INTERNATIONAL JOURNAL OF ECONOMIC SOCIAL SCIENCE AND MANAGEMENT LAW
Peer Reviewed, Referred & Indexed Journal
E-ISSN: 3070-0558
VOL.7, NO.3 (2026)

When Decisions Are Delegated to Algorithms: A Concise Review of Employee Reactions to AI-Driven Human Resource Management

Aseel Hadi Mahmood
Department of qaulity assurnace management, Ministry of Higher Education and Scientific Research, Baghdad, Iraq
aseelhadi@gmail.com

Abstract
However, while many aspects of HRM are delegated to AI and algorithmic systems (e.g., CV-screening, performance evaluation, platform-based labor coordination), much less is known about how workers and job-seekers make sense of and experience such systems. This literature has been scattered across different areas and disciplines, with limited cross-over. This review synthesizes research into employees' and job applicants' reactions to AI-enabled HRM across the HR value chain. It draws on theories of organizational justice, technology acceptance and trust, algorithm dislike, the psychological contract, identity threat, and technostress to theorize the conditions under which reactions to AI-enabled HRM are positive or negative. We present an overarching, multilevel framework integrating worker experience and perceptions, human-AI collaborations, and organization design (such as explainability and employee voice). Drawing on this framework, we highlight the contingent nature of responses, tensions within a young evidence base, and the need for theory-driven longitudinal research.

Keywords: *algorithmic HRM; employee reactions; organisational justice; algorithm aversion; explainable AI*

1. Introduction

Many aspects of the employment relationship have been delegated. From the machine learning software that predicts the chances of a job candidate being a good fit before a recruiter sees their application to the daily contracting, pricing, and performance evaluation of couriers and drivers, firms delegate and automate whatever they can, and perhaps more. Decision rights have been transferred from managers to systems, which has been justified in terms of speed and reliability, but the effects of these changes for people have been less frequently discussed. Tambe et al. (2019) note that a large gap exists between the promise of AI in HR and the reality of its current use and technical performance.

By AI-driven or algorithmic HRM, we mean the use of machine learning, natural language processing and other data-driven techniques to inform and/or automate people-related decisions across the employment life cycle (Budhwar et al., 2022). By employee or applicant reactions, we mean attitudes, perceptions, emotions and behaviors towards such systems, including perceptions of fairness, trust or suspicion, acceptance or resistance and any potential resultant impact on wellbeing and intentions. This review highlights the reactions, for good reason. It is a deliberately constraining choice, but it is a choice to synthesize what we know (and where we don't), and to make suggestions for a rapidly developing field of study. Thus, this article concludes with a stepwise integration of these function-by-function descriptions into a multilevel account, as well as a discussion of its implications, both practical and theoretical.

2. Conceptual and theoretical background

No single theory comprehensively accounts for employee reactions to the output of algorithms, but each theory provides perception into a variety of employee responses. For example, under organizational justice, employees are expected to evaluate algorithm outputs in terms of distributive, procedural and interactional criteria, and perceive a lack of human judgment in algorithmic decisions as procedurally impoverished, even when outcomes are accurate. Rodgers et al. (2022) provide an

explicitly ethical, process-based account of algorithmic decision-making for HRM, which states that fairness depends on how a decision is made, not on what a decision is.

Acceptance and trust provide a second lens. Studies applying technology-acceptance logic to the HR arena indicate that managers' intentions to use AI, for functions such as talent acquisition, are mediated by attitudes towards usability and perceived usefulness (Pillai & Sivathanu, 2020). A related unresolved debate about algorithm dislike and algorithm appreciation (depending on the task, transparency, and whether the person interacting with the (system) is its object or user) suggests that (people) can be averse to algorithmic advice, especially after the (system) makes a mistake, or trust the algorithm. Murray et al. (2020) frame this discussion in terms of conjoined agency, such that the relationship is no longer focused on using a particular tool, but on how agency between person and system is shared.

Three additional perspectives speak to the affective and relational stakes. The psychological contract identifies automated changes to hiring, evaluation, or task allocation as potential violations of implicit expectations about how one will be treated. Identity threats to meaningful work: AI identity threat captures how capable, meaningful work is being encroached upon. Bankins and Formosa (2023) explore how AI can either improve or weaken meaningful work depending on task design. Conservation of resources and technostress explain fatigue and strain. Malik et al. (2021) report mixed experiences of employees in Industry 4.0 environments. According to Kong et al. (2021), higher awareness of AI is related to job burnout and modified career competences. Work design theory suggests that some dimensions of AI technostress can lead to stronger adoption intention, but not without other conditions, as shown by Chang et al. (2024). The authors argue that the benefits or harms of digital technologies depend on whether the technologies promote or weaken autonomy, feedback and the use of and development of human skills (Parker & Grote, 2019). Table 2 summarizes these lenses and their differential predictions.

3. Employee reactions to AI across the HR value chain

The reactions differ with the HR activity, how visible the system is, and how much discretion it takes away. Table 1 outlines the basic pattern, which is repeated throughout the value chain.

Fairness perceptions are relevant in recruitment and selection settings. Risk of adverse impact in terms of discrimination is highest at its maximum information asymmetry, when applicants are exposed to screening and video assessment. According to Chen (2023), AI driven recruitment systems reproduce and increase discrimination found in historic labor market data. Albaroudi et al. (2024) identify and describe technical mitigations with varying degrees of success in practice. Hunkenschroer and Luetge (2022) find that the ethics of recruitment by AI are a double-edged sword. While automation may lower the risk of human bias, there are less transparent forms of bias introduced by algorithmic processes. Applicants are more likely to accept algorithmic recruitment when they are aware of the process and retain the ability to appeal to a human recruiter.

On the other hand, performance management and monitoring can lead to more polarized outcomes. Parker and Grote (2019) argued that continuous data-driven monitoring can be seen as surveillance and reduce autonomy, which are key job characteristics to promote healthy work. Whereas intrusive monitoring leads to technostress and burnout (Malik et al., 2021; Kong et al., 2021), people analytics remains largely invisible to the people being analyzed. This means that the reaction is more about how people feel about their privacy, consent, and the legitimacy of inferences based on private information than task execution. Tambe et al. (2019) argue this fragility is something employees can sense but not articulate due to small sample sizes and contested labels for outcomes in HR data.

For gig and platform work, algorithmic management represents possibly the most extreme instance of delegating decision-making to algorithms. In app-work, according to Duggan et al. (2019), there is no human mediation in allocation, pricing, and evaluation, suggesting that the very nature of employment has changed. Reactions are of resistance, workarounds and a sense of loss of agency, since this route to conciliate a manager's judgment is also denied. Across the four domains generative AI has added a

new overlay, with Budhwar et al. (2023) and Chowdhury et al. (2024) noting both the draw of productivity and the ambivalence of trust, authorship, and craft that ChatGPT and other tools introduce. Morandini et al. (2023) also found that reactions are bound up with upskilling and reskilling, as people do better when they think a credible career path exists in spite of the implementation of AI rather than fearing obsolescence.

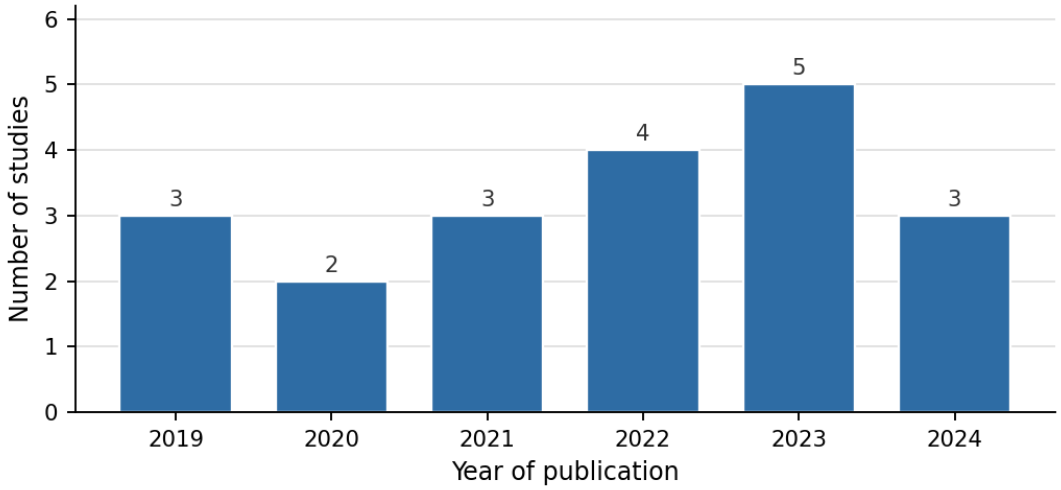


Figure 1. Distribution of the reviewed studies by year of publication (N = 20).

Figure 1 indicates how new this line of analysis is, given that so many of the publications happened in just the past few years, a sign of a field with unresolved questions and not yet a well-established and settled set of issues.

Table 1. AI applications across the HR value chain and typical employee reactions.

HR function	AI / algorithmic application	Typical employee reaction or concern
Recruitment & selection	Automated CV screening, video assessment	Fairness doubts; fear of hidden bias
Performance management & monitoring	Continuous scoring, digital tracking	Surveillance unease; reduced autonomy
Workforce / people analytics	Predictive attrition and profiling models	Privacy concern; contested inferences
Algorithmic management of gig work	App-based task allocation and rating	Lost voice; resistance and workarounds

4. Discussion: an integrative framework

The function level picture thus leads us to note that employees' reactions to AI-enabled HRM depend both on their appraisal of AI and of the human-AI collaborative mechanisms, as well as on contextual factors. Using one of the frames in isolation would thus be misleading. However, the same system may also be procedurally unjust, identity-threatening, and engender technostress for the same employee at the same time. Table 2 outlines the competing lenses set against which predictions can and must be tested.

Table 2. Theoretical lenses on employee reactions to AI in HRM.

Theoretical lens	Core idea	Implication for employee reactions
Organisational justice	Fairness of outcomes and process	Opaque decisions feel procedurally unfair
Technology acceptance & trust	Usefulness and ease drive uptake	Perceived value raises willingness to use
Algorithm aversion vs appreciation	Deference to advice varies	Errors and opacity trigger rejection
Psychological contract	Implicit mutual expectations	Automation can be read as breach
AI identity threat	Threat to competence and meaning	Encroachment prompts defensive reactions
Conservation of resources / technostress	Strain from resource loss	Monitoring and overload cause burnout

Embedded in a multi-level framework is the appraisal of fairness, trust, threat and strain, at the individual level. At the human-AI team level, Murray et al. (2020) ask how agency is shared and whether the employee experiences the system as collaborator or overseer. At the organizational level, capability, governance, and design choices determine the conditions in which the lower levels operate. For example, Chowdhury et al. (2022) argue that delivering value from AI in HRM relies on an orchestrated capability and not technology per se, and Trenerry et al. (2021) show that digital-transformation readiness is a three-level property across employees, leaders, and systems. Figure 2 illustrates the integrative conceptual framework, linking the three levels with the relevant design levers.

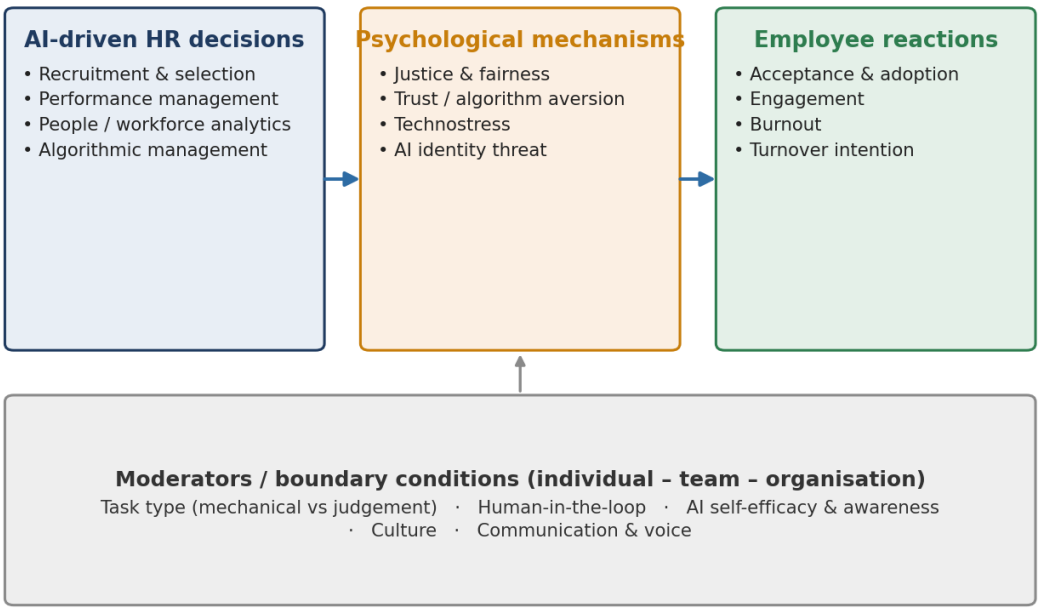


Figure 2. An integrative multilevel framework of employee reactions to AI-driven HRM.

Two levers are especially important. First, responsible and explainable AI: when systems can justify their decisions and their governance is transparent, the justice and trust deficits identified above narrow. This is particularly important for generative AI (Budhwar et al., 2023; Chowdhury et al., 2024). The

second component is employee voice. However, where people can contest, appeal and shape algorithmic decision-making, the psychological-contract and identity-threat mechanisms are dampened. Where voice is not an option, as is much of platform work (Duggan et al., 2019), the mechanisms are strengthened. Generative tools provide a new context for management theory, not just an extension of theories from earlier tools, Korzyński et al. (2023) suggest, providing opportunities for new conceptualisation.

Yet, their robustness differs: most of the evidence is based on cross-sectional studies, sector specific (e.g. IT services and hospitality) and self-reported. Findings are heterogeneous, at times even contradictory, e.g. the technostress-yet-adoption pattern (Chang et al. 2024). Instead it should be seen as an organizing scaffold for this relatively young field, rather than a validated model.

5. Implications for practice

Yet for practice, the message is that acceptance is constructed, and algorithmic responses are as much about the process as the result. Organizations that provide explanation, contestability, and human review in algorithmic HR decision-making will be more positively received than those that optimize for classification accuracy (Rodgers et al., 2022). In recruitment, transparency about where and how AI will be used (and auditing for the biases Chen, 2023; Albaroudi et al., 2024) can address their key concern. In performance management, prioritizing monitoring design and implementation focused on preserving autonomy and the quality of feedback, rather than solely the quantity of data captured, can address technostress issues articulated by Malik et al. (2021). Visible investment in reskilling, for example, can be an important signal that AI can complement rather than replace employees (Morandini et al., 2023). Indeed, adopting a stance of deployment as an organizational capability with appropriate governance (Chowdhury et al., 2022) conveys these enabling conditions on an organizational level. In the gig and platform context, channeling worker voice into a rating query or allocation appeal directly targets the mechanisms that Duggan et al. (2019) document as often stripped away. None of these mechanisms is costless, whereas each compromises some tradeoff between speed, simplicity, and legitimacy. The wager of this review is that legitimacy is what sustains acceptance over time.

6. Limitations and future research

This, then, is a short, interpretive, nonsystematic, and selective review of the literature. It is intended to summarize, and provoke, rather than to quantify. While we have not attempted a complete review, there are certainly gaps in the literature. More research is needed to understand how reactions to interaction evolve as users gain experience, and whether the reaction is fleeting or lasting. Furthermore, the algorithm dislike-appreciation debate remains open, and studies on the boundary conditions of each side are needed. The responses to generative AI also require further theorizing (Budhwar et al., 2023; Korzyński et al., 2023). Moreover, more empirical work is needed on the issues of identity and meaningful work raised by Bankins and Formosa (2023). Indeed, notwithstanding the international spread of the phenomena Budhwar et al. (2022) describe, cross-cultural and cross-sectoral comparison remains sparse. Finally, Parker and Grote (2019) suggest that stronger grounding in work-design theory might link reactions to known job redesign levers that operate around algorithmic systems rather than against them.

7. Conclusion

By offloading people decisions to algorithms, the dynamics of organizing, management, and being managed effectively change. Employees' and applicants' responses to algorithmic management are not universally favorable or adverse; their views are informed by considerations of fairness, trust, identity, and strain, as well as design and governance decisions, at the level of the algorithm. I suggest thinking about individual perception, human-AI collaboration, and organizational capability as a multilevel phenomenon. The field is young, its evidence uneven, and its central debates unsettled. The question is not if employees are accepting of AI in HRM, but rather, in which circumstances the delegation to algorithms can be experienced as fair, meaningful and trustworthy.

References

Albaroudi, E., Mansouri, T., & Alameer, A. (2024). A Comprehensive Review of AI Techniques for Addressing Algorithmic Bias in Job Hiring. *AI*, *5*(1), 383–404. https://doi.org/10.3390/ai5010019

Bankins, S., & Formosa, P. (2023). The Ethical Implications of Artificial Intelligence (AI) For Meaningful Work. *Journal of Business Ethics*, *185*(4), 725–740. https://doi.org/10.1007/s10551-023-05339-7

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Cooke, F. L., Decker, S., DeNisi, A. S., Dey, P. K., Guest, D., Knoblich, A. J., Malik, A., Paauwe, J., Papagiannidis, S., Patel, C., Pereira, V., Ren, S., & 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

Budhwar, P., Malik, A., Silva, M. T. T. D., & Thevisuthan, P. (2022). Artificial intelligence – challenges and opportunities for international HRM: a review and research agenda. *The International Journal of Human Resource Management*, *33*(6), 1065–1097. https://doi.org/10.1080/09585192.2022.2035161

Chang, P., Zhang, W., Cai, Q., & Guo, H. (2024). Does AI-Driven Technostress Promote or Hinder Employees' Artificial Intelligence Adoption Intention? A Moderated Mediation Model of Affective Reactions and Technical Self-Efficacy. *Psychology Research and Behavior Management*, *Volume 17*, 413–427. https://doi.org/10.2147/prbm.s441444

Chen, Z. (2023). Ethics and discrimination in artificial intelligence-enabled recruitment practices. *Humanities and Social Sciences Communications*, *10*(1). https://doi.org/10.1057/s41599-023-02079-x

Chowdhury, S., Budhwar, P., & Wood, G. (2024). Generative Artificial Intelligence in Business: Towards a Strategic Human Resource Management Framework. *British Journal of Management*, *35*(4), 1680–1691. https://doi.org/10.1111/1467-8551.12824

Chowdhury, S., Dey, P. K., Joel-Edgar, S., Bhattacharya, S., Rodríguez-Espíndola, O., Abadie, A., & Truong, L. (2022). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review*, *33*(1), 100899–100899. https://doi.org/10.1016/j.hrmr.2022.100899

Duggan, J., Sherman, U., Carbery, R., & McDonnell, A. (2019). Algorithmic management and app-work in the gig economy: A research agenda for employment relations and HRM. *Human Resource Management Journal*, *30*(1), 114–132. https://doi.org/10.1111/1748-8583.12258

Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-Enabled Recruiting and Selection: A Review and Research Agenda. *Journal of Business Ethics*, *178*(4), 977–1007. https://doi.org/10.1007/s10551-022-05049-6

Kong, H., Yuan, Y., Baruch, Y., Bu, N., Jiang, X., & Wang, K. (2021). Influences of artificial intelligence (AI) awareness on career competency and job burnout. *International Journal of Contemporary Hospitality Management*, *33*(2), 717–734. https://doi.org/10.1108/ijchm-07-2020-0789

Korzyński, P., Mazurek, G., Altmann, A., Ejdys, J., Kazlauskaitė, R., Paliszkiewicz, J., Wach, K., & Ziemba, E. (2023). Generative artificial intelligence as a new context for management theories: analysis of ChatGPT. *Central European Management Journal*, *31*(1), 3–13. https://doi.org/10.1108/cemj-02-2023-0091

Malik, N., Tripathi, S. N., Kar, A. K., & Gupta, S. (2021). Impact of artificial intelligence on employees working in industry 4.0 led organizations. *International Journal of Manpower*, *43*(2), 334–354. https://doi.org/10.1108/ijm-03-2021-0173

Morandini, S., Fraboni, F., Angelis, M. D., Puzzo, G., Giusino, D., & Pietrantoni, L. (2023). The Impact of Artificial Intelligence on Workers' Skills: Upskilling and Reskilling in Organisations. *Informing*

Science The International Journal of an Emerging Transdiscipline, *26*, 039–068. https://doi.org/10.28945/5078

Murray, A., Rhymer, J., & Sirmon, D. G. (2020). Humans and Technology: Forms of Conjoined Agency in Organizations. *Academy of Management Review*, *46*(3), 552–571. https://doi.org/10.5465/amr.2019.0186

Parker, S. K., & Grote, G. (2019). Automation, Algorithms, and Beyond: Why Work Design Matters More Than Ever in a Digital World. *Applied Psychology*, *71*(4), 1171–1204. https://doi.org/10.1111/apps.12241

Pillai, R., & Sivathanu, B. (2020). Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. *Benchmarking An International Journal*, *27*(9), 2599–2629. https://doi.org/10.1108/bij-04-2020-0186

Rodgers, W., Murray, J. M., Stefanidis, A., Degbey, W. Y., & Tarba, S. Y. (2022). An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. *Human Resource Management Review*, *33*(1), 100925–100925. https://doi.org/10.1016/j.hrmr.2022.100925

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. *California Management Review*, *61*(4), 15–42. https://doi.org/10.1177/0008125619867910

Trenerry, B., Chng, S., Wang, Y., Suhaila, Z. S., Lim, S. S., Lu, H., & Oh, P. H. (2021). Preparing Workplaces for Digital Transformation: An Integrative Review and Framework of Multi-Level Factors. *Frontiers in Psychology*, *12*, 620766–620766. https://doi.org/10.3389/fpsyg.2021.620766