Yet this labor is indispensable for critical outcomes such as organizational cohesion, employee engagement, and workplace climate (Kahn, 1993). The HRM literature largely ignores this contradiction, and the exclusion of care labor is also closely related to neoliberal management logic. While the neoliberal understanding of HRM constructs the employee as an entrepreneurial subject individually responsible for their own performance, it pushes collective caring relations into the domain of individual responsibility (Bal & Dóci, 2018). Within this framework, care labor is treated not as an organizational responsibility but as the employee's personal capacity or resilience. The rise of concepts such as psychological resilience, self-management, and emotional intelligence contributes to reframing care labor as an individual rather than an institutional matter (Franzosa et al., 2019). This reframing further deepens the invisibility of care labor. While organizations directly benefit from care labor, they do not assume responsibility, at the institutional level, for the conditions under which this labor is produced. Outcomes such as burnout, emotional erosion, and the intensification of the care burden are interpreted as individual failure or inadequacy (Fredriksen & Scharlach, 1999; Keleş & Aydın Göktepe, 2020) rather than being addressed as a consequence of organizational design. The HRM literature often reproduces this individualizing discourse without questioning it.

The concept of organizational blindness, defined and distinguished from related constructs in Section 2.1, offers the analytical bridge from this literature review to the remainder of the study: care labor is positioned within HRM's dominant knowledge-production regime as a practice that carries no epistemic value, which keeps it off the agenda of organizational policy and strategy regardless of individual managers' awareness. The rise of digitalization and AI-based HRM practices, examined in Section 2.5, does not introduce this exclusion; it inherits and, as the conceptual model in Section 2.7 will show, reinforces it.

2.5. Algorithmic Management, Measurability, and New Regimes of Invisibility

The rapid spread of digitalization and AI-based applications in the field of human resource management in recent years points to a fundamental transformation in organizational decision-making processes. This new form of management, conceptualized as *algorithmic management*, enables core HRM functions such as recruitment, performance evaluation, promotion, compensation, and talent management to be carried out through data-driven and automated systems (Turner, 2025). This transformation is often presented with promises of neutrality, objectivity, and efficiency; however, the normative assumptions underlying these promises are not sufficiently questioned (Lindebaum et al., 2020). It would be a mistake, however, to ground this critique in the claim that algorithms are technically incapable of registering care, relational, or emotional contributions. Contemporary AI systems routinely process unstructured text, voice, sentiment, and behavioral trace data—performance-review comments, peer feedback, meeting transcripts, Slack or email metadata—and are in principle fully capable of representing relational behavior as data (Tarafdar et al., 2023). The more defensible question, and the one this study pursues, is not whether such behavior can be measured, but which behaviors organizations choose to define as performance-relevant data in the first place, how these behaviors are then operationalized into variables or classification categories, and which forms of contribution are consequently given decision weight once they enter an AI-HRM system. This reframing matters because it relocates the source of exclusion from a technical limitation of AI—which would be solved simply by adding more sophisticated models—to an organizational choice about what counts as performance, which cannot be solved by better engineering alone, as developed in the conceptual model in Section 2.7.

AI-based HRM should not be treated as a single, homogeneous technology; the mechanisms through which organizational blindness is institutionalized differ by function. In recruitment and CV screening, natural-language-processing models trained on prior hiring patterns can treat career interruptions, part-time employment history, and informal language associated with caregiving responsibilities as proxy variables that depress a candidate's score, even when the model contains no explicit gender variable—the widely reported case of Amazon's discontinued recruiting tool (Dastin, 2018), which learned to penalize resumes containing the word "women's" (e.g., "women's chess club captain"), illustrates how a proxy variable can reconstruct a protected category the system was never given directly. In performance evaluation, systems built on output-based metrics—sales closed, tickets resolved, lines of code committed—structurally exclude contributions such as mentoring, informal coordination, or conflict de-escalation unless these are separately specified as inputs, which they typically are not (Section 2.4).

In promotion and talent management, algorithmic succession-planning and "high-potential" identification tools trained on historical promotion data inherit whatever selection criteria produced that history, so that informal relational contributions that were never rewarded in the past are not retrospectively recognized by a model trained on that same past. In people analytics and workforce planning, aggregate dashboards built from the same underlying variables reproduce the exclusion at a further remove, since organizational decisions about hiring needs, restructuring, or attrition risk are made by reading patterns out of data that already reflects Stages 1–3 of the model in Section 2.7, without any mechanism to flag what the data never captured. Empirical work on algorithmic management supports each of these mechanisms in general terms: algorithmic control systems intensify the measurement of the behaviors they do capture while leaving unmeasured behaviors

structurally invisible to the worker-evaluation process (Kellogg et al., 2020), and systematic reviews of algorithmic discrimination in personnel selection find that proxy variables correlated with gender, rather than gender itself, are the primary mechanism through which such systems disadvantage women candidates (Köchling & Wehner, 2020).

Unlike classical forms of organizational blindness, this new regime of invisibility rests on a technological ground of legitimacy. Because algorithmic decision systems operate through mathematical models and statistical inferences, their outputs are often perceived as objective and scientific. Critical technology studies, however, clearly demonstrate that algorithms are not independent of social values and power relations (Noble, 2018). Algorithms embody the assumptions, priorities, and blind spots of those who design them. Algorithmic systems used in the HRM context are trained on datasets historically built upon male-dominated work norms and performance definitions (Bandara et al., 2025). These datasets carry the traces of organizational histories that had already marginalized care labor. AI-based HRM practices, therefore, not only reflect existing inequalities but also render them more systematic and scalable. The algorithmic non-recognition of care labor causes those who produce this labor to be pushed even further down the organizational value hierarchy.

The algorithmic management literature largely focuses on outcomes such as increased efficiency, faster decision-making, and the reduction of human bias. However, this literature does not sufficiently discuss the question of which forms of labor algorithmic systems code as valuable. Measurability is not a technical preference but a normative filter. This filter pushes relational and context-dependent practices such as care labor outside the system. Thus, AI not only inherits existing forms of blindness but also institutionally reproduces them. In this context, the concept of *algorithmic blindness* offers a functional analytical framework for explaining why care labor becomes systematically invisible within digital HRM practices. Algorithmic blindness refers to the exclusion of certain forms of labor not because they are unsuited to data representation, but because they have not been defined as data at all. Care labor is perceived as noise by algorithmic systems and is thus left outside decision models.

This exclusion, however, is only one of two parallel failure modes identified in the conceptual model developed in Section 2.7. *Algorithmic invisibility*, as just described, occurs when a form of contribution is simply absent from the categories a system represents. A second and analytically distinct failure mode is *algorithmic hypervisibility*: certain relational or emotional behaviors are not absent from the data at all, but are captured asymmetrically and subjected to intensified measurement and correction, without being correspondingly rewarded. Sentiment-analysis tools applied to written communication, for instance, can flag tone, assertiveness, or emotional expression in ways that disproportionately scrutinize women's communicative style without granting any credit for the relational labor that style often accomplishes. Invisibility and hypervisibility can therefore coexist within the same organization across different HRM functions—a contribution invisible to a promotion algorithm may be a closely monitored liability within a performance-monitoring one—producing asymmetric exposure rather than uniform neglect. Algorithmic blindness produces significant consequences for organizational decision-making processes. Care labor that remains invisible in performance evaluation systems also finds no corresponding recognition in promotion and reward mechanisms. This creates a structural disadvantage, particularly for women employees. To the extent that the care and emotional labor undertaken by women within organizations goes unrecognized by algorithmic systems, it becomes wasted labor that contributes nothing to career

advancement. Moreover, algorithmic management further deepens the individualization of care labor. Because algorithms operate through individual performance measurements detached from context, they are ill-equipped to grasp care labor as a collective organizational practice. This causes care labor to be reframed not as an organizational resource but as an individual act of self-sacrifice (Parent-Rocheleau & Parker, 2022; Tarafdar et al., 2023). Care labor is thus rendered invisible while its responsibility is simultaneously placed on the individual.

The account developed above should not be read as implying that algorithmic systems uniformly worsen gender-based disadvantage relative to unaided human judgment. A body of empirical research finds that, under some conditions, structured algorithmic decision rules can reduce certain forms of human bias that are otherwise difficult to discipline—for instance, by applying identical criteria across candidates regardless of an evaluator's mood, fatigue, or implicit stereotyping on a given day (Köchling & Wehner, 2020). Structured or blind algorithmic screening has, in some documented cases, increased the representation of women and other underrepresented groups relative to unstructured human screening, precisely because it removes certain idiosyncratic human judgments from the process. The argument of this study is therefore not that algorithmic systems are necessarily worse than the human judgment they replace, but that whichever system—human or algorithmic—is used, it operates on a definition of performance and value (Stage 1 of the model in Section 2.7) that was already narrowed before any comparison between human and algorithmic fairness becomes possible. A fairer algorithm, in this sense, can still institutionalize organizational blindness if it is built to optimize for the same output-based performance definition that excluded care and relational labor in the first place.

This distinction clarifies a tension left unresolved in Sections 2.4 and 2.5: whether the exclusion of care and relational labor from AI-HRM systems originates in biased historical data or in the underlying logic of organizational measurement itself. The model in Section 2.7 treats these as operating at different, mutually reinforcing stages rather than as competing explanations. Biased historical data is a Stage 2 problem: even where an organization's stated performance definition (Stage 1) is formally gender-neutral, the historical record used to train a system reflects decades of decisions made under a narrower definition, so the data inherits the exclusion regardless of current intent. The logic of measurement is a Stage 1 problem: an output-based, individually attributable definition of performance will continue to exclude relational contributions from datafication even if the historical data used to build a new system were somehow perfectly unbiased. Debiasing the data (addressing Stage 2 alone) without revisiting what counts as performance (Stage 1) will therefore correct historical distortions within the existing performance definition without expanding that definition to include what it never measured in the first place—which is why Proposition 4 (Section 2.7) locates the more effective point of intervention upstream, at Stages 1 and 2 together, rather than at Stage 3 alone.

A further tension concerns the proposal, implicit in much of the preceding argument, that making care and relational labor visible to algorithmic systems would correct its exclusion. The invisible-work literature has long cautioned that formalizing and measuring previously informal labor carries a double edge: it can secure recognition and reward, but it can equally convert a previously autonomous, discretionary practice into a monitored and controlled one (Star & Strauss, 1999). If an organization began scoring informal mentoring, emotional support, or conflict mediation as a tracked performance input, this would address the invisibility this study has described, but it would

simultaneously extend algorithmic monitoring into a domain of work whose relational and situational character may be degraded by exactly the kind of standardized measurement that performance systems require. This is not a reason to abandon the goal of recognition, but it means that recognition and surveillance are not independent design choices: a feminist data ethics response to algorithmic invisibility (Section 2.6) must therefore specify not only how care labor is made visible, but who controls that visibility, for what purpose, and with what employee input—a boundary condition this study treats as a precondition for ethical implementation rather than as a detail to be resolved later.

2.6. Feminist Data Ethics and Gender-Sensitive HRM Algorithms

Feminist data ethics provides a robust analytical and normative framework for the gender-sensitive transformation of AI-based human resource management practices. Feminist data ethics rejects the assumption that data constitutes a neutral means of representation. On the contrary, it questions within which social relations data is produced, which experiences it includes or excludes, and which power structures it reproduces (D'Ignazio & Klein, 2020). This approach makes it possible to conduct the ethical evaluation of AI systems not solely on the basis of outcomes, but also through data collection processes, classification regimes, and modeling assumptions. In the HRM context, this means questioning not only whether algorithms produce discriminatory outcomes, but also which forms of labor they render recognizable and valuable.

Gender-sensitive algorithm design can be regarded as a practice-oriented extension of feminist data ethics. This approach requires gender inequalities to be addressed at the algorithmic design stage both as a risk and as a structural phenomenon. In HRM algorithms, this necessitates redefining traditionally invisibilized forms of labor—such as care labor, emotional labor, and relational work—as integral parts of organizational value production. At this point, the central issue concerns not only how care labor should be measured by algorithmic systems, but also why and through which conceptual framework this labor should be recognized. Feminist theory conceptualizes care labor not merely as a set of individual behaviors but also as a collective practice that ensures the sustainability of organizational functioning (Bahn et al., 2020; Harcourt, 2026; Thelen, 2015). This understanding requires HRM algorithms to broaden their definitions of performance, competency, and contribution. Gender-sensitive HRM algorithms should therefore be regarded as normative interventions that reshape organizational value regimes.

The feminist data ethics perspective moves beyond transparency and accountability in algorithmic decision-making processes, centering instead the questions of whose knowledge, whose experience, and whose labor is accepted as data (Gray & Witt, 2021). In HRM practices, this is considered to require both the prevention of gender-based discrimination and the rewriting of the definition of organizational contribution. The exclusion of care labor from data representation is not a technical shortcoming but an epistemological choice, and feminist data ethics both renders this choice visible and calls it into question.

Another core principle of gender-sensitive algorithms is contextuality. Feminist epistemology approaches universal, context-independent claims to knowledge with skepticism (Candidatu & Leurs, 2023; Jarrahi et al., 2021). This approach requires HRM algorithms to be designed in ways that take organizational, sectoral, and cultural contexts into account. Because care labor is a context-sensitive practice, it is unlikely to be adequately captured by standardized performance metrics. For this reason, feminist data ethics advocates that algorithmic systems incorporate flexible, pluralistic, and

contextual decision mechanisms. Feminist data ethics further emphasizes the participation of diverse actors in the design and use processes of algorithmic systems (Ali et al., 2025; Leurs, 2017). In the HRM context, this requires the inclusion in the process not only of software developers and senior managers, but also of the employees who actually produce care labor. Participatory design principles are critical for enabling the experiential knowledge of care labor to be reflected in algorithmic models. This is thought to enable care labor to become not merely a represented but also a negotiated category. Within this framework, feminist data ethics departs from classical ethical approaches to AI-based HRM practices. The aim goes beyond ensuring that algorithms do no harm; it is to redefine which forms of labor underlie organizational value production. This redefinition makes it possible to lift care labor out of algorithmic blindness and place it at the center of organizational knowledge.

Translating these principles into HRM practice requires moving from general ethical commitments to specific governance mechanisms targeted at the stages identified in the conceptual model (Section 2.7). Four such mechanisms are proposed here. First, algorithmic impact assessment conducted before an AI-HRM system is deployed should explicitly ask which categories of contribution the system's training data and feature set include and exclude (Stage 2), rather than auditing only the system's statistical fairness once built (Stage 3); this reframes impact assessment as a question about what was made into data, not only about how the resulting model performs. Second, periodic algorithmic auditing should track not only disparate outcomes across gender but also disparate capture—whether forms of contribution associated with informal relational work are represented in the system's inputs at all, and whether they are represented symmetrically, avoiding both invisibility and hypervisibility as distinguished in Section 2.5. Third, meaningful human oversight should be retained specifically at decision points where algorithmic outputs bear on promotion, compensation, or termination, with human reviewers given explicit authority and guidance to weigh forms of contribution the system could not capture—oversight that is procedurally real rather than a routine sign-off. Fourth, employee participation in redefining performance categories (Stage 1) should precede system design rather than follow it: the employees who perform informal care and relational labor are positioned, by virtue of that experience, to identify what a given system's categories leave out, and participatory design processes should treat this as domain expertise rather than as a consultation exercise. These four mechanisms correspond to Proposition 4 in Section 2.7, which locates effective intervention at Stages 1 and 2 of the model rather than at Stage 3 alone. Where relevant, regulatory developments reinforce rather than substitute for these mechanisms: the European Union's AI Act (European Parliament and Council of the European Union, 2024), for instance, classifies AI systems used in recruitment, performance evaluation, and promotion as high-risk applications subject to mandatory risk management, data governance, and human oversight requirements, which gives organizations an external compliance basis for adopting measures of exactly this kind. This study does not undertake a legal analysis of such regulation; the point is only that governance mechanisms grounded in feminist data ethics are not merely normatively desirable but increasingly aligned with binding regulatory expectations in at least some jurisdictions.

2.7. A Conceptual Model of Algorithmically Institutionalized Organizational Blindness

The preceding sections suggest that organizational blindness toward care, emotional, and relational labor is not produced at a single point but accumulates across a sequence of organizational and technical choices. This section makes that sequence explicit as a conceptual model (Figure 1), synthesizing Sections 2.1 through 2.6 into a chain of six stages: (1) Organizational definitions of

value and performance → (2) datafication and representation choices → (3) AI-HRM data structures and decision rules → (4) under- or distorted representation of particular forms of contribution → (5) HRM decisions (recruitment, evaluation, promotion, workforce planning) → (6) gendered outcomes that feed back into, and further entrench, organizational definitions of value and performance. At Stage 1, organizations define performance and competence in ways that privilege outputs over process—a choice this study has argued (Section 2.4) reflects an existing organizational value hierarchy rather than a technical necessity. At Stage 2, this definition governs which behaviors are selected for measurement and how they are operationalized into variables, fields, or categories; care, relational, and informal coordination work are disproportionately left out of this selection not because they cannot be represented, but because Stage 1's definitions did not treat them as performance-relevant in the first place. At Stage 3, AI-HRM systems inherit the categories fixed at Stage 2: the system's decision rules, proxy variables, and classification logics operate only on what Stage 2 made available as data. At Stage 4, this produces two distinct failure modes rather than one undifferentiated "invisibility": algorithmic invisibility, in which a form of contribution is simply absent from the model and therefore carries zero weight in any decision, and algorithmic hypervisibility, in which a form of contribution is captured but captured asymmetrically—for instance, when sentiment or tone in written communication is scored, and women's communicative or emotional labor becomes subject to more intensive measurement and correction than men's, without being correspondingly rewarded in promotion or pay decisions. At Stage 5, HRM decisions act on these distorted or missing representations, so that otherwise identical contributions yield different organizational consequences depending on whether and how they were captured at Stage 3. At Stage 6, the resulting patterns of who advances and who does not feed back into Stage 1: they confirm, under the appearance of data-driven objectivity, the organization's existing definition of what counts as valuable work, closing the loop and institutionalizing the blindness identified at the outset. It is this closed loop—not any single stage in isolation—that this study identifies as the mechanism of algorithmically institutionalized organizational blindness, and it is this loop that distinguishes the concept from algorithmic bias (a property of Stage 3 alone) and from organizational myopia (a property of Stage 1 alone). From this model, four theoretical propositions can be stated:

P$_{1.}$ The more an organization's definition of performance (Stage 1) is built on output-based, individually attributable metrics, the fewer relational and process-oriented contributions will be selected for datafication at Stage 2, independent of the technical sophistication of the AI-HRM system subsequently deployed.

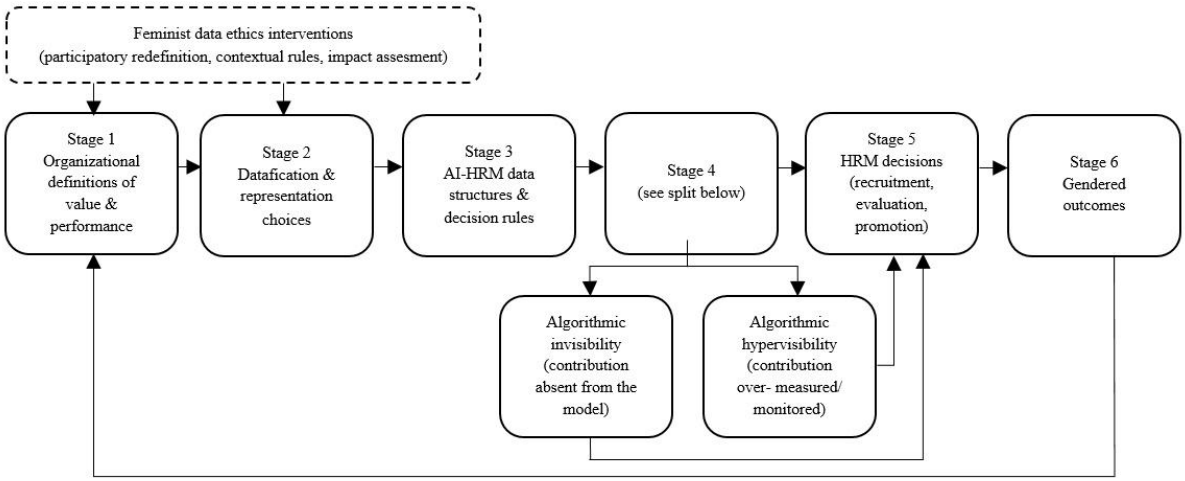
P$_{2.}$ Algorithmic invisibility and algorithmic hypervisibility are not alternative outcomes but can co-occur across different HRM functions within the same organization: a contribution may be invisible to a promotion algorithm while a related behavior (e.g., communication tone) is simultaneously hypervisible to a performance-monitoring algorithm, producing asymmetric exposure rather than uniform neglect.

P$_{3.}$ Because Stage 6 feeds back into Stage 1, the institutionalization of organizational blindness is expected to strengthen over successive HRM cycles in the absence of deliberate intervention, as each cycle's outcomes are read as confirmation of the prior definition of value rather than as an artifact of what was and was not measured.

P4. Interventions aligned with feminist data ethics (Section 2.6)—participatory redefinition of performance categories, contextual and pluralistic decision rules, and algorithmic impact assessment—are positioned at Stages 1 and 2 of the model, and are therefore expected to be more effective at interrupting the feedback loop than interventions aimed only at Stage 3 (e.g., debiasing an existing model's outputs without revisiting what it measures).

Figure 1

A Conceptual Model of Algorithmically Institutionalized Organizational Blindness



This model directly addresses the distinction, raised in Section 2.5, between a problem of biased historical data and a problem of the underlying logic of organizational measurement: the model shows these as operating at different stages (Stage 2 and Stage 1, respectively) and as mutually reinforcing rather than competing explanations. It also provides the structure against which the mechanisms discussed in Section 2.5 for specific HRM functions can be located, and against which the feminist data ethics interventions discussed in Section 2.6 can be evaluated for where, rather than simply whether, they intervene.

3. Conclusion and Recommendations

This study has examined how organizational blindness toward care, emotional, and relational labor becomes institutionalized in AI-based human resource management, developing feminist labor theory and the concept of organizational blindness into an explicit, stage-based conceptual model (Section 2.7) rather than leaving the argument at the level of a general claim that algorithms can reproduce inequality. Returning to the three research questions posed in the Introduction, the study offers the following answers.

First, organizational blindness operates in AI-based HRM as a patterned failure of formal evaluation and recognition systems to register certain contributions as labor at all—a failure that is conceptually distinct from algorithmic bias, which concerns how fairly a system treats the categories it already represents, and from organizational myopia, which concerns a bounded time horizon rather than a bounded category of recognition (Section 2.1). A system can be statistically unbiased with respect to the variables it models and remain organizationally blind to a form of contribution it never represents in the first place.

Second, this blindness becomes institutionalized through the six-stage cycle developed in Section 2.7: organizational definitions of performance shape which behaviors are selected for datafication, which in turn shape what AI-HRM systems can represent and decide upon, producing HRM outcomes that feed back into, and confirm, the original definition of performance. The mechanisms through which this occurs differ by HRM function—proxy variables in recruitment screening, output-based metrics in performance evaluation, inherited historical criteria in promotion and talent management, and aggregate pattern-reading in people analytics and workforce planning (Section 2.5)—so that AI-based HRM should not be treated as a single, homogeneous source of exclusion.

Third, this institutionalization produces two distinguishable and potentially co-occurring failure modes: algorithmic invisibility, in which a contribution is simply absent from a system's categories, and algorithmic hypervisibility, in which a contribution is captured but subjected to asymmetric scrutiny without corresponding reward (Section 2.5). Feminist data ethics addresses both by relocating intervention to the earliest stages of the model—redefining what counts as performance and what is selected for datafication—rather than treating fairness as a property to be added to an already-built system. Translated into practice, this yields four concrete governance mechanisms: algorithmic impact assessment focused on data exclusion rather than only on outcome fairness, auditing for disparate capture as well as disparate outcomes, meaningful human oversight at consequential decision points, and employee participation in redefining performance categories before systems are designed (Section 2.6).

This study is subject to several limitations that should condition how its contribution is read. As a conceptual study, it does not test the six-stage model or its four propositions (Section 2.7) against empirical data; the model specifies a mechanism and generates testable claims, but it does not itself establish that the mechanism operates as described in any particular organization or sector. The literature synthesized here is drawn predominantly from English-language, Western-institutional sources, and the extent to which the model's stages and mechanisms generalize to other labor-market, regulatory, and cultural contexts remains an open question rather than an assumption embedded in the argument. The distinction between informal care/relational labor and Hochschildian emotional labor (Section 2.2) is conceptually motivated but has not been operationalized or validated against existing measurement instruments, and the four governance mechanisms proposed in Section 2.6 are derived from the model rather than from an assessment of their feasibility or cost within specific organizational settings.

For HRM practice, the study's recommendations follow directly from Section 2.6 rather than from a general appeal to "ethical AI": organizations procuring or building AI-HRM systems should require a pre-deployment impact assessment that documents which forms of contribution the system's data and features exclude, not only how its outputs are distributed by gender; should extend algorithmic auditing to disparate capture in addition to disparate outcomes; should preserve human decision authority, with explicit guidance, at the points where algorithmic outputs affect promotion, compensation, or termination; and should involve employees who perform informal relational work in defining performance categories before, rather than after, a system is designed. Where applicable regulatory frameworks—such as the EU AI Act's classification of employment-related AI as high-risk (European Parliament and Council of the European Union, 2024)—already require elements of risk management, data governance, and human oversight, these can serve as an institutional entry point for adopting the mechanisms proposed here.

Future empirical research follows directly from the model developed in Section 2.7. The four propositions (P1–P4) are each open to empirical test: P1 and P2 could be examined through comparative case studies of organizations with different performance-definition regimes and different AI-HRM functions, testing whether output-based performance definitions are associated with lower datafication of relational contributions and whether invisibility and hypervisibility co-occur across functions within the same organization; P3 could be examined longitudinally, tracking whether the exclusion of care and relational labor from HRM decisions strengthens over successive evaluation cycles in organizations that have not intervened at Stages 1–2; and P4 could be examined through field experiments or quasi-experimental comparisons of organizations that adopt participatory, Stage-1/Stage-2 interventions against those that adopt only Stage-3 debiasing. Comparative research across sectors, and across organizations operating under different regulatory regimes, would further clarify how far the model's six stages travel beyond the conceptual argument developed here.

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