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Original Article

Generative Artificial Intelligence and the Future of Human Resource Management: A Conceptual Perspective on Opportunities, Challenges, and Ethical Issues

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Abstract

Generative artificial intelligence (GenAI), a class of foundation models that produce text, images, voice and code, is diffusing rapidly into human resource management (HRM). Drawing on an integrative conceptual review of peer-reviewed literature published between 2016 and 2026, this paper develops a conceptual perspective on the opportunities, challenges and ethical issues that GenAI creates for the HR function. The analysis addresses three questions: what GenAI adds to established AI-augmented HRM; which organisational and ethical tensions it intensifies; and how those tensions can be governed. The paper argues that GenAI differs from earlier HR analytics less in the tasks it targets than in how it produces them — probabilistic, opaque and communicative artefacts that blur the boundary between assisting and substituting human judgement. This generative turn amplifies three ethically salient properties: opacity, the scalability of bias, and the simulation of interpersonal relationship. A conceptual framework is proposed that links GenAI affordances to four HR outcomes through decision quality, perceived fairness and employee trust, moderated by AI governance maturity and human oversight capacity. The paper concludes with a research agenda and practical implications for responsible, human-centred GenAI adoption in HRM.

Keywords: Generative Artificial Intelligence; Human Resource Management; Algorithmic Fairness; AI Ethics; Algorithmic Management; Human–AI Collaboration

Introduction

The release of publicly accessible large language models in late 2022 marked a discontinuity in organisational automation. Unlike analytics systems that classify, score or predict, generative artificial intelligence (GenAI) produces content — job advertisements, interview questions, appraisal narratives, coaching dialogue, images and code — that is fluent, contextually plausible and inexpensive to generate at scale (Feuerriegel et al., 2024). HRM is built on the production of text and the management of meaning, which makes it an unusually exposed domain (Budhwar et al., 2023).

The HR function has absorbed successive digital waves, from e-HRM and workforce analytics to AI-augmented HRM (Strohmeier, 2020; Vrontis et al., 2022; Prikshat et al., 2023). GenAI nonetheless differs in kind. It is general-purpose rather than task-specific, probabilistic rather than deterministic, and conversational rather than merely computational (Budhwar et al., 2023). Charlwood and Guenole (2022) show that such systems confront HR with paradoxes: they can increase consistency while eroding perceived fairness, and release capacity while displacing judgement.

The consequences are consequential in both senses of the word. HR decisions shape livelihoods and are frequently legally protected, which raises the ethical salience of algorithmic intervention (Leicht-Deobald et al., 2019). Regulation has begun to crystallise: the European Union's AI Act classifies systems used for recruitment, selection and work-related decision-making as high risk, triggering obligations of risk management, data governance, technical documentation, logging, transparency and human oversight (Wright, 2025).

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This paper asks three questions. First, how does GenAI differ from previous generations of HR technology? Second, what opportunities and challenges does it create across core HR functions? Third, which ethical issues does it intensify, and how can they be governed? The contribution is a synthesised conceptual perspective that integrates adoption and ethics scholarship into a governance-oriented framework for HRM.

Theoretical Foundations

1 From Digital HRM to AI-Augmented HRM

Digital HRM describes the sociotechnical configuration through which HR activities are delivered by information technology (Strohmeier, 2020). Systematic reviews show that AI has been applied to recruitment and selection, training, performance management and retention, with stronger evidence for efficiency than for effectiveness (Vrontis et al., 2022). Prikshat et al. (2023) locate AI-augmented HRM across antecedent, assimilation and consequence stages, concluding that value depends on complementary human and organisational resources rather than on algorithms alone.

2 Affordances, Control and the Generative Turn

A sociotechnical affordance lens holds that technology's organisational effects emerge from the interaction between material features and social context. Kellogg et al. (2020) describe algorithmic technologies as creating a new "contested terrain of control" that reshapes who decides, what is visible and how work is evaluated; Duggan et al. (2023) show how platform workers experience such control as simultaneous dependence and detachment. GenAI adds four distinctive affordances: generativity (novel content across modalities), conversationality (natural-language interaction), opacity (limited insight into how outputs are produced) and scalability (near-zero marginal cost of content) (Bender et al., 2021; Feuerriegel et al., 2024).

3 Ethical Framing

Technology-acceptance perspectives explain adoption but remain silent on moral acceptability. Mittelstadt (2019) argues that principles alone cannot guarantee ethical practice without institutional translation and enforcement, and explainability research shows that transparency is a means to accountability rather than an end in itself (Barredo Arrieta et al., 2020). This paper therefore treats adoption and ethics as jointly constitutive of HRM's generative future.

Method

This is a conceptual paper employing an integrative review strategy. Literature was identified through searches of scholarly databases using combinations of the terms generative AI, ChatGPT, large language models, human resource management, recruitment, algorithmic bias, algorithmic management and AI ethics. Priority was given to peer-reviewed articles in Scopus- and Web of Science-indexed journals, supplemented by seminal conference papers and regulatory scholarship. Bibliographic details for every source were verified against Crossref metadata. The inclusion window spanned 2016 to 2026, capturing both foundational AI-HRM reviews and post-2022 GenAI scholarship. Analysis was thematic rather than systematic: sources were coded into opportunity, challenge and ethical domains, from which the framework was abductively derived. No formal protocol, quality appraisal or meta-analytic procedure was applied, and the resulting propositions remain to be tested empirically.

Opportunities

1 Recruitment and Selection

GenAI is most visibly deployed at the top of the talent funnel. It drafts job descriptions and person specifications, generates structured interview guides, summarises résumés and conducts conversational first-round screening. Reported benefits include reduced time-to-hire, lower administrative cost and closer alignment between job requirements and candidate profiles (Koteczki et al., 2025). Integrated risk analysis suggests, however, that these gains are contingent on process redesign and human verification rather than on tool deployment alone (Jiang et al., 2025).

2 Learning and Development

Generative systems enable content creation at a granularity previously infeasible, allowing adaptive learning pathways, scenario simulations, real-time feedback and on-demand micro-learning to be produced and revised continuously (Budhwar et al., 2023; Melão & Reis, 2026). The promise is developmental personalisation at scale, though evidence on learning outcomes remains thin.

3 Employee Experience and HR Service Delivery

Conversational agents handle routine enquiries, draft policy communications, summarise engagement-survey verbatims and coach managers through difficult conversations. Survey evidence indicates that practitioners currently use GenAI for drafting, summarising and ideation rather than for autonomous decision-making (Melão & Reis, 2026).

4 Augmenting the HR Professional

Much of HR's workload is communicative and repetitive — precisely the profile GenAI addresses. Delegating drafting releases capacity for judgement-intensive work such as conflict resolution, culture building and ethical deliberation, provided roles are redesigned rather than merely trimmed (Fenwick et al., 2024).

Challenges

1 Reliability and Epistemic Quality

Large language models optimise plausibility rather than truth. They may fabricate facts, over-generalise from skewed training corpora, and reproduce gendered and racialised language patterns (Bender et al., 2021). Because their outputs are fluent, errors are harder to detect than in rule-based systems, and HR professionals frequently lack the statistical literacy required to interrogate model reasoning (Angrave et al., 2016; Tambe et al., 2019).

2 Organisational Capability and Data Readiness

Adoption depends on data infrastructure, analytic skills and managerial interpretation, and HR has historically under-invested in all three (Angrave et al., 2016). Prikshat et al. (2023) show that assimilation is impeded by fragmented systems and unclear ownership, leaving the interpretative "last mile" stubbornly human.

3 Work Design and Control

GenAI extends algorithmic control into communicative work. It can standardise voice, mandate scripts and render interactions auditable, potentially displacing relational labour that employees value and that organisations depend

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upon (Kellogg et al., 2020; Duggan et al., 2023). Attendant anxiety itself carries performance costs.

4 Organisational Paradoxes

Charlwood and Guenole (2022) identify paradoxes that GenAI deepens: personalisation versus standardisation, transparency versus privacy, efficiency versus equity, and automation versus augmentation. Because GenAI can serve either pole, resolution is a governance choice rather than a technical default.

Ethical Issues

1 Bias and Discrimination

Algorithmic hiring has repeatedly produced disparate outcomes. Raghavan et al. (2020) find that vendor "de-biasing" claims seldom survive scrutiny, and Köchling and Wehner (2020) document discrimination arising across the pipeline from sourcing to development. Controlled audits of GPT-based résumé screening identify measurable racial, gender and disability bias (Glazko et al., 2024). Fabris et al. (2025) show that fairness metrics are plural and mutually incompatible, making metric selection a normative rather than technical decision, and Mehrabi et al. (2021) catalogue how bias enters at data, algorithm and deployment stages. GenAI compounds these risks because it can generate the evaluative criteria as well as apply them, and because its outputs resist attribution.

2 Privacy and Surveillance

GenAI's appetite for data collides with privacy. Employee communications, sentiment, behavioural signals and biometric data can be repurposed for inference, shifting workplace monitoring from observation towards prediction (Leicht-Deobald et al., 2019). Such surveillance risks breaching data-protection duties while corroding the very trust it purports to measure.

3 Transparency, Explainability and Accountability

Opaque models make contested decisions difficult to contest. Explainability research clarifies what technical transparency can and cannot deliver (Barredo Arrieta et al., 2020), while governance scholarship warns that transparency without enforcement is performative (Mittelstadt, 2019). For HR this raises an acute question: who is accountable when a generative system recommends rejection?

4 Autonomy, Dignity and Simulated Relationship

GenAI can simulate empathy in coaching and counselling. Where employees mistake simulation for regard, the harm is to dignity rather than accuracy. Valtonen et al. (2025) find that AI adoption affects wellbeing indirectly, through task optimisation and safety, rather than directly, implying that interaction design rather than technology determines outcomes; Fenwick et al. (2024) argue that HR must actively protect the human character of the employment relationship.

5 Regulatory Compliance

The EU AI Act's high-risk designation imposes lifecycle obligations on employment-related AI, including risk management, data governance, logging, transparency and human oversight (Wright, 2025). Compliance is demanding for procured, general-purpose models whose provenance and training data are frequently undisclosed. Davidson et al. (2025) propose an ethics framework tailored to AI-HRM development and use, and Jiang et al. (2025) offer an integrated risk-analysis approach; both imply that governance must be designed in rather than bolted on.

A Conceptual Framework

The framework proposed here links GenAI affordances to HR outcomes through three mediating mechanisms and two moderating conditions. GenAI's affordances — generativity, conversationality, opacity and scalability — act on HR processes. Their effect on outcomes (efficiency, fairness, employee wellbeing and decision quality) is mediated by decision quality, understood as the accuracy and consistency of HR judgements; by perceived fairness, understood as candidates' and employees' evaluations of procedural and interactional justice; and by employee trust in HR and management. The strength and direction of these paths are moderated by AI governance maturity — auditing, documentation, accountability and data protection — and by human oversight capacity, meaning the availability of trained, empowered decision-makers able to interrogate and override outputs. Where both moderators are strong, affordances are more likely to translate into augmentation; where they are weak, the same affordances translate into opacity, bias amplification and eroded trust. The framework is deliberately parsimonious and falsifiable, specifying moderation rather than asserting universal effects.

Table 1. Linking GenAI affordances to HR outcomes through mediating mechanisms and governance conditions.

GenAI affordance	Illustrative HR application	Mediating mechanism	Governance condition
Generativity (content creation at scale)	Job descriptions, interview guides, learning content	Decision quality	Accuracy verification and content review
Conversationality (natural-language interaction)	Screening chatbots, employee-service agents, coaching	Perceived fairness	Disclosure of AI involvement to candidates and staff
Opacity (limited output traceability)	Candidate scoring, performance narratives	Employee trust	Explainability requirements and audit trails
Scalability (near-zero marginal cost)	Continuous feedback, always-on HR service	Perceived fairness and trust	Human oversight capacity and escalation routes

Implications

1 Theoretical Implications

The framework extends AI-augmented HRM theorising (Prikshat et al., 2023) by specifying what is genuinely novel about generative systems and by treating ethics as endogenous to adoption rather than a downstream corrective. It also bridges sociotechnical and normative traditions: affordances explain what technology invites, while governance explains which invitations organisations accept.

2 Practical Implications

Four implications follow. First, treat GenAI as decision support with mandatory human review for consequential outcomes. Second, adopt documentation and audit practices consonant with the EU AI Act's high-risk regime, extending them to jurisdictions without equivalent rules (Wright, 2025). Third, audit for bias at the point of use and against multiple fairness criteria rather than a single metric (Fabris et al., 2025). Fourth, disclose AI involvement to candidates and employees, and invest in HR capability so that oversight is substantive rather than ceremonial (Davidson et al., 2025; Fenwick et al., 2024).

Limitations and Future Research

Three limitations qualify these arguments. The paper is conceptual: the framework is proposed rather than tested, and its propositions await empirical validation. The evidence base is dominated by research from high-income, English-speaking contexts, limiting transferability. And the technology is advancing faster than the literature, so capability claims may date quickly. Future research should test the framework's moderation hypotheses with multi-source field data; conduct longitudinal audits of generative hiring tools to determine whether bias attenuates with model iteration; examine candidate and employee perceptions of simulated empathy and AI disclosure; evaluate whether the EU AI Act's high-risk regime changes practice on the ground; and develop validated instruments for AI governance maturity in the HR function.

Conclusion

GenAI does not merely accelerate existing HR automation; it introduces a form of automation that produces meaning, simulates relationship and conceals its own reasoning. The opportunities — faster hiring, personalised development, responsive HR service and relieved administrative burden — are genuine but conditional. The challenges and ethical issues are equally real, and the high-risk designation of employment-related AI signals that regulators treat these systems as consequential. Whether GenAI augments or erodes the HR function will be settled by governance choices: whether organisations treat it as a tool to be supervised or an oracle to be obeyed.

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Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of thesis paper.

References

1. Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: Why HR is set to fail the big data challenge. Human Resource Management Journal, 26(1), 1–11. https://doi.org/10.1111/1748-8583.12090
2. Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., et al. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, 58, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012
3. Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? In Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (pp. 610–623). ACM. https://doi.org/10.1145/3442188.3445922
4. Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., & Cooke, F. L. (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
5. Charlwood, A., & Guenole, N. (2022). Can HR adapt to the paradoxes of artificial intelligence? Human Resource Management Journal, 32(4), 729–742. https://doi.org/10.1111/1748-8583.12433
6. Davidson, J., Schnepp, J., Buttrick, H., & Gupta, A. (2025). A framework for ethical AI-HRM development and use. AI and Ethics, 6(1), Article 28. https://doi.org/10.1007/s43681-025-00858-7
7. Duggan, J., Carbery, R., McDonnell, A., & Sherman, U. (2023). Algorithmic HRM control in the gig economy: The app-worker perspective. Human Resource Management, 62(6), 883–899. https://doi.org/10.1002/hrm.22168
8. Fabris, A., Baranowska, N., Dennis, M. J., Graus, D., Hacker, P., Saldivar, J., Zuiderveen Borgesius, F., & Biega, A. J. (2025). Fairness and bias in algorithmic hiring: A multidisciplinary survey. ACM Transactions on Intelligent Systems and Technology, 16(1), 1–54. https://doi.org/10.1145/3696457
9. Fenwick, A., Molnar, G., & Frangos, P. (2024). Revisiting the role of HR in the age of AI: Bringing humans and machines closer together in the workplace.

Frontiers in Artificial Intelligence, 6, Article 1272823. https://doi.org/10.3389/frai.2023.1272823

10. Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. Business & Information Systems Engineering, 66(1), 111–126. https://doi.org/10.1007/s12599-023-00834-7
11. Glazko, K., Mohammed, Y., Kosa, B., Potluri, V., & Mankoff, J. (2024). Identifying and improving disability bias in GPT-based resume screening. In Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency (pp. 687–700). ACM. https://doi.org/10.1145/3630106.3658933
12. Jiang, Y., Cai, Z., & Wang, X. (2025). Leverage generative AI for human resource management: Integrated risk analysis approach. The International Journal of Human Resource Management, 36(11), 1929–1959. https://doi.org/10.1080/09585192.2025.2544972
13. 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
14. Koteczki, R., Csikor, D., & Balassa, B. E. (2025). The role of generative AI in improving the sustainability and efficiency of HR recruitment process. Discover Sustainability, 6(1), Article 601. https://doi.org/10.1007/s43621-025-01484-3
15. Köchling, A., & Wehner, M. C. (2020). Discriminated by an algorithm: A systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment and HR development. Business Research, 13(3), 795–848. https://doi.org/10.1007/s40685-020-00134-w
16. Leicht-Deobald, U., Busch, T., Schank, C., Weibel, A., Schafheitle, S., Wildhaber, I., & Kasper, G. (2019). The challenges of algorithm-based HR decision-making for personal integrity. Journal of Business Ethics, 160(2), 377–392. https://doi.org/10.1007/s10551-019-04204-w
17. Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. ACM Computing Surveys, 54(6), 1–35. https://doi.org/10.1145/3457607
18. Melão, N., & Reis, J. (2026). Generative artificial intelligence in HRM practice: Patterns, profiles, and theoretical insights. Administrative Sciences, 16(3), Article 113. https://doi.org/10.3390/admsci16030113
19. Mittelstadt, B. (2019). Principles alone cannot guarantee ethical AI. Nature Machine Intelligence, 1(11), 501–507. https://doi.org/10.1038/s42256-019-0114-4
20. Prikshat, V., Malik, A., & Budhwar, P. (2023). AI-augmented HRM: Antecedents, assimilation and multilevel consequences. Human Resource Management Review, 33(1), Article 100860. https://doi.org/10.1016/j.hrmr.2021.100860
21. Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency (pp. 469–481). ACM. https://doi.org/10.1145/3351095.3372828
22. Strohmeier, S. (2020). Digital human resource management: A conceptual clarification. German Journal of Human Resource Management, 34(3), 345–365. https://doi.org/10.1177/2397002220921131
23. 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
24. Valtonen, A., Saunila, M., Ukko, J., Treves, L., & Ritala, P. (2025). AI and employee wellbeing in the workplace: An empirical study. Journal of Business Research, 199, Article 115584. https://doi.org/10.1016/j.jbusres.2025.115584
25. 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. The International Journal of Human Resource Management, 33(6), 1237–1266. https://doi.org/10.1080/09585192.2020.1871398
26. Wright, S. (2025). Artificial intelligence and work: A review of the European policy landscape. Journal of Industrial Relations, 67(5), 794–805. https://doi.org/10.1177/00221856251394780