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Algorithmic Management, Employee Agency, and Workplace Well-Being : A Systematic Review of AI-Enabled HRM and Organizational Behavior Research

1. Introduction

1.1 Background of AI-Enabled Human Resource Management: Artificial intelligence (AI) is reshaping HRM through technologies such as machine learning, natural language processing, predictive analytics, and automation. These technologies are increasingly used in recruitment, performance management, workforce planing, training, and talent management to enhance efficiency and decision quality (Vrontis et al., 2022).

AI-enabled HRM marks a shift from traditional administrative HR practices toward data-driven and predictive people management. Organizations increasingly employ algorithmic systems to support hiring, performance evaluation, turnover prediction, and strategic workforce planning, giving rise to a "smart HRM" paradigm (Marler & Boudreau, 2017).

While AI offers significant benefits in automation and evidence-based decision-making, it also raises concerns regarding autonomy, privacy, fairness, transparency, and employee well-being (Budhwar et al., 2023). Scholars further argue that algorithmic systems may reinforce biases, reduce human discretion, and create perceptions of organizational injustice, making AI-enabled HRM a critical research area (Minbaeva, 2021).

Key Words : Algorithmic Management, Employee Agency, Systematic Review, traditional administrative AI-Enabled HRM, Organizational Behavior Research, Artificial intelligence (AI), technologies, strategic workforce planning, organizational behavior perspective, human-centered AI governance.

HRM Era	Primary Characteristics	Dominant Technologies	Decision-Making Approach
Traditional HRM	Administrative personnel management	Paper-based systems	Human judgment
Electronic HRM (e-HRM)	Digital HR processes	HRIS, ERP systems	Human-supported digital decisions
HR Analytics Era	Data-driven HR decisions	Business analytics, dashboards	Evidence-based decisions
AI-Enabled HRM	Predictive and automated HR systems	Machine learning, AI, NLP	Algorithm-assisted decisions
Algorithmic HRM	Autonomous decision support and monitoring	Advanced AI and predictive algorithms	Human–AI collaborative decisions

Table 1 : Evolution of HRM Toward AI-Enabled Human Resource Management.

From an organizational behavior perspective, employee responses to AI are influenced by trust, transparency, explainability, perceived usefulness, and job insecurity concerns. These perceptions affect technology acceptance, engagement, commitment, and workplace well-being (Jarrahi et al., 2023). Consequently, integrating HRM and OB perspectives is essential to understand how AI influences both organizational outcomes and employee experiences.

As organizations increasingly transition toward algorithmically mediated workplaces, there is a growing need to integrate HRM and OB perspectives to better understand how AI technologies affect both organizational performance and employee experiences. Such integration is particularly important because technological efficiency alone cannot guarantee sustainable organizational success unless employee well-being, trust, and agency are simultaneously preserved.

1.2 Rise of Algorithmic Management in Modern Workplaces: The growth of AI, big data analytics, and digital monitoring technologies has accelerated the emergence of algorithmic management, where organizational decisions are partially or fully delegated to computational systems. Unlike conventional technology-enabled management, algorithmic management employs algorithms for task allocation, performance evaluation, behavioral monitoring, reward determination, and workplace decision-making, thereby reshaping managerial authority and employer–employee relationships (Kellogg et al., 2020).

Algorithmic management is commonly conceptualized as a socio-technical system integrating data collection, predictive analytics, and automated decision rules to coordinate work activities (Möhlmann & Zalmanson, 2017). Although initially examined in gig and platform-based work environments, it is increasingly adopted across traditional sectors, including finance, healthcare, manufacturing, retail, and professional services (Jarrahi et al., 2023).

From an HRM perspective, organizations utilize AI-driven systems to optimize workforce allocation, scheduling, performance evaluation, and evidence-based decision-making (Budhwar et al., 2023). However, concerns persist regarding reduced transparency, procedural injustice, and limited employee participation, creating tensions between efficiency objectives and employee-centered HR practices (Minbaeva, 2021).

Organizational behavior research suggests that employee acceptance of algorithmic systems depends largely on perceptions of fairness, explainability, trustworthiness, and organizational support rather than technical capability alone (Lee et al., 2015; Newman et al., 2020). Opaque decision processes often generate resistance, reduced commitment, and lower organizational trust (Meijerink et al., 2021).

A major concern involves the shift from traditional supervision to continuous algorithmic monitoring. Employee behaviors are increasingly quantified and evaluated through data-driven control mechanisms, altering established forms of managerial oversight (Kellogg et al., 2020). Although such systems may improve accountability and objectivity, excessive surveillance can increase stress, weaken psychological safety, and reduce autonomy, a core psychological need linked to motivation and well-being (Deci et al., 2017).

Perspective	Primary Focus	Expected Benefits	Major Concerns
Strategic HRM	Workforce optimization and performance enhancement	Efficiency, scalability, consistency	Reduced employee participation
Organizational Behavior	Employee perceptions and behavioral responses	Improved role clarity and feedback	Trust deficits, resistance
Organizational Justice	Fairness and transparency of decisions	Reduced human bias	Procedural opacity
Socio-Technical Systems	Human–technology interaction	Improved coordination	Misalignment between technology and human needs
Critical Management Studies	Power and control mechanisms	Enhanced managerial oversight	Surveillance, autonomy erosion

Table 2: Dominant Perspectives on Algorithmic Management in Contemporary Literature.

The literature reports mixed employee outcomes from algorithmic management. Some studies indicate that algorithmic systems improve decision consistency, reduce managerial bias, and enhance role clarity (Jarrahi et al., 2023). In contrast, others associate algorithmic management with job insecurity, emotional exhaustion, technostress, and perceptions of dehumanization (Wood et al., 2019). These contrasting findings suggest that employee responses depend on contextual factors such as organizational culture, leadership, AI literacy, and human oversight.

Consequently, recent research has shifted from whether organizations should adopt algorithmic management to how such systems can coexist with employee agency and well-being. This perspective supports human-centered AI governance, emphasizing transparency, explainability, employee participation, and ethical oversight to balance technological efficiency with human sustainability (European Commission, 2024). Nevertheless, the literature remains fragmented across HRM, organizational behavior, information systems, and management disciplines, limiting integrated understanding of algorithmic management outcomes.

Overall, scholars agree that algorithmic management represents a significant transformation in managerial control and workforce governance. However, debate persists regarding whether its effects are beneficial or detrimental. While HRM research emphasizes efficiency and value creation, OB studies focus on autonomy, fairness, trust, and well-being. Current evidence suggests that outcomes are contingent upon factors such as transparency, human oversight, organizational culture, and leadership. As a result, understanding how algorithmic management shapes employee agency has emerged as a critical research challenge.

1.3 Employee Agency as a Critical HRM–OB Construct: Employee agency refers to an individual's capacity to exercise discretion, influence work processes, and make meaningful decisions within organizational contexts. In AI-enabled workplaces, agency has emerged as a central construct because algorithmic systems increasingly shape task allocation, performance evaluation, scheduling, and behavioral monitoring (Kellogg et al., 2020). Consequently, the integration of AI into HRM extends beyond technological adoption and directly influences employees' perceptions of autonomy, control, and self-determination.

Perspective	Impact on Agency	Key Outcome
Automation Perspective	Reduced discretion and control	Compliance, dependency
Augmentation Perspective	Enhanced decision support	Empowerment, productivity
Human-Centered AI Perspective	Shared human–AI decision-making	Trust, engagement
Surveillance Perspective	Perceived loss of autonomy	Resistance, stress

Table 3. AI Systems and Employee Agency: Contrasting Perspectives.

From a Self-Determination Theory perspective, autonomy is a fundamental psychological need supporting motivation, engagement, and well-being (Deci et al., 2017). Algorithmic management may restrict employee agency by transferring decision-making authority to opaque systems, thereby reducing discretion and participation (Meijerink et al., 2021). Conversely, AI can enhance agency through decision support, workload reduction, and greater focus on higher-value activities (Jarrahi et al., 2023). These findings highlight AI's dual role as both an enabling and constraining force.

Employee responses are shaped less by technology itself than by its design and governance. Transparent algorithms, employee voice, and human oversight strengthen perceptions of control, fairness, and trust (Newman et al., 2020), whereas opaque and surveillance-oriented systems are associated with resistance, disengagement, and dehumanization (Wood et al., 2019).

From an HRM perspective, employee agency functions as a key mechanism through which AI-enabled practices affect behavioral and well-being outcomes. Reduced agency may weaken motivation and commitment, whereas enhanced agency can promote engagement, learning, and adaptive performance. Although scholars agree on the importance of employee agency, debate remains regarding whether algorithmic systems primarily constrain or enhance autonomy. Current evidence suggests that outcomes depend largely on governance structures, transparency, and human oversight, making workplace well-being a critical consequence of altered employee agency.

1.4 Workplace Well-Being in AI-Mediated Contexts: Workplace well-being reflects employees' psychological, emotional, and occupational functioning within organizations. The growing use of AI and algorithmic management has increased interest in how technology-mediated work systems affect well-being. According to the Job Demands–Resources (JD-R) framework, AI can act as both a resource that improves efficiency and a demand that increases monitoring, workload pressure, and uncertainty (Bakker & Demerouti, 2017).

Evidence suggests a dual effect. AI-enabled systems can reduce repetitive work, support decision-making, and improve role efficiency, thereby enhancing job satisfaction and engagement (Budhwar et al., 2023). However, continuous monitoring, algorithmic evaluations, and perceived job displacement may contribute to technostress, anxiety, emotional exhaustion, and burnout (Tarafdar et al., 2019). Employee well-being is also influenced by perceptions of autonomy, fairness, and trust, indicating that outcomes depend more on organizational implementation practices than on technology alone (Jarrahi et al., 2023).

Positive Effects	Negative Effects
Reduced routine workload	Technostress
Improved decision support	Surveillance anxiety
Enhanced productivity	Emotional exhaustion

Positive Effects	Negative Effects
Increased role efficiency	Job insecurity
Better resource allocation	Burnout risk

Table 4. AI and Workplace Well-Being: Contrasting Effects.

Recent studies increasingly advocate a human-centered AI approach, emphasizing transparency, employee participation, and ethical governance as essential mechanisms for protecting well-being in digitally managed workplaces (European Commission, 2024). Consequently, workplace well-being has emerged as a critical outcome variable in AI-enabled HRM and organizational behavior research.

The literature consistently portrays workplace well-being as a central consequence of algorithmic management and AI-enabled HRM. While AI can enhance efficiency and support employee performance, excessive monitoring, reduced autonomy, and uncertainty may undermine psychological well-being. These findings suggest that well-being outcomes depend largely on how organizations balance technological optimization with human-centered work design, thereby motivating the need to identify the unresolved research gaps within this emerging field.

1.5 Research Problem and Knowledge Gaps: Despite rapid growth in AI-enabled HRM and algorithmic management research, the literature remains fragmented across human resource management, organizational behavior, information systems, and technology management disciplines (Meijerink et al., 2021). Existing studies predominantly emphasize technological efficiency, predictive capabilities, and organizational performance, while comparatively limited attention has been devoted to employee-centered outcomes such as agency, autonomy, trust, and well-being (Budhwar et al., 2023).

A major gap concerns the absence of an integrated framework explaining how algorithmic management influences employee well-being through underlying behavioral mechanisms. While HRM studies largely focus on AI adoption and workforce optimization, OB research emphasizes psychological responses, resulting in theoretical fragmentation and limited cross-disciplinary integration (Jarrahi et al., 2023). Furthermore, empirical evidence remains inconsistent regarding whether algorithmic systems empower employees through decision support or constrain them through surveillance and control (Kellogg et al., 2020).

The literature is also characterized by three methodological limitations. First, most studies employ cross-sectional designs, limiting causal understanding of long-term effects. Second, evidence is heavily concentrated in developed economies and platform-based work settings, restricting generalizability to conventional organizational contexts. Third, limited research simultaneously examines employee agency and workplace well-being within AI-mediated environments (Meijerink et al., 2021).

Consequently, a systematic synthesis integrating HRM and OB perspectives is necessary to explain how algorithmic management affects employee agency and, ultimately, workplace well-being.

Research Area	Current Limitation	Future Need
HRM Research	Technology-centric focus	Employee-centered perspective
OB Research	Fragmented constructs	Integrated explanatory models
Methodology	Predominantly cross-sectional	Longitudinal studies
Context	Gig/platform work dominance	Traditional organizations
Outcomes	Isolated variables	Agency–well-being linkage

Table 5. Major Knowledge Gaps in Existing Literature.

Current scholarship provides substantial evidence regarding AI adoption but offers limited understanding of the mechanisms through which algorithmic management shapes employee experiences. Theoretical fragmentation, inconsistent findings, and contextual limitations highlight the need for an integrative review linking algorithmic management, employee agency, and workplace well-being. Addressing these gaps forms the central objective of the present study.

1.6 Objectives and Contributions of the Review: The primary objective of this review is to systematically synthesize fragmented evidence on algorithmic management, employee agency, and workplace well-being within AI-enabled organizational contexts. Specifically, the review seeks to integrate HRM and OB perspectives to explain how AI-driven managerial systems influence employee experiences and behavioral outcomes. The review pursues four objectives:

1. To examine the evolution and conceptualization of algorithmic management
2. To identify the mechanisms through which algorithmic systems affect employee agency
3. To synthesize evidence regarding the consequences of AI-enabled management for workplace well-being
4. To develop an integrated framework linking technological, psychological, and organizational dimensions of AI-mediated work (Jarrahi et al., 2023; Meijerink et al., 2021).

The study contributes to the literature in three ways. First, it bridges HRM and OB scholarship, which have largely evolved in parallel despite examining similar phenomena. Second, it positions employee agency as a central explanatory mechanism connecting algorithmic management with well-being outcomes. Third, it advances a human-centered perspective by identifying organizational conditions under which AI systems can support both performance and employee sustainability (Budhwar et al., 2023).

Objective	Expected Contribution
Review algorithmic management literature	Conceptual clarification
Examine employee agency	Mechanism identification
Analyze well-being outcomes	Outcome synthesis
Develop integrated framework	Theory integration
Identify future research directions	Agenda development

Table 6. Objectives and Expected Contributions.

The increasing adoption of AI-enabled management systems necessitates a comprehensive understanding of their implications beyond operational efficiency. By integrating insights from HRM and OB, this review positions employee agency as a critical link between algorithmic management and workplace well-being, thereby providing the conceptual foundation for the subsequent methodological and theoretical sections.

2. Methodology

2.1 Review Design & Search Strategy: This study adopts a Systematic Literature Review (SLR) methodology to synthesize fragmented evidence on algorithmic management, employee agency, and workplace well-being. SLRs provide a transparent, replicable, and theory-building approach for consolidating knowledge across multidisciplinary domains, making them particularly suitable for emerging research areas characterized by conceptual dispersion (Tranfield et al., 2003; Snyder, 2019).

The review focuses on peer-reviewed studies indexed in major academic databases, including Scopus, Web of Science, ScienceDirect, Emerald, and SpringerLink. Search strings combined key concepts such as *algorithmic management*, *AI-enabled HRM*, *artificial* *intelligence at work*, *employee agency*, *employee autonomy*, *workplace well-being*, and *organizational behavior*. Boolean operators (AND/OR) were employed to maximize retrieval accuracy and conceptual coverage. Consistent with review best practices, backward and forward citation tracking was additionally performed to identify influential studies omitted through database searches (Page et al., 2021).

Component	Description
Databases	Scopus, WoS, ScienceDirect, Emerald, Springer
Keywords	Algorithmic Management, AI-HRM, Employee Agency, Workplace Well-Being
Search Logic	Boolean operators (AND/OR)
Sources	Peer-reviewed journal articles
Language	English
Review Type	Systematic Literature Review

Table 7. Search Strategy Framework.

The adoption of a systematic review methodology enhances transparency and reproducibility while enabling cross-disciplinary integration of HRM, OB, and technology management literature. A rigorous search strategy ensures comprehensive coverage of studies examining the intersection of AI-enabled management, employee agency, and well-being.

2.2 Inclusion and Exclusion Criteria and 2.4 Data Extraction and Analysis: To ensure methodological rigor, only peer-reviewed journal articles explicitly examining algorithmic management, AI-enabled HRM, employee agency, autonomy, trust, or workplace well-being were included. Conference papers, editorials, book reviews, dissertations, and non-English publications were excluded. Studies lacking direct relevance to workplace or organizational contexts were also removed.

Following screening, relevant studies were subjected to thematic analysis. Data extraction focused on research context, theoretical foundations, methodological approaches, key constructs, and principal findings. Subsequently, studies were grouped into recurring themes, enabling identification of dominant theoretical perspectives, convergent findings, and unresolved debates within the literature (Braun & Clarke, 2006).

Inclusion Criteria	Exclusion Criteria
Peer-reviewed articles	Editorials and commentaries
Workplace-related studies	Non-organizational contexts
English-language publications	Non-English studies
AI, HRM, OB, well-being focus	Unrelated technology studies
Empirical or conceptual research	Book reviews and dissertations

Table 8. Eligibility Criteria.

The screening and extraction process ensured conceptual relevance and methodological consistency across selected studies. Thematic analysis further facilitated the integration of fragmented findings and the identification of major explanatory mechanisms linking algorithmic management with employee outcomes.

2.3 PRISMA Screening Process: The study followed the PRISMA 2020 framework to ensure transparency and reproducibility in study identification, screening, eligibility assessment, and final inclusion. Duplicate records were removed before title, abstract, and full-text screening. Studies not directly addressing algorithmic management, AI-enabled HRM, employee agency, or workplace well-being were excluded. The structured screening process minimized selection bias and enhanced methodological rigor (Page et al., 2021).

Stage	Purpose
Identification	Database search and record collection
Screening	Removal of duplicates and irrelevant studies
Eligibility	Full-text assessment
Inclusion	Final studies retained for review

Table 9.PRISMA Screening Stages.

3. Theoretical Foundations

3.1 Job Demands–Resources Theory & Self-Determination Theory: The Job Demands–Resources (JD-R) Theory explains how workplace characteristics influence employee well-being through the interaction of job demands and resources (Bakker & Demerouti, 2017). Within AI-enabled workplaces, algorithmic monitoring, performance pressure, and digital surveillance function as demands, whereas decision support, workload reduction, and information accessibility operate as resources. Consequently, AI may simultaneously enhance productivity and generate strain depending on implementation context.

Complementing this perspective, Self-Determination Theory (SDT) emphasizes autonomy, competence, and relatedness as fundamental psychological needs influencing motivation and well-being (Deci et al., 2017). Algorithmic systems that restrict discretion may undermine intrinsic motivation, whereas AI designed to augment employee decision-making can strengthen autonomy and engagement. Together, JD-R and SDT provide a robust foundation for understanding how algorithmic management influences employee agency and workplace well-being.

Theory	Core Construct	Relevance to AI Workplaces
JD-R Theory	Demands and Resources	Explains well-being outcomes
SDT	Autonomy, Competence, Relatedness	Explains employee agency and motivation

Table 10. Theoretical Relevance to the Present Review.

JD-R Theory explains the well-being consequences of AI-mediated work systems, while SDT clarifies how algorithmic management influences employee agency through autonomy-related mechanisms. Together, these theories establish the psychological foundation for examining employee responses to AI-enabled management.

3.2 Organizational Justice Theory & Social Exchange Theory: Organizational Justice Theory (OJT) explains employee reactions to organizational decisions through perceptions of distributive, procedural, and interactional fairness (Colquitt et al., 2001). In AI-enabled workplaces, concerns regarding algorithmic opacity, bias, and explainability have positioned procedural justice at the center of contemporary debates. Employees are more likely to accept algorithmic decisions when decision rules are transparent, consistent, and perceived as fair (Newman et al., 2020). Conversely, opaque systems may trigger distrust, resistance, and reduced organizational commitment.

Social Exchange Theory (SET) posits that employee attitudes and behaviors are shaped by reciprocal relationships between individuals and organizations (Cropanzano & Mitchell, 2005). AI systems perceived as supportive, fair, and beneficial strengthen positive exchange relationships, fostering trust, engagement, and discretionary behaviors. However, excessive surveillance and perceived loss of control may be interpreted as organizational exploitation, weakening reciprocity and increasing withdrawal intentions (Meijerink et al., 2021).

Together, OJT and SET explain why employee perceptions, rather than technological capabilities alone, often determine the success or failure of algorithmic management initiatives.

Theory	Core Focus	AI-Related Concern	Expected Outcome
Organizational Justice Theory	Fairness perceptions	Transparency, bias, explainability	Trust and acceptance
Social Exchange Theory	Reciprocity relationships	Organizational support vs. surveillance	Engagement or withdrawal

Table 11. Justice and Exchange Perspectives in AI-Enabled Workplaces.

OJT emphasizes fairness as a prerequisite for algorithmic legitimacy, whereas SET highlights reciprocity as a driver of employee attitudes toward AI systems. Both theories suggest that employee perceptions mediate the relationship between algorithmic management and organizational outcomes, reinforcing the importance of human-centered AI governance.

3.3 Socio-Technical Systems Theory: Socio-Technical Systems Theory (STS) argues that organizational effectiveness emerges from the joint optimization of social and technological subsystems rather than technological advancement alone (Trist & Bamforth, 1951). Within AI-enabled workplaces, this perspective challenges deterministic assumptions that algorithmic systems automatically improve organizational outcomes. Instead, employee well-being, trust, and performance depend on how technological capabilities align with human needs, organizational structures, and work processes (Benders et al., 2006).

Technical Subsystem	Social Subsystem	Desired Outcome
AI algorithms	Employee agency	Human-centered decisions
Data analytics	Organizational culture	Trust and acceptance
Automation systems	Leadership and governance	Sustainable performance
Monitoring technologies	Employee well-being	Balanced optimization

Table 12. Socio-Technical Perspective on Algorithmic Management.

Recent AI scholarship increasingly adopts a socio-technical perspective, emphasizing that algorithmic management outcomes are contingent upon human oversight, employee participation, ethical governance, and organizational culture (Jarrahi et al., 2023). Consequently, AI should be viewed not as a replacement for human judgment but as part of an integrated human–technology system.

STS provides the overarching theoretical lens for this review by integrating technological efficiency with human sustainability. The theory suggests that algorithmic management produces favorable outcomes only when technological systems are aligned with employee agency, fairness, and well-being. This perspective forms the conceptual bridge to the thematic review of algorithmic management and employee agency.

4. Algorithmic Management and Employee Agency

4.1 Algorithmic Control and Employee Autonomy & Transparency, Explainability, and Employee Trust: Algorithmic management fundamentally restructures employee autonomy by transferring elements of managerial discretion from human supervisors to data-driven systems. While organizations adopt algorithmic control to improve efficiency, consistency, and monitoring accuracy, employees often perceive reduced discretion when algorithms determine task allocation, scheduling, and performance evaluation (Kellogg et al., 2020). According to Self-Determination Theory, diminished autonomy weakens intrinsic motivation and psychological well-being, making employee agency a critical concern in AI-mediated workplaces (Deci et al., 2017).

However, the consequences of algorithmic control are contingent upon transparency and explainability. Research consistently demonstrates that employees are more likely to trust algorithmic decisions when decision criteria are understandable, consistent, and open to review (Newman et al., 2020). Explainable AI reduces uncertainty and strengthens procedural justice perceptions, whereas opaque algorithms create distrust, resistance, and perceived loss of control (Meijerink et al., 2021). Consequently, employee trust emerges as a key mechanism through which algorithmic systems influence behavioral and organizational outcomes.

Dimension	Positive Condition	Negative Condition	Outcome
Autonomy	Decision support	Excessive control	Motivation vs. resistance
Transparency	Explainable systems	Opaque algorithms	Trust vs. distrust
Monitoring	Developmental feedback	Surveillance focus	Engagement vs. stress
Evaluation	Fair procedures	Black-box decisions	Acceptance vs. skepticism

Table 13. Algorithmic Control, Transparency, and Employee Outcomes.

The literature suggests that employee responses to algorithmic management are shaped less by automation itself than by perceptions of autonomy and transparency. Trust functions as a critical mediating mechanism, indicating that human-centered design and explainability are essential for sustaining employee agency in AI-enabled workplaces.

4.2 Employee Voice and Participation in AI-Driven Workplaces and 4.4 Human–AI Collaboration and Empowerment: Employee voice refers to the ability of individuals to influence organizational decisions and express concerns regarding workplace practices. In AI-driven environments, participation in the design, implementation, and evaluation of algorithmic systems has emerged as a critical determinant of acceptance and legitimacy (Meijerink et al., 2021). Research indicates that employees demonstrate higher trust and lower resistance when opportunities exist to challenge, review, or contribute to algorithmic decisions (Jarrahi et al., 2023).

Beyond participation, recent scholarship increasingly conceptualizes AI as an augmentation rather than replacement technology. Human–AI collaboration frameworks argue that AI systems generate the greatest value when they complement human judgment, creativity, and contextual understanding rather than substitute them (Raisch & Krakowski, 2021). Under such conditions, AI can enhance employee agency by reducing routine work and supporting informed decision-making. Conversely, exclusion from decision processes and overreliance on automation may create perceptions of dehumanization and dependency.

Factor	Low Level	High Level
Employee Voice	Resistance	Acceptance
Human Oversight	Dependency on AI	Shared decision-making
Participation	Low legitimacy	High legitimacy
Human–AI Collaboration	Substitution logic	Augmentation logic

Table 14. Employee Participation and Human–AI Collaboration.

The literature increasingly favors an augmentation perspective in which AI complements rather than replaces human capabilities. Employee voice, participation, and human oversight emerge as critical conditions for preserving agency and fostering positive human–AI collaboration. These insights provide the foundation for examining broader organizational behavior outcomes associated with AI-enabled HRM.

5. AI-Enabled HRM and Organizational Behavior Outcomes

5.1 AI-Enabled HRM and Organizational Justice and 5.2 Trust in AI-Based HR Decisions: AI-enabled HRM increasingly influences recruitment, promotion, performance appraisal, and workforce planning decisions, raising concerns regarding organizational justice. Drawing on Organizational Justice Theory, employees evaluate AI-driven decisions based on procedural fairness, consistency, and transparency rather than technological sophistication alone (Colquitt et al., 2001). Although algorithmic systems may reduce human biases, concerns persist regarding embedded biases, data quality, and opaque decision rules (Newman et al., 2020).

Trust represents a critical mechanism linking algorithmic decisions with employee acceptance. Research indicates that trust in AI depends on perceived competence, fairness, explainability, and accountability (Glikson & Woolley, 2020). Employees are more likely to support AI-driven HR practices when human oversight remains present and decision processes are understandable. Conversely, opaque systems weaken trust and increase skepticism toward organizational decisions (Meijerink et al., 2021).

Construct	Positive Condition	Negative Condition
Procedural Justice	Transparency	Opacity
Distributive Justice	Fair outcomes	Perceived bias
Trust in AI	Explainability	Black-box decisions
Decision Acceptance	Human oversight	Full automation

Table 15. Justice and Trust in AI-Enabled HRM.

Justice perceptions and trust jointly determine employee acceptance of AI-enabled HRM systems. Existing evidence suggests that algorithmic effectiveness alone is insufficient; legitimacy depends on fairness, transparency, and accountability mechanisms embedded within organizational decision processes.

5.2 AI, Employee Motivation and Engagement and 5.4 Employee Resistance and Behavioral Responses: The relationship between AI and employee motivation remains theoretically contested. Self-Determination Theory suggests that AI systems can enhance motivation when they support autonomy, competence, and decision quality; however, motivation declines when employees perceive algorithmic control as restrictive or coercive (Deci et al., 2017). Empirical studies indicate that AI-assisted work environments may improve engagement through reduced routine workload and improved performance feedback, but these benefits diminish when monitoring intensity becomes excessive (Budhwar et al., 2023).

Employee resistance represents a common behavioral response to perceived threats associated with automation. Resistance is often driven by fears of job displacement, loss of autonomy, reduced human interaction, and distrust of algorithmic decisions (Jarrahi et al., 2023). Research increasingly demonstrates that participation, AI literacy, and transparent communication can mitigate resistance and strengthen technology acceptance.

Outcome	Positive Driver	Negative Driver
Motivation	Autonomy support	Algorithmic control
Engagement	Decision assistance	Excessive monitoring
Acceptance	Transparency	Uncertainty
Resistance	Job insecurity reduction	Perceived replacement

Table 16. AI and Employee Behavioral Outcomes.

AI influences employee motivation and engagement through its impact on autonomy and perceived control. Resistance emerges primarily when employees interpret AI as a threat rather than a support mechanism. These findings highlight the importance of employee-centered implementation strategies and provide a foundation for examining AI's implications for workplace well-being.

6. Human–AI Collaboration and Workplace Well-Being

6.1 Psychological Well-Being and Technostress & Job Satisfaction and Employee Engagement: Psychological well-being has emerged as a central outcome in AI-enabled workplaces because algorithmic systems simultaneously function as productivity-enhancing resources and psychological stressors. Drawing on JD-R Theory, AI can reduce cognitive burden through decision support and task automation; however, excessive monitoring, information overload, and continuous connectivity often generate technostress, defined as stress arising from technology-related demands (Bakker & Demerouti, 2017; Tarafdar et al., 2019).

The relationship between AI and job satisfaction remains mixed. Studies indicate that AI-supported work environments can enhance satisfaction and engagement by improving efficiency, reducing repetitive work, and increasing perceived competence (Budhwar et al., 2023). Conversely, concerns regarding surveillance, loss of control, and job insecurity negatively affect satisfaction and engagement. Evidence suggests that perceived autonomy and trust mediate these relationships, highlighting the importance of human-centered implementation practices (Jarrahi et al., 2023).

AI influences well-being through competing resource and demand mechanisms. While automation may strengthen engagement and satisfaction, these benefits can be undermined by technostress and perceived loss of autonomy, reinforcing the importance of balanced human–technology integration.

62 Burnout, Emotional Exhaustion and Work–Life Balance & Human-Centered AI and Employee Well-Being: Burnout and emotional exhaustion have become increasingly relevant in algorithmically managed workplaces. Continuous monitoring, performance optimization pressures, and expectations of constant availability may intensify emotional strain and contribute to exhaustion (Wood et al., 2019). Research indicates that employees experiencing limited autonomy and heightened surveillance report higher levels of fatigue, stress, and psychological withdrawal (Tarafdar et al., 2019).

Work–life balance is similarly affected by AI-enabled systems. While flexible technologies can support boundary management and productivity, constant digital connectivity often blurs distinctions between work and personal life, increasing role overload and work intrusion (Budhwar et al., 2023). In response, recent scholarship advocates a human-centered AI approach emphasizing transparency, employee participation, autonomy preservation, ethical governance, and meaningful human oversight (European Commission, 2024). Such practices are associated with healthier work environments and more sustainable well-being outcomes.

Risk Factor	Human-Centered Intervention
Burnout	Workload regulation
Emotional exhaustion	Autonomy support
Surveillance concerns	Transparency
Work–life conflict	Boundary protection
AI distrust	Human oversight

Table 17. Human-Centered AI and Employee Well-Being.

The literature suggests that negative well-being outcomes are not inevitable consequences of AI adoption but largely depend on organizational design choices. Human-centered AI governance can mitigate burnout, preserve work–life balance, and strengthen employee well-being, positioning employee welfare as a critical criterion for evaluating algorithmic management effectiveness.

7. Leadership and Human-Centered AI Governance

7.1 Digital and AI-Augmented Leadership & Ethical Leadership in Algorithmic Workplaces: The rise of AI-enabled workplaces has expanded leadership responsibilities beyond traditional people management toward managing human–AI interactions. AI-augmented leadership emphasizes leveraging algorithmic insights while retaining human judgment, empathy, and contextual decision-making (Raisch & Krakowski, 2021). Leaders increasingly function as interpreters of algorithmic outputs, balancing technological efficiency with employee needs.

Simultaneously, ethical leadership has gained prominence due to concerns regarding algorithmic bias, transparency, privacy, and accountability. Ethical leaders promote fairness, explainability, and responsible technology use, thereby enhancing employee trust and reducing resistance to AI-driven decisions (Martin, 2019). Research suggests that leadership behavior significantly influences employee perceptions of legitimacy and acceptance of algorithmic systems.

Leadership Dimension	Primary Function	Employee Outcome
AI-Augmented Leadership	Human–AI decision integration	Confidence and adaptability
Ethical Leadership	Fairness and accountability	Trust and legitimacy
Digital Leadership	Technology adoption support	Acceptance and engagement
Transformational Leadership	Change facilitation	Reduced resistance

Table 18. Leadership Roles in AI-Enabled Workplaces.

The literature increasingly positions leadership as a critical moderator of employee responses to AI. Effective leaders balance algorithmic efficiency with human values, ensuring that technological adoption strengthens rather than undermines trust, fairness, and employee well-being.

7.2 Human-Centered AI Governance & Towards Responsible AI-Enabled Organizations: Human-centered AI governance advocates designing and deploying AI systems in ways that preserve human agency, dignity, and well-being. Rather than prioritizing efficiency alone, this perspective emphasizes transparency, employee participation, accountability, and human oversight as core governance principles (European Commission, 2024). Such mechanisms reduce perceived risks associated with surveillance, bias, and loss of autonomy.

The concept of responsible AI-enabled organizations extends this perspective by integrating ethical, legal, and organizational considerations into AI governance frameworks. Recent scholarship argues that sustainable AI adoption requires balancing organizational performance objectives with employee-centered outcomes, including trust, fairness, and psychological well-being (Dwivedi et al., 2023). Consequently, responsible AI is increasingly viewed as a strategic governance capability rather than a purely technological concern.

Emerging evidence suggests that the long-term success of AI-enabled organizations depends on governance systems that balance technological innovation with human sustainability. Human-centered governance therefore represents the critical link between algorithmic management, employee agency, and workplace well-being, providing the conceptual basis for the integrated framework developed in the next section.

8. Integrated Conceptual Framework : The reviewed literature suggests that the relationship between AI-enabled management and employee outcomes is neither direct nor deterministic. Rather, algorithmic systems influence workplace well-being through intermediate psychological and behavioral mechanisms. Across HRM and OB research, employee agency, trust, and fairness perceptions consistently emerge as central explanatory constructs linking algorithmic management with organizational outcomes (Meijerink et al., 2021; Jarrahi et al., 2023).

Component	Role in Framework
Algorithmic Management	Antecedent
Autonomy, Trust, Fairness	Perceptual Mechanisms
Employee Agency	Core Mediator
Engagement, Motivation, Resistance	Behavioral Outcomes
Workplace Well-Being	Proximal Outcome
Organizational Sustainability	Distal Outcome
Leadership, Culture, AI Literacy	Moderators

Table 20. Integrated Framework Components.

Building upon JD-R Theory, Self-Determination Theory, Organizational Justice Theory, Social Exchange Theory, and Socio-Technical Systems Theory, the proposed framework conceptualizes algorithmic management as a workplace antecedent influencing employee perceptions and behaviors. Employee agency functions as the primary mediating mechanism, while leadership, organizational culture, AI literacy, and human oversight operate as contextual moderators. The framework integrates fragmented findings into a unified explanation of how AI-enabled HRM shapes workplace well-being and organizational sustainability.

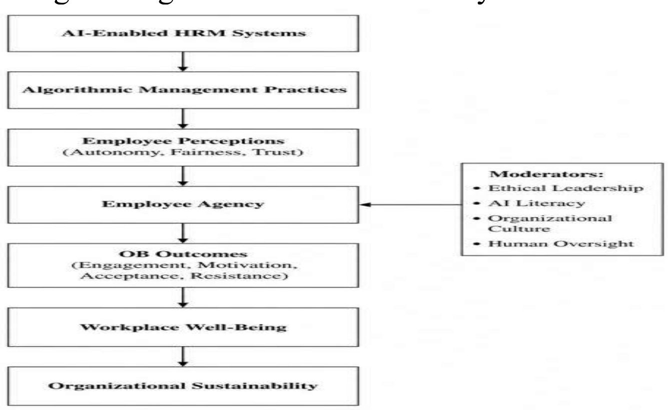

Figure 12 Integrated Conceptual Framework.

The proposed framework advances the literature by positioning employee agency as the central mechanism connecting algorithmic management with workplace well-being. The model shifts attention from technology adoption alone toward the human processes through which AI generates organizational consequences, providing a foundation for future empirical testing.

9. Future Research Agenda : Despite significant growth in AI-enabled HRM research, several theoretical and methodological gaps remain unresolved. First, longitudinal evidence examining the long-term effects of algorithmic management on employee well-being remains limited. Second, existing studies predominantly focus on developed economies and platform-based work settings, restricting contextual generalizability. Third, employee agency remains under-theorized despite its central role in explaining behavioral responses to AI systems (Kellogg et al., 2020).

Future research should investigate how AI literacy, ethical leadership, organizational culture, and human oversight influence employee adaptation to algorithmic management. Greater integration of HRM, OB, and information systems perspectives is also required to develop more comprehensive explanatory

Future scholarship should move beyond adoption-focused research toward understanding the conditions under which AI enhances both organizational performance and employee well-being. Particular attention should be devoted to employee agency, contextual moderators, and longitudinal outcomes.

10. Conclusion : This review synthesized multidisciplinary evidence on algorithmic management, employee agency, and workplace well-being within AI-enabled organizational contexts. The findings indicate that algorithmic management represents a fundamental transformation in workforce governance, extending managerial control through data-driven decision systems while simultaneously creating opportunities for enhanced productivity and decision support.

Across theoretical perspectives, employee agency emerged as the critical mechanism linking algorithmic management with organizational behavior outcomes and workplace well-being. The literature further demonstrates that employee responses are strongly shaped by perceptions of autonomy, fairness, transparency, and trust rather than technological capabilities alone. Consequently, the effects of AI are contingent upon organizational design choices, leadership practices, and governance structures.

The review contributes to HRM and OB scholarship by integrating fragmented evidence into a unified framework that explains how AI-enabled HRM systems influence employee experiences and organizational sustainability. Ultimately, the long-term success of algorithmic management depends not only on technological sophistication but also on the extent to which organizations preserve human agency, well-being, and ethical responsibility within increasingly digital workplaces.

References :

1. Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Paauwe, J., & 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.
2. Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2023). Algorithmic management in a work context. *Big Data & Society, 10*(1), 1–16.
3. Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR Analytics. *International Journal of Human Resource Management, 28*(1), 3–26.
4. Minbaeva, D. (2021). Disruption in human resource management: Artificial intelligence and strategic people management. *Human Resource Management Review, 31*(4), 100820.
5. Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *International Journal of Human Resource Management, 33*(6), 1237–1266.
6. Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Paauwe, J., & 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.
7. Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-determination theory in work organizations: The state of a science. *Annual Review of Organizational Psychology and Organizational Behavior, 4*(1), 19–43.
8. European Commission. (2024). *Guidelines on trustworthy and human-centric artificial intelligence in the workplace*. European Commission.
9. Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2023). Algorithmic management in a work context. *Big Data & Society, 10*(1), 1–16.

10. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410.
11. Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). Working with machines: The impact of algorithmic and data-driven management on human workers. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 1603–1612.
12. Meijerink, J., Boons, M., Keegan, A., & Marler, J. H. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *International Journal of Human Resource Management, 32*(12), 2545–2562.
13. Minbaeva, D. (2021). Disruption in human resource management: Artificial intelligence and strategic people management. *Human Resource Management Review, 31*(4), 100820.
14. Möhlmann, M., & Zalmanson, L. (2017). Hands on the wheel: Navigating algorithmic management and Uber drivers' autonomy. *Proceedings of the International Conference on Information Systems*, 1–17.
15. Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias is not fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes, 160*, 149–167.
16. Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work, Employment and Society, 33*(1), 56–75.
17. Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-determination theory in work organizations: The state of a science. *Annual Review of Organizational Psychology and Organizational Behavior, 4*(1), 19–43.
18. Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2023). Algorithmic management in a work context. *Big Data & Society, 10*(1), 1–16.
19. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410.
20. Meijerink, J., Boons, M., Keegan, A., & Marler, J. H. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *International Journal of Human Resource Management, 32*(12), 2545–2562.
21. Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias is not fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes, 160*, 149–167.
22. Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work, Employment and Society, 33*(1), 56–75.
23. Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology, 22*(3), 273–285.
24. Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Paauwe, J., & 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.
25. European Commission. (2024). *Guidelines on trustworthy and human-centric artificial intelligence in the workplace*. European Commission.
26. Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2023). Algorithmic management in a work context. *Big Data & Society, 10*(1), 1–16.
27. Tarafdar, M., Cooper, C. L., & Stich, J. F. (2019). The technostress trifecta: Techno eustress, techno distress and design. *Information Systems Journal, 29*(1), 6–42.

28. Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Paauwe, J., & 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.
29. Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2023). Algorithmic management in a work context. *Big Data & Society, 10*(1), 1–16.
30. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410.
31. Meijerink, J., Boons, M., Keegan, A., & Marler, J. H. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *International Journal of Human Resource Management, 32*(12), 2545–2562.
32. Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Paauwe, J., & 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.
33. Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2023). Algorithmic management in a work context. *Big Data & Society, 10*(1), 1–16.
34. Meijerink, J., Boons, M., Keegan, A., & Marler, J. H. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *International Journal of Human Resource Management, 32*(12), 2545–2562.
35. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, n71.
36. Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research, 104*, 333–339.
37. Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management, 14*(3), 207–222.
38. Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101.
39. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, n71.
40. Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management, 14*(3), 207–222.
41. Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology, 22*(3), 273–285.
42. Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-determination theory in work organizations: The state of a science. *Annual Review of Organizational Psychology and Organizational Behavior, 4*(1), 19–43.
43. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, n71.
44. Colquitt, J. A., Conlon, D. E., Wesson, M. J., Porter, C. O., & Ng, K. Y. (2001). Justice at the millennium: A meta-analytic review of 25 years of organizational justice research. *Journal of Applied Psychology, 86*(3), 425–445.

45. Cropanzano, R., & Mitchell, M. S. (2005). Social exchange theory: An interdisciplinary review. *Journal of Management, 31*(6), 874–900.
46. Meijerink, J., Boons, M., Keegan, A., & Marler, J. H. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *International Journal of Human Resource Management, 32*(12), 2545–2562.
47. Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias is not fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes, 160*, 149–167.
48. Benders, J., Pepper, K., & van Hootegem, G. (2006). First organize, then automate: A modern socio-technical view on ERP systems and teamworking. *New Technology, Work and Employment, 21*(3), 242–251.
49. Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2023). Algorithmic management in a work context. *Big Data & Society, 10*(1), 1–16.
50. Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting. *Human Relations, 4*(1), 3–38.
51. Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-determination theory in work organizations: The state of a science. *Annual Review of Organizational Psychology and Organizational Behavior, 4*(1), 19–43.
52. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410.
53. Meijerink, J., Boons, M., Keegan, A., & Marler, J. H. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *International Journal of Human Resource Management, 32*(12), 2545–2562.
54. Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias is not fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes, 160*, 149–167.
55. Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2023). Algorithmic management in a work context. *Big Data & Society, 10*(1), 1–16.
56. Meijerink, J., Boons, M., Keegan, A., & Marler, J. H. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *International Journal of Human Resource Management, 32*(12), 2545–2562.
57. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210.
58. Colquitt, J. A., Conlon, D. E., Wesson, M. J., Porter, C. O., & Ng, K. Y. (2001). Justice at the millennium: A meta-analytic review of organizational justice research. *Journal of Applied Psychology, 86*(3), 425–445.
59. Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627–660.
60. Meijerink, J., Boons, M., Keegan, A., & Marler, J. H. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *International Journal of Human Resource Management, 32*(12), 2545–2562.
61. Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias is not fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes, 160*, 149–167.
62. Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Paauwe, J., & 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.

63. Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-determination theory in work organizations: The state of a science. *Annual Review of Organizational Psychology and Organizational Behavior, 4*(1), 19–43.
64. Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2023). Algorithmic management in a work context. *Big Data & Society, 10*(1), 1–16.
65. Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology, 22*(3), 273–285.
66. Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Paauwe, J., & 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.
67. Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2023). Algorithmic management in a work context. *Big Data & Society, 10*(1), 1–16.
68. Tarafdar, M., Cooper, C. L., & Stich, J. F. (2019). The technostress trifecta: Techno eustress, techno distress and design. *Information Systems Journal, 29*(1), 6–42.
69. Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Paauwe, J., & 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.
70. European Commission. (2024). *Guidelines on trustworthy and human-centric artificial intelligence in the workplace*. European Commission.
71. Tarafdar, M., Cooper, C. L., & Stich, J. F. (2019). The technostress trifecta: Techno eustress, techno distress and design. *Information Systems Journal, 29*(1), 6–42.
72. Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work, Employment and Society, 33*(1), 56–75.
73. Martin, K. (2019). Ethical implications and accountability of algorithms. *Journal of Business Ethics, 160*(4), 835–850.
74. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210.
75. Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., et al. (2023). So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI. *International Journal of Information Management, 71*, 102642.
76. European Commission. (2024). *Guidelines on trustworthy and human-centric artificial intelligence in the workplace*. European Commission.
77. Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2023). Algorithmic management in a work context. *Big Data & Society, 10*(1), 1–16.
78. Meijerink, J., Boons, M., Keegan, A., & Marler, J. H. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *International Journal of Human Resource Management, 32*(12), 2545–2562.
79. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410.
80. Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Paauwe, J., & 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
81. Colquitt, J. A., Conlon, D. E., Wesson, M. J., Porter, C. O., & Ng, K. Y. (2001). Justice at the millennium: A meta-analytic review of 25 years of organizational justice research. *Journal of Applied Psychology, 86*(3), 425–445. https://doi.org/10.1037/0021-9010.86.3.425
82. Cropanzano, R., & Mitchell, M. S. (2005). Social exchange theory: An interdisciplinary review. *Journal of Management, 31*(6), 874–900. https://doi.org/10.1177/0149206305279602
83. Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-determination theory in work organizations: The state of a science. *Annual Review of Organizational Psychology and Organizational Behavior, 4*(1), 19–43. https://doi.org/10.1146/annurev-orgpsych-032516-113108
84. Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M., Al-Busaidi, K. A., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., ... Wright, R. (2023). So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642
85. European Commission. (2024). *Guidelines on trustworthy and human-centric artificial intelligence in the workplace*. European Commission.
86. Glikson, 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
87. Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2023). Algorithmic management in a work context. *Big Data & Society, 10*(1), 1–16. https://doi.org/10.1177/20539517231177672
88. Kellogg, K. C., Valentine, M. A., & 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
89. Meijerink, J., Boons, M., Keegan, A., & Marler, J. H. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *International Journal of Human Resource Management, 32*(12), 2545–2562. https://doi.org/10.1080/09585192.2021.1879208
90. Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias is not fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes, 160*, 149–167. https://doi.org/10.1016/j.obhdp.2020.03.008
91. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

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