The Faceless Employer: Algorithmic HRM, Psychological Contract Mutation, and the Erosion of Occupational Self

Dr. BELINGA BESSALA Jacob Patrick
Senior Lecturer
Applied Economics and Management Laboratory
Faculty of Economics and Applied Management, University of Douala
P.O Box: 4032, Douala, Cameroon
ORCID: 0000-0001-7236-0564
E-mail: jacob.belinga@outlook.com

Abstract

When algorithms evaluate, promote, and discipline workers, who exactly is the employer? This article argues that the deployment of machine-learning AI in human resource management (HRM) does not merely breach or violate the psychological contract. It mutates it structurally by generating what we term the faceless employer: an algorithmic decisional entity that exercises managerial authority without the four relational attributes historically grounding such authority: visibility, moral accountability, reciprocal obligation capacity, and interpersonal recognition. Building on and departing from Charlwood and Guenole's (2022) paradox analysis, we develop an integrative three-stage model introducing three interconnected constructs (the faceless employer, psychological contract mutation, and erosion of the occupational self) supported by four formal propositions and anchored in secondary empirical evidence. We argue that the paradox of AI in HRM, previously conceived at the organizational level, is simultaneously enacted at the individual psychological level, and that without deliberate HR intervention to restore human relational presence alongside algorithmic systems, the erosion of workers' occupational self follows a self-reinforcing path from which recovery becomes progressively more difficult. The article contributes to the ongoing dialogue on AI and work by shifting attention from algorithmic bias and efficiency, both well-covered terrain, to the under-theorised relational and identity consequences of depersonalised managerial authority.

Keywords: artificial intelligence, psychological contract, occupational identity, algorithmic management, human resource management, faceless employer

DOI: 10.7176/EJBM/18-4-05
Publication date: April 30th 2026

Practitioner Notes

• AI-driven HRM does not merely change how HR processes work; it changes the fundamental nature of the employment relationship, raising new managerial risks that conventional HR metrics cannot detect.

• The concept of the faceless employer identifies a structural gap in contemporary people management: when algorithmic systems make consequential decisions about workers, no human agent remains accountable for those decisions in the worker's relational experience.

• Psychological contract mutation, unlike classical breach, is not an event but a cumulative process. Organizations deploying AI in HRM should monitor early indicators, such as declining discretionary effort, increased procedural complaints, and withdrawal from informal organizational life, as signals of mutation rather than mere disengagement.

• HR professionals play an important role in connecting people: their job is not to stop AI from being used but to keep the human aspect of work by ensuring clear and responsible decision-making alongside AI systems.

• Organizations introducing AI into people management decisions should embed deliberate mechanisms of interpersonal recognition, including regular structured conversations between managers and employees about AI-mediated outcomes, and should conduct psychological contract impact assessments before, during, and after deployment.

1. Introduction

A manager who has never met the employee she disciplines, whose reasoning cannot be questioned in a corridor conversation, and who lacks the capacity to feel guilt when a decision proves unjust: this is not a thought experiment. It is the operational reality emerging in organizations that delegate core people-management functions to machine-learning algorithms (Kellogg et al., 2020; van den Broek et al., 2021). The growing literature on artificial intelligence (AI) in human resource management (HRM) has rightly scrutinized problems of bias, fairness, and regulatory design (Charlwood & Guenole, 2022; Tambe et al., 2019). What it has largely neglected is a more foundational question: what happens to the employment relationship itself when the locus of managerial authority shifts from a human being, one capable of moral recognition and relational reciprocity, to an algorithmic system that is structurally incapable of either?

Charlwood and Guenole (2022), in the most comprehensive theoretical treatment of AI paradoxes in HRM to date, demonstrated that optimistic and pessimistic visions of AI's organizational impact coexist in a dynamic equilibrium that the HR profession must actively navigate. Their analysis, grounded in Smith and Lewis's (2011) paradox theory and the labor process tradition, illuminated the structural tensions between efficiency and equity, between automation and augmentation. It is a foundational contribution. But it operates at the level of organizations, industries, and professions. The worker, the individual whose career is shaped, whose performance is scored, whose hire or dismissal is recommended by an algorithm, appears in that analysis primarily as a subject of managerial concern, not as a psychological agent whose subjective experience of the employment relationship is itself being transformed.

That transformation is the subject of this article. We argue that AI-driven HRM produces a specific psychological event for which the existing literature on psychological contracts, occupational identity, and algorithmic management has not yet developed adequate theoretical tools. When a worker's promotion decision is determined by an opaque ML system, when their performance is monitored by sensors, and their shifts allocated by a scheduling algorithm, the implicit contract built on mutual recognition, reciprocal obligation, and the attribution of decisions to a morally accountable human agent undergoes a structural transformation we term psychological contract mutation.

This mutation is distinct from classical psychological contract breach (Morrison & Robinson, 1997; Rousseau, 1989) in a critical respect: it is not the violation of a specific promise by an identifiable agent. It is the disappearance of the agent who was supposed to make promises at all. The result is a progressive erosion of what we call the occupational self, that is, the worker's capacity to experience themselves as a recognized, autonomous, and morally accountable subject within the employment relationship. This erosion, unlike disengagement or burnout, is structurally produced by the architecture of algorithmic authority rather than by any particular managerial failure,

Three theoretical contributions organize this article. First, we introduce the faceless employer as a theoretical construct designating the algorithmic principal in the employment relationship, an entity that exercises consequential authority over workers while being structurally incapable of the relational attributes on which the legitimacy of that authority historically rested. Second, we develop psychological contract mutation as a category analytically distinct from breach and violation, capturing the structural reconfiguration of contractual expectations when the employer loses its face. Third, we introduce erosion of occupational self to theorize the individual-level consequence of this mutation, a process qualitatively different from the loss of autonomy documented in labor process research and one that existing theories of occupational identity have not been designed to capture.

Our approach follows the methodology of integrative literature review (Torraco, 2005): a form of research that critiques, synthesises, and reconceptualises existing knowledge to generate new theoretical frameworks. The specific variant we adopt is a theoretical integrative review with secondary empirical anchoring; its protocol, search strategy, and inclusion criteria are detailed in Section 2.3. In line with that protocol, we deliberately exclude gig-economy platform work, whose employment relationship differs fundamentally from the conventional settings our framework addresses, and set aside generative AI to focus on machine-learning decisional systems; we return to generative AI in Section 4 as a boundary condition. Algorithmic bias and regulation, treated extensively by Charlwood and Guenole (2022), receive only contextual mention. The article proceeds as follows. Section 2 surveys the two bodies of literature whose intersection we occupy and specifies our review protocol. Section 3 develops our theoretical framework and advances four formal propositions. Section 4 positions our argument in relation to Charlwood and Guenole's paradox analysis. Section 5 draws out implications and a future research agenda. Section 6 concludes.

2. Theoretical Background and Literature Review

2.1 AI in HRM: What the literature has seen and what it has not

The scholarship on AI in HRM has grown rapidly since the mid-2010s, moving from early conceptual mappings (Strohmeier & Piazza, 2013, 2015) through industry surveys (Bailie & Butler, 2018; Guenole & Feinzig, 2019) to increasingly theoretically ambitious accounts. Three research streams dominate the field: fairness, bias, and adverse impact (Charlwood & Guenole, 2022; Hutchinson & Mitchell, 2019; Ployhart & Holtz, 2008); algorithmic management as labor control (Kellogg et al., 2020; Thompson, 2010); and the strategic and professional dimensions of AI adoption (Prikshat et al., 2021; Raisch & Krakowski, 2021). These streams have produced genuine insight. Yet collectively they share a structural blind spot: the unit of analysis has been the organization, the industry, or the profession. The worker, the individual whose career is managed, scored, and decided upon by algorithmic systems, has appeared primarily as a subject of concern rather than as a subject of inquiry.

Empirical research on worker responses to algorithmic management has concentrated on gig workers on digital platforms (Duggan et al., 2020; Möhlmann et al., 2021), a context substantially different from the conventional employment relationships in which HR AI systems are now deployed (Langer & Landers, 2021). Van den Broek et al.'s (2021) ethnographic study of an ML hiring system in a multinational firm, the field's richest empirical account of AI-HRM in practice, revealed how developers actively excluded domain expertise from the design process, privileging data-driven predictions over contextual human judgment. Charlwood and Guenole (2022) read this finding through the lens of organizational risk. We interpret this finding from a distinct perspective: the act of eliminating human expertise from AI design establishes the faceless employer. The moment the human decision-maker is architected out of the system, the worker loses their relational counterpart in the employment contract. This is not a design flaw to be corrected; it is the founding gesture of a new form of authority.

Green et al. (2021), drawing on the UK Skills and Employment Survey, documented that workers across occupational categories experience increased work intensity and reduced job autonomy, trends attributed partly to algorithmic management tools. We reinterpret their findings: what they measured as declining autonomy is the observable behavioral surface of a deeper psychological process: the erosion of occupational self. The reduction in decision latitude is a symptom of a structural mutation in the worker's relationship to the authority that governs them.

2.2 Psychological contract theory: Foundations, developments, and a critical limit

Psychological contract theory, since Rousseau's (1989, 1995) foundational formulations, has provided one of organizational behavior’s most productive frameworks for understanding the subjective dimension of the employment relationship. The psychological contract designates an individual’s beliefs about the terms of a reciprocal exchange agreement with their organisation, an implicit set of promises and obligations that both parties regard as binding (Rousseau, 1989). Morrison and Robinson (1997) distinguished breach, the perception that the organisation has failed to fulfill obligations, from violation, the intense emotional response of betrayal. Three decades of research have traced breach consequences across commitment, turnover intention, citizenship behavior, and performance (Zhao et al., 2007). The theory’s architecture, however, rests on an assumption so foundational it has rarely required articulation: the employer is a human agent, or at least an entity capable of intention, moral accountability, and recognizing the worker as a relational subject. Guest (2004) made this implicit assumption explicit, emphasizing that the psychological contract requires active agency on both sides: the employer must be perceived as an entity that intends, communicates, and can be held accountable. Conway and Briner (2005) reinforced this by showing that employees’ attributions of employer intent are central to determining whether unmet expectations lead to perceptions of breach.

The breach and violation model fails to adequately capture what happens when an algorithm makes the relevant decisions. An algorithm does not make promises. It processes inputs and generates outputs. It cannot choose to recognize a worker’s exceptional effort, exercise discretion in an employee’s favor, or be appealed to as a moral agent. The literature has begun registering this difficulty. Sherman et al. (2025) have theorized how gig workers form psychological contracts with non-human algorithmic agents through anthropomorphization, attributing intentions to systems that have none. Tomprou and Lee (2022) demonstrated experimentally that algorithmic agents reduce perceived employer commitment to relational inducements during recruitment and that human agents generate greater breach perceptions when relational inducements are under-delivered. Cheng et al. (2025) documented that AI awareness triggers psychological contract breach perceptions in service workers, mediated by moral identity concerns. These are significant contributions, but they treat algorithmic authority as a modifier of existing contract dynamics rather than as a transformation of the contractual relationship’s nature, which could fundamentally alter how service workers perceive their roles and responsibilities in the workplace.

Nishii et al.’s (2008) foundational work on HR attributions adds a critical dimension: employees do not respond to HR practices directly but to the reasons they attribute to management for adopting those practices. When the management behind a practice is an algorithmic system without discernible intentions, the attribution process itself breaks down. The worker cannot determine whether the algorithm’s decision reflects a commitment to their development, a cost-cutting motive, or intentionality. This attributional opacity is, we argue, a precondition for psychological contract mutation.

Two broader intellectual traditions illuminate the stakes of this transformation. In social philosophy, Honneth’s (1995) theory of recognition provides the most developed account of what it means to be acknowledged as a subject: individuals develop self-confidence through love, self-respect through legal rights, and self-esteem through social solidarity. When the authority that evaluates a worker’s contribution is an algorithm incapable of recognition in Honneth’s sense, all three dimensions of self-realisation are placed under threat. Zuboff’s (2019) analysis of surveillance capitalism offers the macro-level complement: algorithmic systems extract behavioural data and convert it into prediction products, rendering human experience as raw material for commercial processing. The faceless employer, as we theorise it, is the HR-specific instantiation of what Zuboff describes at a systemic level: the conversion of the employment relationship from a site of reciprocal obligation into a site of unilateral data extraction. Coeckelbergh (2020), writing on AI ethics, identifies a "responsibility gap" that arises when autonomous systems make consequential decisions: no one bears full moral responsibility for outcomes, because agency is distributed across designers, deployers, and algorithms. This responsibility gap is precisely what produces the "collapse of accountability" vector in our mutation framework. The gap in the HRM literature is now visible: psychological contract theory assumes a dyadic structure in which both parties are capable of obligation. When one party is an algorithmic system structurally incapable of obligation, the contract does not merely break; it changes in kind. Existing categories are insufficient. What is needed is a concept of mutation rather than breach and a theory of what mutation does to the worker’s occupational self.

2.3 Scope and method of the integrative review

Our approach follows the methodology of integrative literature review as defined by Torraco (2005): a form of research that critiques, synthesises, and reconceptualises existing knowledge to generate new theoretical frameworks. Unlike systematic reviews, which pursue comprehensive coverage of a defined evidence base, integrative reviews are designed for theory-building from mature and emerging literatures. Our specific variant, a theoretical integrative review with secondary empirical anchoring, combines conceptual argumentation with the analytical reinterpretation of published empirical findings. The empirical evidence we mobilise is illustrative rather than exhaustive: it serves to ground, test, and complicate our theoretical propositions rather than to demonstrate their statistical generalisability.

The review proceeded in three stages. In the first stage (literature mapping), we searched Scopus, Web of Science, and the EBSCO Business Source Complete database for peer-reviewed articles and book chapters published between 1989 (the year of Rousseau's foundational psychological contract article) and 2025, combining three clusters of keywords: algorithmic HRM terms ("artificial intelligence", "machine learning", "algorithmic management", "AI-HRM"), psychological contract terms ("psychological contract", "contract breach", "contract violation", "employer obligation"), and occupational identity terms ("occupational identity", "professional identity", "work identity", "recognition at work"). Reference tracking from the most cited articles complemented the database searches. In the second stage (selection), we retained works meeting three inclusion criteria: theoretical or empirical contribution to at least one of the three clusters; relevance to conventional employment relationships (excluding gig-economy platform work, which involves fundamentally different contractual arrangements, and excluding generative AI, which we address separately in Section 4 as a boundary condition of our framework); and peer-reviewed status or recognised scholarly authority (classic books by Rousseau, Honneth, Zuboff, and Weber; MIT Press and Oxford University Press monographs). Works on algorithmic bias and regulatory design, already extensively covered by Charlwood and Guenole (2022), were read for context but not systematically included. In the third stage (synthesis), we organised retained works around the three constructs we develop (faceless employer, psychological contract mutation, erosion of occupational self), using van den Broek et al. (2021), Green et al. (2021), Jarrahi et al. (2021), Kellogg et al. (2020), Langer and Landers (2021), and Tomprou and Lee (2022) as the principal empirical anchors for our theoretical vectors, as summarised in Table 2 below. This approach is appropriate for our research question, which is theoretical and conceptual in nature, seeking to name and formalise a phenomenon that existing frameworks have not yet captured.

3. Theoretical Framework

3.1 The faceless employer: Conceptualization

We define the faceless employer as an algorithmic decision-making system that exercises consequential managerial authority over employment-related outcomes (hiring, performance evaluation, promotion, scheduling, and termination) while lacking the four relational attributes that historically ground the legitimacy of managerial authority: (i) visibility, the capacity to be identified as the source of a decision; (ii) moral accountability, the capacity to be held responsible for consequences; (iii) reciprocal obligation capacity, the capacity to incur and honor obligations to the worker; and (iv) interpersonal recognition, the capacity to acknowledge the worker's individuality, effort, and claims.

Two clarifications are necessary. First, the faceless employer is not the technology per se but the organizational arrangement in which algorithmic authority operates without a visible, accountable human intermediary. A hiring algorithm supervised by an HR professional who explains, overrides, and takes responsibility for its outputs does not produce a faceless employer. The faceless employer emerges when the algorithm's output becomes the decision, and when the human in the loop is reduced to a procedural formality rather than a substantive relational presence.

Second, the faceless employer is analytically distinct from historical forms of depersonalized management. Taylorist work organization produced standardized procedures and hierarchical monitoring, but Taylor's system still retained a human supervisor as the face of authority, accountable to workers and to the organization. Weber's (1947) ideal-type bureaucracy operated through codified rules that were humanly authored, humanly interpreted, and humanly contestable; behind every rule stood an authority that could, in principle, be questioned. Digital Taylorism in gig platforms (Moore, 2019; Kellogg et al., 2020) operates through algorithmic control but within a pseudo-employment context where the contractual relationship itself is contested. The faceless employer, as we theorize it, operates within conventional employment relationships, in offices, hospitals, warehouses, and service operations, where workers retain full employee status and its accompanying expectations of relational management. The difference between imperfect human authority and algorithmic authority is not one of degree but of kind.

Mayer et al.'s (1995) integrative model of organizational trust illuminates why this distinction matters. Their model identifies three antecedents of trust: perceived ability, benevolence, and integrity of the trustee. An algorithmic system may score adequately on perceived ability (it can be seen as competent at processing data). But benevolence (concern for the trustor's welfare beyond the trustee's self-interest) and integrity (adherence to principles the trustor finds acceptable) require moral agency that algorithms lack by design. Glickson and Woolley's (2020) review of empirical research on human trust in AI confirmed that humans consistently struggle to develop the relational trust they readily extend to competent human colleagues, a finding they attributed to the absence of perceived social presence, intentionality, and moral agency. The faceless employer is, in trust-theoretical terms, an authority that can be relied upon but not trusted in the interpersonal sense that psychological contracts require.

Proposition 1: The higher the degree of decisional autonomy granted to algorithmic systems in HRM practices, that is, the lower the substantive involvement of identifiable human agents in employment decisions, the more fully the organization constitutes a faceless employer, and the more severely the relational basis of the psychological contract is undermined.

3.2 Psychological contract mutation: The mechanism

A psychological contract breach is an event: a specific promise perceived to have gone unfulfilled by an identifiable obligor. Violation is an affective state: intense negative emotion following a significant breach (Robinson & Morrison, 2000). Both concepts preserve the dyadic structure of the contract: they describe what happens when an obligation is not met. They do not describe what happens when the very structure of obligation is transformed.

Psychological contract mutation, as we define it, is a structural transformation of the nature of the employment contract, not the failure to fulfil existing terms but the replacement of a relational logic of obligation (in which both parties are capable of commitment and recognition) by a transactional logic of processing (in which one party processes data and generates outputs, while the other receives decisions). The mutation accumulates through repeated exposure to algorithmic authority and proceeds through three vectors.

The first is opacity of obligation. When a worker cannot understand why they were denied promotion, cannot identify the criteria against which they were assessed, and cannot appeal to an agent who can explain the decision's grounds, the implicit promise that employment rewards merit becomes unverifiable. Charlwood and Guenole (2022) discussed this as the 'black box' problem; we argue it is not merely technical but contractually destabilizing. Van den Broek et al.'s (2021) ethnography operationalises this vector with particular precision: by documenting how developers of an ML hiring system in a multinational firm systematically excluded HR domain expertise from the design process, they show that opacity is not an accidental byproduct of complexity but a constitutive feature of how such systems are built. The criteria the algorithm applies are, by design, unknowable to the workers it governs and, crucially, to the HR professionals who would conventionally have been the accountable obligors. The second is the elimination of reciprocity. Kellogg et al. (2020) identified three algorithmic control mechanisms (recommending, restricting, and recording) that share a unilateral character: they generate prescriptions for workers but create no corresponding obligations. Reciprocity cannot survive a relationship in which one party acts exclusively as a rule-generator. Van den Broek et al.'s (2021) finding again speaks directly to this vector: the very act of architecting the human expert out of the system removes the agent who was structurally positioned to incur reciprocal obligation toward the worker. The third is the collapse of accountability. Classical employment relationships distribute moral accountability through a hierarchy of human agents, a chain that gives the relationship its normative structure. Algorithmic systems disrupt this chain not by making unfair decisions but by eliminating the human agent to whom accountability could be attributed (Adams-Prassl, 2019). Green et al.'s (2021) longitudinal UK evidence, showing simultaneous increases in work intensity and declines in job autonomy attributable to algorithmic tools, provides the observable behavioural signature of this vector: when autonomy contracts without a human agent being responsible for the contraction, workers experience the loss as diffuse rather than attributable, which is the experiential form accountability collapse takes. Jarrahi et al. (2021), examining algorithmic management as a sociotechnical process in standard work contexts, documented how algorithmic opacity generates information asymmetries that consolidate managerial power while eroding workers' capacity to understand, contest, or negotiate decisions. Their findings corroborate all three mutation vectors simultaneously: opacity of obligation (workers cannot see why decisions are made), elimination of reciprocity (algorithms consolidate unilateral control), and collapse of accountability (responsibility is diffused across technical systems and organisational actors). Langer and Landers (2021), reviewing experimental evidence on worker reactions to algorithmic decisions, found that workers targeted by automated decisions report lower perceptions of procedural justice and reduced trust in organisational decision-making, effects that persist even when algorithmic decisions are demonstrably more accurate than human ones. This finding is significant because it suggests that mutation is driven not by the quality of decisions but by the relational mode through which decisions are delivered. Table 2 synthesises the correspondence between the three mutation vectors and the principal empirical findings that anchor them.

Table 2. Mapping the Three Mutation Vectors to Principal Empirical Anchors

Mutation vector	Empirical finding reinterpreted through our framework	Source
Opacity of obligation	Developers of an ML hiring system systematically excluded HR domain expertise from design, rendering decision criteria constitutively unknowable to workers and to the HR agents who would otherwise be the accountable obligors.	Van den Broek et al. (2021)
Opacity of obligation	Algorithmic opacity generates information asymmetries that prevent workers from understanding, contesting, or negotiating decisions, making the implicit promise of merit-based reward unverifiable.	Jarrahi et al. (2021)
Elimination of reciprocity	Three algorithmic control mechanisms (recommending, restricting, recording) generate unilateral prescriptions for workers without creating corresponding obligations on the system's part, dissolving the basis of reciprocal exchange.	Kellogg et al. (2020)
Elimination of reciprocity	Architecting human experts out of the ML system removes the agent structurally positioned to incur reciprocal obligation toward the worker; recruitment decisions are produced without a committed human counterpart.	Van den Broek et al. (2021)
Elimination of reciprocity	Workers exposed to algorithmic agents perceive lower employer commitment to relational inducements than when equivalent inducements are delivered by a human counterpart, indicating relational deficit structurally baked into the algorithmic interface.	Tomprou & Lee (2022)
Collapse of accountability	Workers across occupational categories report simultaneous increases in work intensity and declines in job autonomy attributable to algorithmic tools; loss of autonomy is experienced as diffuse rather than attributable to an accountable human agent.	Green et al. (2021)
Collapse of accountability	Workers targeted by automated decisions report lower perceptions of procedural justice and reduced trust even when algorithmic decisions are more accurate than human ones, confirming that accountability loss operates independently of decisional quality.	Langer & Landers (2021)

Read together, these anchors support the claim that the three vectors are not mere conceptual distinctions: each has observable empirical manifestations in studies that were not designed with our framework in mind but whose findings the framework parsimoniously organises.

Proposition 2: Algorithmic HRM produces psychological contract mutation, understood as a structural transformation from a relational to a transactional contractual logic, through three cumulative vectors: opacity of obligation, elimination of reciprocity, and collapse of accountability. This mutation follows a self-reinforcing path: as relational infrastructure atrophies (managerial relational competencies, time allocated to human-mediated decisions, cultures of interpersonal accountability), the institutional conditions for reversing the mutation progressively diminish.

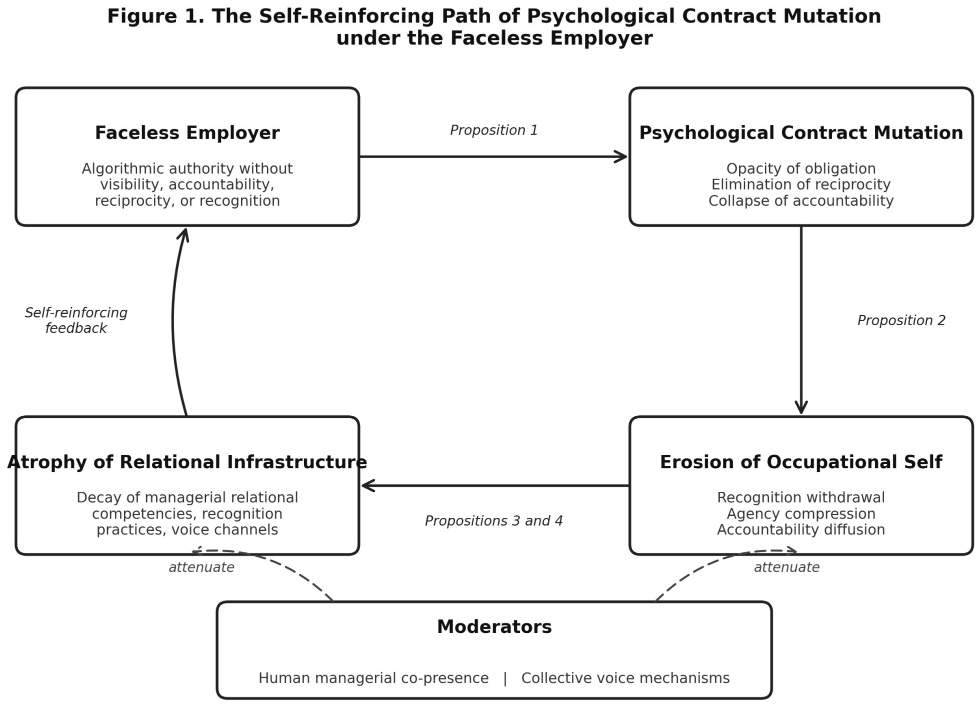

Figure 1. The self-reinforcing path of psychological contract mutation under the faceless employer. Solid arrows represent the causal chain advanced in Propositions 1 to 4; the curved arrow represents the reinforcement loop through which erosion of occupational self atrophies the relational infrastructure that could restore accountable human authority. Dashed arrows indicate the moderating channels through which human managerial co-presence and collective voice mechanisms attenuate the erosion process.

Proposition 3: Psychological contract mutation produced by algorithmic HRM is qualitatively distinct from classical breach and violation: it does not arise from a specific unfulfilled promise but from the structural replacement of the obligor, the dissolution of the relational principal rather than the failure of any particular relational act.

3.3 The typology of mutation: A theoretical model

The mutation process does not take a single form. Its trajectory and consequences vary along two dimensions: the type of contract that existed prior to algorithmic transformation (transactional versus relational, following Rousseau's (1995) foundational distinction, and the degree of algorithmic substitution, augmentation of human decision-making versus replacement of it, following Raisch and Krakowski (2021). Table 1 presents the resulting typology.

Table 1. A Typology of Psychological Contract Mutation in Algorithmic HRM

	Algorithmic Augmentation (human agent remains visible and accountable)	**Algorithmic Substitution (human agent displaced or absent)**
Relational Contract (trust, loyalty, long-term investment)	Quadrant 1: Negotiated Reconfiguration. The worker perceives AI as a tool governed by a known, accountable human. Relational logic is preserved; mutation is resisted or absorbed.	Quadrant 2: Symbolic Betrayal. The worker experiences the disappearance of the relational employer as a profound breach of trust. Mutation is acute and rapid; occupational self-erosion is severe.
Transactional Contract (exchange of effort for specified rewards)	Quadrant 3: Instrumental Adaptation. The worker adapts algorithmically mediated rules as an extension of existing transactional logic. Mutation is partial; occupational self-erosion is moderate.	Quadrant 4: Cold Dissolution. The worker experiences the contract as wholly depersonalized. The transactional logic is fulfilled, but all relational residue is eliminated. Occupational self-erosion is gradual but total.

The typology's critical insight is that the combination of relational contracts and algorithmic substitution

(Quadrant 2) produces the most severe form of mutation. Workers who invested trust, loyalty, and long-term commitment in a human employer experience the displacement of that employer by an algorithm as what we call symbolic betrayal, not a specific broken promise but the elimination of the promiser. Conversely, workers with transactional contracts under augmentation conditions (Quadrant 3) may adapt with minimal identity disruption. The "moderate" level of occupational self-erosion in Quadrant 3 requires explicit clarification, since our core argument is that mutation is a structural transformation rather than a matter of subjective sensitivity. We do not claim that the occupational self is inherently less vulnerable in transactional contracts. The mutation still occurs structurally: the obligor still changes in nature, the three vectors (opacity, elimination of reciprocity, collapse of accountability) still operate. What is moderated in Quadrant 3 is the perceived salience of mutation, not its structural reality. Three reasons converge to produce this attenuation. First, transactional contracts place less identity weight on the relational dimension of the employment bond, so the dissolution of the relational obligor removes a smaller share of what the worker had invested in the relationship. Second, augmentation preserves a visible human intermediary who can still function as the proximate face of the decision, absorbing part of the accountability vector even when the algorithm does the substantive work. Third, because transactional workers never expected personalised recognition, its absence is not immediately interpreted as a breach. Quadrant 3 is therefore best described as the zone of silent mutation: structural transformation is fully underway but phenomenologically muted, which makes it empirically harder to detect and theoretically dangerous to overlook. The contrast with Quadrant 4 reinforces this reading: when substitution removes the human intermediary entirely, even transactional workers exhaust the available compensations, and erosion becomes gradual but, over the long term, total. This variation is empirically consequential: it predicts that organizations with strong relational employment cultures will experience more severe and more visible mutation effects from AI-HRM adoption than those with already transactional cultures, even though the underlying structural process is the same in both cases.

3.4 Erosion of occupational self: The consequence

We define the occupational self as the individual's capacity to experience themselves as a recognized, competent, and morally accountable subject within the employment relationship, grounded in the perception that one's contributions are seen, evaluated by someone capable of judgement, and connected to outcomes through a chain of reasons that could be communicated and contested. The concept draws on Ibarra's (1999) work on professional identity, Dutton et al.'s (2010) research on identity affirmation at work, Tajfel and Turner's (1979) social identity tradition, and Mirbabaie et al.'s (2022) identification of AI identity threat predictors in the workplace.

The erosion of occupational self is the progressive dissolution of this capacity under conditions of faceless employer authority. It differs from disengagement, burnout, and alienation in its specific causal logic. Disengagement is triggered by a mismatch between effort and reward (Kahn, 1990). Burnout is produced by chronic resource depletion (Maslach & Leiter, 1997). Alienation concerns estrangement from the product of labor (Thompson, 2010). Occupational self-erosion is produced by the structural absence of a relational counterpart, not by an unfair exchange, not by excessive demands, but by the disappearance of the agent to whom the worker's occupational self could present itself for recognition.

Three mechanisms drive the erosion, each grounded in both organisational and philosophical theory. Recognition withdrawal: when the evaluating authority is an algorithm, the worker's identity performance loses its audience. In Honneth's (1995) terms, the "social esteem" dimension of recognition, which depends on one's contributions being acknowledged within a community of value, is rendered impossible when the evaluating authority cannot recognise value. Expertise, initiative, and professional judgment become invisible to a system that processes behavioural data without recognising its meaning. Agency compression: as algorithmic systems prescribe increasingly granular aspects of work, the scope for autonomous decision-making shrinks, and with it the experiential basis for perceiving oneself as a professional agent. Van den Broek et al.'s (2021) ethnography documents this compression as developers systematically excluded professional expertise from the ML system's design. Accountability diffusion: when negative outcomes result from algorithmic decisions, workers can identify no agent to hold responsible, producing a form of learned helplessness regarding the employment relationship.

Proposition 4: Psychological contract mutation produced by the faceless employer generates a form of occupational self-erosion qualitatively distinct from disengagement, burnout, or alienation, characterized by the progressive dissolution of the worker's experience of being recognized as a relational subject by an accountable authority. This erosion is moderated by (a) the degree of human managerial co-presence maintained alongside algorithmic systems and (b) workers' access to collective voice mechanisms (trade union representation, works councils), such that higher co-presence and stronger voice attenuate the erosion process.

The collective voice moderator warrants a more granular specification, because its logic is not self-evident. A plausible reading would be that trade union or works council presence simply restores the missing face of the employer by introducing a human relational counterpart into an otherwise faceless configuration. We reject that reading: the union does not, and structurally cannot, become the employer. The employer remains the entity that sets the terms of the employment contract and bears the corresponding legal and economic obligations, and collective voice institutions stand beside, not in place of, that entity. We propose instead that collective voice attenuates occupational self-erosion through three distinct mechanisms that operate at different points of the framework in Figure 1. First, as a compensatory site of recognition: works councils, union locals, and shop-floor representation structures provide an alternative relational arena in which workers' contributions, grievances, and professional claims can be acknowledged by human counterparts (representatives, peers) who are structurally capable of reciprocity, even while the employer-side obligor remains algorithmic. The recognition deficit at the employer-worker interface is thus partially offset at the worker-collective interface, without being resolved there. Second, as institutional pressure for human accountability: codetermination rights and negotiated limits on algorithmic management force employers to maintain identifiable human decision-makers within the algorithmic loop. Doellgast et al.'s (2023) comparative study of works council and union responses to algorithmic management in German and Norwegian telecommunications firms shows that worker representatives mobilised co-determination rights and data protection laws to constrain remote monitoring, preserve workforce discretion, and require that algorithmic tools be accompanied by named human agents accountable for their use. In our terms, these interventions do not restore the employer's face but reconstruct the accountability chain that the faceless employer had broken, partially reinstating the collapse-of-accountability vector. Third, as collective contestation capacity: unions and works councils can challenge individual algorithmic decisions on behalf of workers, triggering explanation, revision, or reversal. Aloisi and Gramano (2019) document how, in EU contexts, such contestation transforms algorithmic decisions from unilateral outputs into disputable organisational acts that must be justified in relational terms. Collective voice thus does not restore the face of the employer, but it alters the conditions under which facelessness operates: it forces elements of visibility, accountability, and procedural reciprocity back into the system, attenuating (not neutralising) the occupational self-erosion pathway. The implication is important for Proposition 4: the moderator works by partial reconstruction of the vectors at the collective level, not by direct restoration of the dyadic relational contract at the individual level. Workers remain, at the point of algorithmic decision, alone before a faceless system; collective voice ensures that this aloneness is neither total nor unreviewable.

4. Discussion

Charlwood and Guenole (2022) argued that AI in HRM cannot be understood through either optimistic or pessimistic scenarios alone; both coexist in productive tension. Their analysis operates at the level of organizational outcomes and professional practice. Our argument descends from theirs but shifts the register. The paradox of AI in HRM is enacted at two levels simultaneously. At the organizational level, the paradox is between efficiency and equity. At the individual psychological level, it is the paradox between the worker's rational acknowledgment of AI's potential utility and their subjective experience of diminishment when that same AI replaces the human authority whose recognition constituted their occupational self. A worker can simultaneously understand that the algorithm is more objective than the biased manager it replaced and experience the loss of that manager's capacity for personal recognition as an erosion of something essential to their occupational self. Both experiences are simultaneously real, and neither resolves the other.

Charlwood and Guenole's prescription, that HR professionals must engage with AI development, acquire data literacy, and anchor algorithmic systems in ethical domain knowledge, is necessary but insufficient under our framework. Domain knowledge prevents technically biased AI. It does not restore the relational face of the employer. The HR professional who masters algorithmic systems but deploys them without rebuilding human presence in consequential decisions risks producing technically fair outcomes delivered by a faceless authority, outcomes satisfying legal and procedural fairness criteria while eroding the psychological conditions under which workers maintain their occupational self.

Three objections must be addressed. First, one might argue that depersonalization of managerial authority is not new: bureaucratic systems have always operated through impersonal rules. This objection has force but misses a structural distinction. Bureaucratic depersonalization operates through codified rules that are humanly authored, humanly interpreted, and humanly contestable. The ML system's outputs are emergent patterns in data whose causal logic even developers may not fully understand (Lebovitz et al., 2021). The difference is not one of degree but of kind.

Second, one might argue that workers adapt, that psychological contracts are renegotiated and new identity forms emerge (Tomprou & Lee, 2022). We accept this partially. Proposition 4 explicitly incorporates moderating conditions under which erosion may be attenuated. But adaptation has limits: adaptation to bureaucracy was possible precisely because bureaucratic authority retained a human face at some level. Adaptation to a wholly faceless authority requires forming a psychological contract with an entity incapable of reciprocity, a qualitatively different challenge.

Third, and most uncomfortable: workers may prefer algorithmic management. Tomprou and Lee (2022) found lower turnover intentions when algorithmic agents under-delivered inducements compared to human agents. This finding is consistent with mutation rather than contradicting it: if the algorithm generates lower expectations of relational inducement, under-delivery is perceived as less betrayal. But reduced turnover intention need not indicate well-being; it may reflect the relational disorientation we theorize, where workers lack a human target for dissatisfaction and therefore express it less. The absence of voice should not be mistaken for the presence of satisfaction.

A fourth question, explicitly excluded from the scope of our review in Section 2.3, now returns as a boundary condition that the framework must address. We set aside generative AI (in particular large language models) to focus on machine-learning decisional systems, because the two technologies pose analytically distinct problems. Yet the rapid adoption of generative AI in HRM for automated feedback generation, personalised career coaching, onboarding conversations, and well-being check-ins (Budhwar et al., 2023) complicates, rather than invalidates, our argument. Generative AI, unlike earlier ML decisional systems, can simulate the very relational attributes whose absence we have theorised as constitutive of the faceless employer. A large language model can address a worker by name, acknowledge their concerns in empathetic register, and produce feedback that reads as if authored by a caring manager. The question is whether this simulation resolves the faceless employer problem or reconfigures it in more insidious form. We argue the latter, and our framework predicts two concurrent effects that future research should distinguish empirically.

The first is a masking effect: generative AI's simulated recognition may delay the worker's perception that the authority they interact with is structurally faceless, extending the phenomenology of relational presence without restoring its substance. The worker who receives warm, personalised feedback from an LLM-based coaching tool may, for a period, form a psychological contract with the simulation itself, experiencing something that looks like recognition, reciprocity, and accountability. On our account, this is the faceless employer wearing a synthetic face: the four relational attributes (visibility, moral accountability, reciprocal obligation capacity, interpersonal recognition) remain absent at the structural level, but their semblance is performed at the interactional surface. Mutation still occurs, because the obligor still cannot incur genuine obligation, but it is phenomenologically disguised, which makes detection (and therefore intervention) harder than in the case of non-communicative ML decisional systems. The second is an accelerated symbolic betrayal effect. When the simulation becomes visible to workers (when they discover that the supportive feedback was generated by a model without understanding, memory, or moral stake), the betrayal is qualitatively different from classical breach. The worker was not merely denied recognition; they received, in lieu of it, its simulacrum, performed by an entity structurally incapable of recognising anything. This doubles the mutation: to the three vectors already theorised (opacity, elimination of reciprocity, collapse of accountability) a fourth suggestion emerges, namely the discovery that the relational performance itself was counterfeit. We therefore expect Quadrant 2 (relational contracts under algorithmic substitution) to be especially vulnerable to generative AI deployment: workers in relational cultures who have invested trust in the "caring" interface are precisely those for whom unmasking produces the sharpest symbolic betrayal. Generative AI does not dissolve the faceless employer phenomenon; it offers it a mask, and in so doing sharpens both the masking and the betrayal variants of mutation. This is the direction in which future empirical work using our framework is, in our view, most urgently needed.

5. Implications and Future Research Directions

5.1 Theoretical implications

This article makes three contributions to the theoretical landscape of AI in HRM. The first is the construct of the faceless employer, a theoretically specified entity that provides a vocabulary for a phenomenon the field has been observing without naming. Following Suddaby's (2010) criteria for construct clarity, we have specified the faceless employer's definitional boundaries, distinguished it from adjacent constructs (algorithmic management, digital Taylorism, and automated decision-making), and identified its necessary and sufficient conditions. The second contribution is psychological contract mutation as a category analytically distinct from breach and violation. This distinction locates the theoretical action in the right place: not in any particular unfulfilled promise but in the structural transformation of the contractual relationship itself. The third is the bridge between paradox theory at the organizational level and occupational identity theory at the individual level, extending Charlwood and Guenole's (2022) paradox analysis to the phenomenological experience of individual workers.

5.2 Practical implications

For HR professionals, the framework issues a precise warning: the delegation of managerial authority to algorithmic systems is not a neutral operational choice. It transforms the relational foundation of the employment relationship. We recommend that organizations adopting AI for people management conduct psychological contract impact assessments, that is, structured evaluations of how algorithmic delegation alters workers' perceived relational conditions, before, during, and after deployment. Proposition 4 suggests a clear practical lever: maintaining genuine human managerial co-presence alongside algorithmic systems. This means not token oversight but preserving substantive human-mediated relational channels: opportunities for workers to raise concerns, negotiate expectations, and receive recognition from morally accountable individuals. Charlwood and Guenole's (2022) argument that the HR profession must actively shape AI deployment is reinforced: without HR professionals serving as relational intermediaries, the faceless employer emerges by default. To operationalise these recommendations, we propose that psychological contract impact assessments should include three diagnostic components. First, a relational attribution audit: structured interviews or surveys asking workers to identify who they believe is responsible for key employment decisions (hiring, evaluation, promotion, discipline), distinguishing between human agents, algorithmic systems, and "the organisation" as abstract entity. A shift in attributions from named human agents toward "the system" or "the algorithm" would signal faceless employer emergence. Second, a mutation-breach differential diagnostic: comparing workers' perceptions using existing psychological contract breach scales (Robinson & Morrison, 2000) with new items capturing the three mutation vectors (opacity of obligation, elimination of reciprocity, collapse of accountability). If workers report high scores on mutation items but low scores on classical breach items, this indicates mutation rather than breach, requiring relational rather than compensatory interventions. Third, an occupational self inventory: periodic assessments of workers' perceived recognition, autonomy, and accountability using adapted identity measures, tracked longitudinally to detect erosion trajectories before they become irreversible.

5.3 Future research agenda

Four research directions follow from our propositions. First, longitudinal qualitative research is needed to trace the faceless employer's emergence in organizational settings. We propose ethnographic field studies (Bailey & Barley, 2020) in organizations deploying AI for core HRM functions (recruitment, performance evaluation, workforce scheduling), with repeated interviews over 18–24 months tracking changes in psychological contract perceptions, employer attributions, and occupational identity narratives. The expected contribution is empirical grounding of Propositions 1 and 2 and documentation of the mutation process as it unfolds.

Second, quasi-experimental research comparing workers managed primarily by algorithms with matched controls managed by human supervisors can test Proposition 3's mechanisms. A mixed-methods design combining validated scales for occupational identity (Ashforth, 2001), psychological contract breach and violation (Robinson & Morrison, 2000), and algorithmically specific measures with qualitative interviews would permit testing whether the erosion pathways (recognition withdrawal, agency compression, and accountability diffusion) are empirically distinguishable and sequentially related.

Third, cross-national comparative research is needed to test Proposition 4's moderating conditions. Countries with strong codetermination frameworks (Germany, the Netherlands, and Scandinavian states) and those with weaker worker voice institutions (the United Kingdom and the United States) offer natural variation in collective voice mechanisms. Doellgast et al.'s (2023) comparative study of union and works council responses to algorithmic management in German and Norwegian telecommunications firms provides a productive template for this research direction, showing how worker representatives mobilise different sources of institutional power (co-determination rights, data protection law, labour cooperation structures) to set limits on algorithmic monitoring and preserve human decisional loci. A natural extension of our framework would be to replicate this comparative design across the three mutation vectors, measuring whether each vector (opacity, elimination of reciprocity, collapse of accountability) is differentially attenuated under different voice regimes, and whether the three mechanisms we identified (compensatory recognition site, pressure for human accountability, collective contestation) operate jointly or substitute for one another. The expected contribution is identification of institutional conditions under which occupational self-erosion is attenuated or accelerated, with direct implications for regulatory policy and for firms selecting algorithmic HRM configurations in different national contexts.

Fourth, a program of action research in collaboration with HR professional bodies (CIPD, SHRM, AHRI) could co-develop and pilot the psychological contract impact assessments we recommend. This would produce both theoretical insight into practical conditions for maintaining relational integrity in AI-mediated HRM and actionable tools for practitioners.

5.4 Limitations

Our framework has clear boundary conditions that should be acknowledged as limitations. It applies to conventional employment relationships where workers have an established psychological contract with a human employer that is subsequently disrupted by algorithmic delegation; it does not directly address gig-economy settings where the employment relationship was algorithmically mediated from inception. The secondary empirical anchoring, while methodologically legitimate, cannot substitute for primary data, and our propositions require the empirical validation outlined above. The framework has been developed predominantly from and for contexts in advanced industrialized economies with mature HR institutional frameworks. Its applicability to emerging economies and the Global South, where algorithmic HRM is spreading rapidly but within institutional configurations characterized by weaker formal employment protections, different cultural expectations of authority, and distinct relational norms, remains an open and urgent question that future research must address.

6. Conclusion

The central question that AI in HRM poses to our discipline is not 'How do we make the algorithm fairer?' Fairness is necessary and eminently achievable, as Charlwood and Guenole (2022) argued with precision. The deeper question is: how do we preserve the condition of the subject for the worker in an employment relationship whose authoritative agent no longer has a face?

This reformulation does not contradict the fairness agenda; it extends it. An algorithmically fair system that produces technically unbiased hiring decisions while systematically eroding workers' occupational self is not, in any complete sense, an ethical system. It achieves procedural equity at the cost of relational justice. The field of HRM, with its foundational commitment to human dignity and mutual flourishing (CIPD, 2020; SHRM, 2014), cannot be satisfied with the first without attending to the second.

The three constructs we have introduced (the faceless employer, psychological contract mutation, and erosion of occupational self) are offered not as a counsel of technological pessimism but as theoretical tools for a more complete diagnosis of what is at stake. The HR profession has agency in shaping how AI transforms the employment relationship. That agency must be exercised not only in the design of fairer algorithms but also in the deliberate preservation of human relational presence alongside them. The face that HRM must restore is not the face of bias and inconsistency that algorithmic systems rightly replace. It is the face of recognition, of the employer who sees the worker as a person, whose decisions can be questioned, whose authority can be challenged, and whose obligations can be enforced. Without that face, the employment contract does not merely change its terms. It changes its nature.

Acknowledgements

The author declares no funding received for the conduct of this research.

Conflict of Interest

The author has no conflicts of interest to declare.

Data Availability Statement

Data sharing is not applicable to this article, as no new data were created or analyzed. This article presents a theoretical integrative review with secondary empirical anchoring; all empirical evidence mobilized is drawn from previously published works cited in the references.

ORCID

Jacob Patrick Belinga Bessala https://orcid.org/0000-0001-7236-0564

References

Adams-Prassl, J. (2019). What if your boss was an algorithm? The rise of artificial intelligence at work. Comparative Labor Law & Policy Journal, 41(1), 123–146.

Aloisi, A., & Gramano, E. (2019). Artificial intelligence is watching you at work: Digital surveillance, employee monitoring, and regulatory issues in the EU context. Comparative Labor Law & Policy Journal, 41(1), 95–122.

Ashforth, B. E. (2001). Role transitions in organizational life: An identity-based perspective. Erlbaum.

Bailey, D., & Barley, S. (2020). Beyond design and use: How scholars should study intelligent technologies. Information and Organization, 30(2), 1–12. https://doi.org/10.1016/j.infoandorg.2020.100286

Bailie, I., & Butler, M. M. (2018). An examination of artificial intelligence and its impact on human resources. CognitionX.

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Lee Cooke, F., Decker, S., DeNisi, A., Dey, P. K., Guest, D., Knoblich, A. J., Malik, A., Paauwe, J., Papagiannidis, S., Patel, C., Pereira, V., Ren, S., Rogelberg, S., Saunders, M. N. K., Tung, R. L., & Varma, A. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. Human Resource Management Journal, 33(3), 606–659. https://doi.org/10.1111/1748-8583.12524

Charlwood, A., & Guenole, N. (2022). Can HR adapt to the paradoxes of artificial intelligence? Human Resource Management Journal, 32(4), 729–742. https://doi.org/10.1111/1748-8583.12433

Cheng, M., Zhang, L., & Wang, H. (2025). The effect of artificial intelligence awareness on frontline service employees' silence: The roles of psychological contract breach and moral identity. International Journal of Contemporary Hospitality Management, 37(5), 1845–1861.

CIPD. (2020). Code of professional conduct. Chartered Institute of Personnel and Development.

Coeckelbergh, M. (2020). AI ethics. MIT Press.

Collings, D. G., Nyberg, A. J., Wright, P. M., & McMackin, J. (2021). Leading through paradox in a COVID-19 world: Human resources comes of age. Human Resource Management Journal, 31(4), 819–833.

Conway, N., & Briner, R. B. (2005). Understanding psychological contracts at work: A critical evaluation of theory and research. Oxford University Press.

Doellgast, V., Wagner, I., & O'Brady, S. (2023). Negotiating limits on algorithmic management in digitalised services: Cases from Germany and Norway. Transfer: European Review of Labour and Research, 29(1), 105–120. https://doi.org/10.1177/10242589221143044

Duggan, J., Sherman, U., Carbery, R., & McDonnell, A. (2020). Algorithmic management and app-work in the gig economy: A research agenda for employment relations and HRM. Human Resource Management Journal, 30(1), 114–132.

Dutton, J. E., Roberts, L. M., & Bednar, J. (2010). Pathways for positive identity construction at work: Four types of positive identity and the building of social resources. Academy of Management Review, 35(2), 265–293.

Glickson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. Academy of Management Annals, 14(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Green, F., Felstead, A., Gallie, D., & Henseke, G. (2021). Working still harder. Industrial and Labor Relations Review. https://doi.org/10.1177/0019793920977850

Guest, D. E. (2004). The psychology of the employment relationship: An analysis based on the psychological contract. Applied Psychology, 53(4), 541–555. https://doi.org/10.1111/j.1464-0597.2004.00187.x

Guenole, N., & Feinzig, S. (2019). The business case for AI in HR. IBM Smarter Workforce Institute.

Honneth, A. (1995). The struggle for recognition: The moral grammar of social conflicts. MIT Press.

Hutchinson, B., & Mitchell, M. (2019). 50 years of test (un)fairness: Lessons for machine learning. In Proceedings of the conference on fairness, accountability, and transparency (pp. 49–58).

Ibarra, H. (1999). Provisional selves: Experimenting with image and identity in professional adaptation. Administrative Science Quarterly, 44(4), 764–791. https://doi.org/10.2307/2667055

Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2021). Algorithmic management in a work context. Big Data & Society, 8(2), 1–14. https://doi.org/10.1177/20539517211020332

Kahn, W. A. (1990). Psychological conditions of personal engagement and disengagement at work. Academy of Management Journal, 33(4), 692–724.

Kellogg, K., Valentine, M., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. Academy of Management Annals, 14(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Langer, M., & Landers, R. (2021). The future of artificial intelligence at work: A review on effects of decision automation and augmentation on workers targeted by algorithms and third party observers. Computers in Human Behavior, 123, 106878.

Lebovitz, S., Levina, N., Lifshitz-Assaf, H., & Lifshitz-Assa, H. (2021). Is AI ground truth really true? The dangers of training and evaluating AI tools based on experts' know-what. MIS Quarterly, 45(3), 1501–1526.

Maslach, C., & Leiter, M. P. (1997). The truth about burnout. Jossey-Bass.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. Academy of Management Review, 20(3), 709–734. https://doi.org/10.5465/amr.1995.9508080335

Mirbabaie, M., Brünker, F., Möllmann, N. R. J., Frick, N. R. J., & Stieglitz, S. (2022). The rise of artificial intelligence: Understanding the AI identity threat at the workplace. Electronic Markets, 32, 73–99. https://doi.org/10.1007/s12525-021-00496-x

Möhlmann, M., Zalmanson, L., Henfridsson, O., & Gregory, R. (2021). Algorithmic management of work on online labor platforms: When matching meets control. Management Information Systems Quarterly, 45(4), 1999–2022.

Moore, P. V. (2019). OSH and the future of work: Benefits and risks of artificial intelligence tools in workplaces. In International conference on human–computer interaction (pp. 292–315). Springer.

Morrison, E. W., & Robinson, S. L. (1997). When employees feel betrayed: A model of how psychological contract violation develops. Academy of Management Review, 22(1), 226–256. https://doi.org/10.5465/amr.1997.9707180265

Nishii, L. H., Lepak, D. P., & Schneider, B. (2008). Employee attributions of the "why" of HR practices: Their effects on employee attitudes and behaviors, and customer satisfaction. Personnel Psychology, 61(3), 503–545. https://doi.org/10.1111/j.1744-6570.2008.00121.x

Ployhart, R. E., & Holtz, B. C. (2008). The diversity–validity dilemma: Strategies for reducing racioethnic and sex subgroup differences and adverse impact in selection. Personnel Psychology, 61(1), 153–172.

Prikshat, V., Malik, A., & Budhwar, P. (2021). AI-augmented HRM: Antecedents, assimilation and multilevel consequences. Human Resource Management Review. https://doi.org/10.1016/j.hrmr.2021.100860

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. Academy of Management Review, 46(1), 192–210.

Robinson, S. L., & Morrison, E. W. (2000). The development of psychological contract breach and violation: A longitudinal study. Journal of Organizational Behavior, 21(5), 525–546.

Rousseau, D. M. (1989). Psychological and implied contracts in organizations. Employee Responsibilities and Rights Journal, 2(2), 121–139.

Rousseau, D. M. (1995). Psychological contracts in organizations: Understanding written and unwritten agreements. Sage.

Sherman, U., Morley, M., & Duggan, J. (2025). Anthropomorphising the algorithm: A 'Theory of Mind' perspective on psychological contract creation in gig work arrangements. Human Resource Management Journal. https://doi.org/10.1111/1748-8583.12599

SHRM. (2014). Code of ethics. Society for Human Resource Management.

Smith, W. K., & Lewis, M. W. (2011). Toward a theory of paradox: A dynamic equilibrium model of organizing. Academy of Management Review, 36(2), 381–403.

Strohmeier, S., & Piazza, F. (2013). Domain driven data mining in human resource management: A review of current research. Expert Systems with Applications, 40(7), 2410–2420.

Strohmeier, S., & Piazza, F. (2015). Artificial intelligence techniques in human resource management: A conceptual exploration. Intelligent Techniques in Engineering Management, 87, 149–172.

Suddaby, R. (2010). Editor's comments: Construct clarity in theories of management and organization. Academy of Management Review, 35(3), 346–357. https://doi.org/10.5465/amr.2010.0481

Tajfel, H., & Turner, J. C. (1979). An integrative theory of intergroup conflict. In W. G. Austin & S. Worchel (Eds.), The social psychology of intergroup relations (pp. 33–47). Brooks/Cole.

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resource management: Challenges and a path forward. California Management Review, 61(4), 15–42. https://doi.org/10.1177/0008125619867910

Thompson, P. (2010). The capitalist labour process: Concepts and connections. Capital & Class, 34(1), 7–14.

Tomprou, M., & Lee, M. K. (2022). Employment relationships in algorithmic management: A psychological contract perspective. Computers in Human Behavior, 126, 106997. https://doi.org/10.1016/j.chb.2021.106997

Torraco, R. J. (2005). Writing integrative literature reviews: Guidelines and examples. Human Resource Development Review, 4(3), 356–367. https://doi.org/10.1177/1534484305278283

van den Broek, E., Sergeeva, A., Huysman, M., & Huysman Vrije, M. (2021). When the machine meets the expert: An ethnography of developing AI for hiring. Management Information Systems Quarterly, 45(3), 1557–1580.

Weber, M. (1947). The theory of social and economic organization (A. M. Henderson & T. Parsons, Trans.). Free Press.

Zhao, H., Wayne, S. J., Glibkowski, B. C., & Bravo, J. (2007). The impact of psychological contract breach on work-related outcomes: A meta-analysis. Personnel Psychology, 60(3), 647–680. https://doi.org/10.1111/j.1744-6570.2007.00087.x

Zuboff, S. (2019). The age of surveillance capitalism: The fight for a human future at the new frontier of power. PublicAffairs.