

## Human-AI Collaboration in HRM: Implications for Employee Engagement and Organizational Performance.

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### Abstract

Artificial Intelligence (AI) has revolutionized the landscape of Human Resource Management (HRM) by reshaping the way companies recruit, develop, and retain employees. This paper explores how the human-AI partnerships in HRM can influence employee engagement and organizational performance. A conceptual framework is developed based on the three theories that link AI-based HRM practices to proximal employee outcomes and distal organizational performance indicators: sociotechnical systems theory, self-determination theory, and technology acceptance model. An analysis of empirical evidence from 2018 to 2024 shows that AI-enhanced HRM positively affects the HRM levels of employee engagement when accompanied by algorithmic transparency, perceived fairness and managerial mediation. On the other hand, ungoverned AI applications can bring up algorithmic bias, cause the loss of trust, and lower motivation. The paper proposes a dual-lens perspective that recognizes the benefits but also the human and ethical challenges involved in AI use in HRM and provides suggestions for HR practitioners, technology providers, and organizational decision-making.

**Keywords:** *Artificial Intelligence; Employee Engagement; Human Resource Management; Organizational Performance; Sociotechnical Systems.*

### 1. Introduction

Artificial Intelligence (AI) has become a powerful tool in every aspect of business, including Human Resource (HR). Whether it involves screening thousands of resumes in seconds with the assistance of AI tools or tracking employee sentiment in real-time using sentiment-analysis software, the speed at which AI is being implemented within Human Resource Management (HRM) is unprecedented (Tambe et al., 2019). According to Grand View Research the global market for AI in HR is expected to grow at an annual rate of nearly 29% from USD 3.9 billion in 2022 to surpass USD 17.6 billion by 2028. These statistics highlight not just the extent of investment, but the significance that organizations place on AI-driven talent management strategies.

However, the organizational implications of this change are still subject to debate. AI can supercharge the analytical muscle of HR professionals, reduce cognitive bias in hiring and firing, and facilitate evidence-based workforce planning on a scale never before possible, proponents say (Cheng & Hackett, 2021). But, critics warn, algorithmic decisions in HR processes can reinforce systemic inequities, reduce employee autonomy, and erode the relational culture that underpins engagement (Raisch & Krakowski,

2021). The conflicting viewpoints indicate that there is a need for a nuanced theoretical explanation that goes beyond the dichotomy of “AI is an enabler” and “AI is a threat.”

This paper discusses this need and advances three related objectives. It first synthesizes existing empirical and theoretical evidence to build a conceptual structure that connects AI-supported HRM practices, the quality of human-AI collaboration, employee engagement, and organizational performance. Second, it explores boundary conditions, such as boundary conditions of algorithmic transparency, perceived fairness, and managerial mediation, that moderate the link between the integration of AI and employee outcomes. Third, it provides practical takeaways for HR professionals and organizational designers who are eager to harness the transformative power of AI while maintaining the human-centric values that fuel sustainable organisational performance.

## **2. Literature Review**

### **2.1. Sociotechnical System Theory**

The theory of sociotechnical systems (STS) suggests that the effectiveness of an organization depends on the co-optimization of the social and technical subsystems, and not on the optimization of either one independently (Trist & Bamforth, 1951). When applied to AI in HRM, STS theory argues that AI tools do not necessarily translate to improved performance, but rather the level of alignment between the technical tools and human skills, organizational design, and cultural values. Boxall and Purcell (2022) furthered this notion by describing HRM as a sociotechnical system that works reciprocally between HR practices, managerial discretion and employee agency. Without proper sociotechnical redesign, the consequences of using AI in this system are frequently a disconnection of the technical and social logic, compromising efficiency and engagement.

### **2.2. Self-Determination Theory**

Self-determination theory (SDT) (Ryan and Deci, 2000) suggests that three psychological needs; autonomy, competence and relatedness, are essential for intrinsic motivation and wellbeing. All of these needs are directly affected by the implementation of AI in HRM. The actual implementation of performance monitoring through automation could limit the degree of autonomy as perceived by employees; AI-recommended skills could improve perceived competence; and HR services through chatbots may reduce employees’ felt relatedness. For example, Meijerink and Bondarouk (2023) found that a high level of AI governance quality explained all of the variance in employee engagement in organisations that had implemented the same AI-based HR platforms using SDT.

### **2.3. Technology Acceptance Model**

Davis (1989) developed the technology acceptance model (TAM) that suggested the two most critical variables affecting peoples’ intention to use a technology are perceived usefulness and perceived ease of use. Later extensions of TAM have added trust, social influence and experience as other factors that have to be considered when it comes to organizational AI adoption (Venkatesh et al., 2003). In the HRM context, TAM proposes that employees’ willingness to collaborate with AI tools and thus gain engagement benefits from collaboration depends on their beliefs of usefulness, understandability and fairness of the tools. Empirical evidence supporting this proposition has been reported by Li et al. (2021) who found that the link between AI adoption and employee OC was mediated by perceived algorithmic fairness.

## **3. Conceptual Framework**

To thematise the main arguments presented in this paper, Figure 1 provides a conceptual framework based on the three theoretical perspectives mentioned above. This pathway isn’t just moderated by algorithmic transparency and perceived fairness, but also by some managerial mediation.

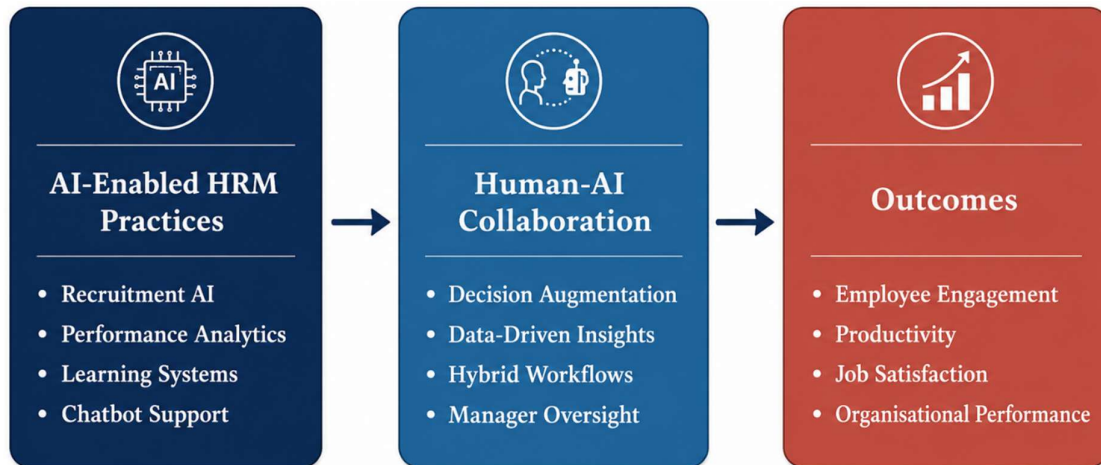


Figure 1. Conceptual Framework: AI-Enabled HRM, Human-AI Collaboration and Organizational Outcomes.

The framework in Figure 1 intentionally places human-AI collaboration as an explicit “mediating construct” between AI adoption and engagement outcomes to ensure that the focus is on human-AI collaboration, not on AI driving engagement. Theoretically, this distinction is significant, as it brings an element of control to the human-AI interface, which, instead of being inherent in the technology, is something that can be managed by the organization.

### 3.1. AI-Enabled HRM Practices

#### 3.1.1. AI in Recruitment and Selection

The use of AI in recruiting and selecting personnel. The role of AI in recruitment and selection. AI can be used in recruitment in various ways, such as the use of natural language processing (NLP) to extract data from resumes and determine if candidates have the required skills or qualifications, or through video-interview systems that analyze facial expressions and speech patterns to gain insights into a candidate’s personality. Uhlmann and Cohen (2005) noted the paradox of structured evaluation – that although algorithmic tools help eliminate idiosyncratic bias, the tools also have the potential to contain historical biases if they are trained on non-representative data. A case study on Amazon’s internal AI recruiting system, which was discovered to systematically devalue applications from women, made this clear, and prompted the company to stop using the system entirely (Dastin, 2018). More recent studies by van den Broek et al. (2019) showed that the algorithmic support for personnel selection in hiring is frequently rejected by managers who did not trust the algorithm’s logic. This put into perspective the extent to which AI tools for recruitments have been successfully integrated in recruitment processes in most organizations.

#### 3.1.2. AI in Performance Management

AI-driven continuous performance management systems gather live behavioural data, provide instant feedback, and forecast employee attrition. Cappelli and Tavis (2018) suggested that this could lead to replacing annual appraisal cycles with more frequent and data-driven feedback cycles that are more effective for developmental purposes. But Kellogg et al. (2020) cautioned that algorithmic management, the process of directing, assessing, and punishing employees with a set of data-driven algorithms, is a qualitatively new method of control that can limit employee voice and heighten stress related to surveillance. In line with SDT’s theory, their longitudinal study of gig-economy workers revealed that a constant algorithmic monitoring system effectually decreased intrinsic motivation, which is when people feel the need to do something because they are able to. In their long-term study of gig-economy workers, they found that the constant algorithmic monitoring system significantly reduced intrinsic motivation, which is when people feel they should do something because they can.

### 3.1.3. AI in Learning and Development

A learning platform which adapts to the learner by exploiting machine learning algorithms to tailor the content, pacing, and assessment. Huang et al. (2015) conducted a meta-analysis of the research evidence and revealed that AI-personalized learning pathways yield effect sizes of  $d = 0.52$  compared to standard training approaches, which is a significant improvement in performance. However, the same meta-analysis identified that motivational effects depended on the agency of the learner: if the learning algorithm was perceived as a prescription they were less likely to feel confident in their abilities and thus less likely to gain. This discovery is consistent with SDT’s autonomy postulate and supports the argument that interface design for human-AI collaboration is critical as much as the complexity and sophistication of the underlying algorithm.

### 3.1.4. AI-Powered HR Service Delivery

Conversational AI agents and intelligent self-service portals have revolutionized how HR services are delivered, enabling employees to access policy information, manage leave, and access benefits support anytime and anywhere. Stone et al. (2015) predicted that automation in transactional HR would allow HR to concentrate more on strategic tasks, a view largely backed up by empirical studies. According to Strohmeier (2020), 248 large European companies were surveyed to determine how AI has affected HR service delivery and found that HR use of AI helps lower administrative processing times by 43% on average, and boost employee satisfaction around HR responsiveness. But the human side of HR service delivery; whether through empathy in addressing employees’ needs during challenging times like career changes or interpersonal conflict, or empathy in dealing with the customer, will not be in the ability of conversational AI, suggesting a future design imperative to direct more complex, emotionally charged cases to human HR service providers.

## 3.2. Employee Engagement in the Age of AI

According to Kahn (1990), employee engagement is defined as the combination of cognitive, emotional, and physical investments into the job role, which is a key determinant of organisational performance-related outcomes such as productivity, customer satisfaction, and voluntary turnover. According to Schaufeli et al. (2002), engagement is a positive and fulfilling state at work involving vigor, dedication and absorption. AI in HRM offers opportunities and risks to every of these dimensions of engagement.

*Table 1: Dimensions of Employee Engagement and AI-HRM Impacts*

Dimension	Definition	AI-HRM Opportunity	AI-HRM Risk
Vigor	High energy & mental resilience at work	Reduced admin burden; more time for meaningful work	Surveillance fatigue from continuous monitoring
Dedication	Sense of significance, enthusiasm & pride	Personalized development signals investment in growth	Algorithmic decisions may feel impersonal & devaluing
Absorption	Full concentration & happy immersion in work	AI handles distractions; enables deep-work focus	AI-generated notifications may fragment attention

*Note:* Engagement dimensions adapted from Schaufeli et al. (2002).

The empirical relationship between AI-driven HRM and employee engagement is beginning to be mapped with greater precision. When AI-augmented PM is perceived to be accurate and fair, the study by Cheng and Hackett (2021) reveals that it positively predicted PM engagement ( $\beta = 0.28, p < 0.001$ ). However, when PM is perceived as being less fair, it negatively predicted PM engagement ( $\beta = -0.19, p < 0.01$ ). This interactive relationship implies that while there is a positive impact of AI on engagement, it is significantly influenced by the quality of governance, which has direct managerial implications.

### 3.3. Organizational Performance Outcomes

Organizational performance is measured in the literature in terms of three dimensions: financial, operational, and human capital (Dyer & Reeves, 1995). Theories suggest that AI-driven HRM can impact each dimension in unique ways.

Table 2: Summary of Empirical Studies on AI-HRM and Organizational Performance (2018–2024)

Study	Sample	AI-HRM Focus	Key Outcome	Effect / Finding
Tambe et al. (2019)	Fortune 500 firms	Predictive analytics in hiring	Workforce quality	23% improvement in hire quality
Li et al. (2021)	n = 892 employees	AI performance mgmt.	Organizational commitment	$\beta = .31$ (fairness moderated)
Meijerink & Bondarouk (2023)	12 HR tech firms	AI service delivery	Employee engagement	Need satisfaction fully mediates
Huang et al. (2015)	Meta-analysis, k=47	Adaptive L&D	Learning performance	d = 0.52 vs. standard training
Strohmeier (2020)	n = 248 firms (EU)	AI-HR chatbots	HR service satisfaction	43% reduction in processing time
Kellogg et al. (2020)	Gig economy workers	Algorithmic monitoring	Intrinsic motivation	Significant negative effect

*Note: L&D = Learning and Development; k = number of studies in meta-analysis.*

The benefits of using AI for HRM come largely in two forms: cost savings from automation in administrative HR functions, and better talent decisions. Organizations that utilized predictive hiring analytics saw a 23% increase in their workforce quality scores over that of control firms, which equated to tangible revenue per employee increases, according to Tambe et al. (2019). Earlier on, researchers in strategic HRM have started to discuss the potential for AI to enhance the human capital advantage by improving person-job and person-organisation fit, leading to reduced voluntary turnover and replacement costs (Boxall & Purcell, 2022).

Improvements in operational performance are probably most easily measured in the area of HR service delivery. Automating transactions; such as leave applications, queries, compliance reporting, frees up HR professionals to focus on strategic partnership activities that add value to the organization. Importantly, Cappelli and Tavis (2018) highlighted the ability of the periodic performance management model to be replaced by a continuous one, which can be made possible by AI analytics, and that this has helped organizations adapt faster to changes in the competitive landscape.

The path between AI-HRM and human capital performance outcomes, such as human capital retention, satisfaction, and capability development, is the most theoretically complex. Human capital performance outcome; such as human capital retention, satisfaction, and capability development, are the most theoretically complex path by which AI-HRM can affect organizational performance. The evidence in the engagement literature proves that engagement is positively linked to absenteeism, customer satisfaction ratings and the productivity of the individual (Schaufeli et al., 2002). Where AI-driven HRM practices are creatively and responsibly designed and managed to maintain and improve employee engagement, they should expect compounding human capital benefits over time.

### 3.4. Moderating Factors

#### 3.4.1. Algorithmic Transparency

Transparency in algorithmic decision-making means making the algorithms' logic and data inputs accessible and understandable to those impacted by HR decisions. Explainable artificial intelligence (XAI) has been studied in organizational settings, and it has been shown that transparency is a prerequisite for procedural justice perceptions (Colquitt et al., 2013). If there is no understanding for employees as to how the AI system rated their performance or why they were not chosen for a development opportunity, this can foster a sense of unfairness, which in turn can impact trust and engagement. This principle is increasingly being codified in the EU AI Act (European Parliament, 2024), which introduces transparency obligations for AI systems with high-risk applications, such as those in the field of job hiring.

#### 3.4.2. Perceived Fairness

According to organizational justice theory, there are four types of organizational justice: distributive, procedural, interpersonal, and informational (Colquitt et al., 2013). All dimensions are involved in the

human resource management (HRM) responses of employees in the era of artificial intelligence (AI). Distributive fairness relates to the equalness of the outcomes as a result of AI (promotions, salary raises, training placements etc.). Procedural fairness asks if those outcomes are based on algorithms that are consistent, accurate and correct? Interpersonal fairness involves how employees are treated with respect in HR processes involving AI. Raisch and Krakowski (2021) made the case that procedural fairness is especially susceptible to being lacking in AI systems, as the algorithm behind their decisions can be obscure, the data they use for learning and decision-making can be biased and the decisions they make can be hard to challenge using traditional grievance processes.

### 3.4.3. Managerial Mediation

In the most automated HR departments, managers still have an important mediating role. Managers translate AI interpretations to their teams, determine which advice from the algorithms will be followed and offer the relational context to turn the data into a discussion about development. Meijerink and Bondarouk (2023) found that manager quality moderated the engagement effects of AI-HR platforms such that the positive effect of AI on engagement was roughly twice as large in teams with high-quality manager–employee relationships. This is congruent with the strategic HRM literature that has consistently identified line managers as the key players in the execution of HR practice and as important links between the HR systems of an organisation and the outcomes of HR (Purcell & Hutchinson, 2007).

## 4. Ethical and Critical Perspectives

Ethics is a crucial aspect of any meaningful discussion on AI-powered HRM. The use of AI in talent management is a complex issue with deep implications for privacy, consent, and power. Intimate knowledge about employees’ psychological states, social networks, and career intentions can be generated from continuous behavioral monitoring, sentiment analysis and attrition prediction algorithms, without their explicit awareness or meaningful consent (Kellogg et al., 2020). The unequal relationship between the organizations in control of AI systems and the employees being watched is a structural justice issue HR staff and organizational leaders must recognize and deal with ethically.

One of the most well documented ethical issues in AI-HRM research is algorithmic bias. AI systems can also be biased when they are trained on biased data, when there are proxy biases (such as a seemingly neutral variable like postcode predicting job performance, which may inadvertently compound historical discrimination) or when existing patterns in their training data reflect historical bias (Dastin, 2018). The difficulty for organisations is that bias in AI systems might be harder to identify and challenge than in human decision making, particularly because algorithmic processes are not as interpretable as human decision-making.

Raisch and Krakowski (2021) proposed a distinction between “augmentation” and “automation” as a way to mediate these ethical issues. Adds human judgment: AI helps to augment information for decision-makers, and maintain accountability with individuals. Automation shifts decision-making to algorithms, resulting in efficiencies but at the expense of human judgement. The authors recommended that in order to ensure accountability of HR decisions, such as career progression, disciplinary action, or redundancy decisions, HR professionals should use augmentation logics while low-stakes transactional processes are good candidates for automation.

## 5. Practical Recommendations

Table 3: *Practical Recommendations for Human-AI Collaboration in HRM*

Stakeholder	Recommendation	Theoretical Basis
HR Leaders	Conduct algorithmic impact assessments before deploying AI in talent decisions	Organizational justice theory; EU AI Act compliance
HR Leaders	Establish human-override mechanisms for all high-stakes AI-generated recommendations	Augmentation vs. automation framework (Raisch & Krakowski, 2021)

Stakeholder	Recommendation	Theoretical Basis
Line Managers	Use AI analytics as conversation starters, not conversation substitutes	SDT – relatedness need; managerial mediation research
Line Managers	Receive training in interpreting and contextualizing AI-generated performance insights	STS co-optimization principle
Technology Designers	Build explainability interfaces that present algorithmic logic in plain, accessible language	TAM – perceived usefulness; XAI literature
Technology Designers	Incorporate diverse and representative data in model training to minimize proxy discrimination	Algorithmic bias research (Dastin, 2018)
Employees	Engage with AI tools as augmentation aids while advocating for transparency in deployment	SDT – autonomy need; Agency-preserving design
<b>Note:</b> SDT = <i>Self-Determination Theory</i> ; STS = <i>Sociotechnical Systems</i> ; TAM = <i>Technology Acceptance Model</i> .		

## 6. Discussion

The synthesis of available evidence presented in this paper suggests that the impact of AI on HRM is both positive and negative, with the specific outcomes ultimately being contingent on the HRM governance structure in which the AI is placed. This finding is in line with the theory of sociotechnical systems, which has long maintained that technology is only one of the two factors needed for organizational performance improvement. While the human and organizational “complements” to AI; managerial skills, algorithmic transparency and fairness governance, and employee voice mechanisms, shape whether AI investment is a human capital advantage.

One of the theoretical contributions in this paper is the establishment of the quality of human-AI collaboration as a mediating construct between the use of AI in HRM and the outcomes of employee engagement. However, previous research has focused on the relationships between adoption and engagement with AI without defining the mechanism by which AI influences engagement. The current set of frameworks contributes to the field by focusing on the experience of working with AI systems, which is the immediate cause of engagement effects, as the driving factor. For the design of human-AI interaction processes, it means that investments should not be carried out only to ensure the good working of the AI tools, but also to ensure processes of human-AI interaction that are designed to help meeting the needs, creating fair perceptions and satisfy relational quality.

The paper also has the consequence of putting the two sides of the argument; AI optimists and AI pessimists, at loggerheads by proving that the binary opposition is a false one. In the reviewed literature, those organizations that enjoyed positive engagement and performance outcomes did so by implementing AI in a way that retained human decision making and relational interaction, and that automated only those transactions where the relational value was not high. This “selective automation” approach is more complex than the AI or no AI binary, and the current framework helps practitioners articulate a theoretically-informed rule for using AI.

## 7. Limitations and Future Research

This paper is mostly conceptual in nature and the structure needs to be validated with empirical data. The empirical studies reviewed are varied in organizational setting, type of AI technology, and type of measure, and direct comparisons are difficult due to these variations, and thus, conclusions from the meta-analysis are limited. Longitudinal, multi-level designs that study the co-evolution of AI-HRM practices and engagement outcomes over time should be encouraged in future research, as this will allow for causal inferences to be drawn that go beyond the current cross-sectional associations reported in the literature.

Furthermore, most empirical research on AI-HRM is conducted in large, technologically advanced companies in the North American and Western Europe regions. There is limited research on the relevance

of these results to SMEs, emerging market settings, and non-knowledge industries. Research that explores the cross-cultural influence of national values, labor market institutions and regulatory contexts on the linkage between AI-HRM and engagement would be an interesting addition to the research stream.

Lastly, the quick progress in AI capability advancement implies that any synthesis of such sort is bound to be obsolete. AI-powered, real-time workforce planning conversations between HR business partners and an AI co-pilot are a recent frontier that falls only partially into the current framework, as are other applications of large language models (LLMs) in HR processes. Theoretical research into the implications of increasingly agentic AI systems which undertake not only analytical, but also relational, communicative, and HR tasks is needed in the future.

## 8. Conclusion

AI has become a transformative force in HRM, and the synergy between human and AI capabilities is one of the most impactful shifts in an organization in the early twenty-first century. Based on the theory of sociotechnical systems, self-determination theory, and the technology acceptance model, this paper has suggested that the quality of human-AI collaboration is a key determinant in the relationship between AI-enabled HRM practices and employee engagement and organizational performance, which is moderated by the three factors of algorithmic transparency, algorithmic fairness, and managerial mediation. This account is supported by the empirical literature, though not conclusively, as it is when governance is good, it is when it is bad that AI negatively impacts HRM effectiveness.

The dual lens model developed here; acknowledging the efficiency opportunities as well as the human-ethical dilemmas of AI in HRM, is aimed at encouraging HRM practitioners to more deliberately consider their choice of AI systems to implement, and researchers to consider variables for governance and interaction quality that will influence the outcomes. With the ongoing evolution of AI capabilities, the need for maintaining a sense of agency, relational dignity, and ethical accountability in talent management will only grow. Those that can rise to this challenge will not only be spared from the risks of reputation and lawsuits stemming from the misuse of AI but will also reap the greater human capital benefits when employees interact with their company's AI systems as an extension rather than a watchful eye or replacing a human.

## Declarations

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### Conflict of Interest

The authors declare no conflict of interest.

### Data Availability


The data supporting the findings of this study are available from the corresponding author upon request.

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