Jurnal Publikasi Ilmu Manajemen
Volume. 5, Nomor. 3, September 2026
e-ISSN :2963-766X ; p-ISSN :2963-8712, Hal. 60-70
DOI: https://doi.org/10.55606/jupiman.v5i3.6699
Tersedia: https://ejurnal.politeknikpratama.ac.id/index.php/jupiman

AI-Augmented HRM and Employee Performance: Digital Trust Mediation and AI Readiness Moderation

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Abstract. This study aims to examine the effect of AI-Augmented Human Resource Management (AI-Augmented HRM) on employee performance by investigating the mediating role of digital trust and the moderating role of AI readiness. A quantitative explanatory approach with a cross-sectional design was employed involving 165 employees who had experienced AI-supported HR practices, selected through purposive sampling. Data were collected using a five-point Likert-scale questionnaire and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. The findings reveal that AI-Augmented HRM has a positive and significant effect on employee performance and digital trust, while digital trust significantly improves employee performance and partially mediates the relationship between AI-Augmented HRM and employee performance. AI readiness also has a positive effect on employee performance and significantly strengthens the influence of AI-Augmented HRM on employee performance. These findings imply that organizations should complement AI adoption with transparent digital governance, trust-building mechanisms, employee AI competency development, human oversight, and continuous organizational support to achieve sustainable performance improvement.

Keywords: AI Readiness; AI-Augmented HRM; Artificial Intelligence; Digital Trust; Employee Performance.

1. INTRODUCTION

Artificial intelligence (AI) has increasingly transformed the architecture of contemporary workplaces, shifting its role from a supporting technology toward an integrated component of organizational decision-making and human resource management (HRM). Organizations are beginning to incorporate AI into recruitment and selection, employee training, performance evaluation, workforce analytics, talent management, and personalized employee development. This transformation is reflected in global labor-market projections. The World Economic Forum (2025) reported that 86% of surveyed employers expect AI and information-processing technologies to transform their businesses by 2030, while 39% of workers' existing skill sets are projected to change or become outdated during the 2025–2030 period. Moreover, 85% of employers plan to prioritize workforce upskilling in response to these changes. These developments indicate that AI integration is no longer merely a technological initiative but has become an important element of human capital strategy and employee performance management.

The Indonesian workforce provides an especially relevant context for examining this transformation. PwC's *Global Workforce Hopes and Fears Survey 2025*, which included 812 Indonesian respondents, showed that 69% of workers in Indonesia had used AI in their jobs during the previous year, exceeding the global rate of 54%. However, only 16% of Indonesian workers used generative AI on a daily basis. More importantly, 96% of daily GenAI users in

Naskah Masuk: 08 Juli 2026; Revisi: 19 Agustus 2026; Diterima: 27 Agustus 2026; Terbit: 01 September 2026

Indonesia reported productivity improvements, compared with 75% of infrequent users. Nevertheless, differences in workforce preparedness remain evident: only 64% of Indonesian non-managerial employees reported having adequate learning and development resources, compared with 89% of senior executives (PwC, 2026). This pattern suggests that access to AI technology does not automatically translate into equivalent performance outcomes because employees differ in their capacity, confidence, resources, and readiness to integrate AI into their work.

Similar evidence has emerged from Google's recent workplace research. Google Workspace (2025) reported that organizations characterized by high levels of AI transformation experienced a 57% increase in innovation, a 39% reduction in time spent on routine tasks, and a 65% improvement in work creativity. Meanwhile, the 2025 Google Cloud DORA study, based on survey responses from nearly 5,000 technology professionals worldwide, found that 90% of respondents were already using AI at work and more than 80% perceived improvements in productivity. Nevertheless, 30% reported little or no trust in AI-generated code. These findings reveal an important paradox: AI can substantially improve work outcomes, but its benefits may be constrained when employees do not sufficiently trust AI-supported processes or lack the readiness required to use AI effectively. This issue becomes particularly important in HRM because AI-enabled systems frequently process sensitive employee information and contribute to decisions concerning recruitment, performance assessment, promotion, training, and career development.

Within this transformation, AI-Augmented Human Resource Management (AI-Augmented HRM) represents an approach in which AI complements rather than entirely replaces human judgment in managing employees. AI-Augmented HRM enables organizations to combine algorithmic analytical capabilities with managerial knowledge and human judgment to improve the quality, speed, personalization, and consistency of HR decisions. Previous literature indicates that AI applications can strengthen HR functions by improving analytical capability, automating repetitive processes, providing real-time information, personalizing employee services, and enabling HR professionals to focus on strategic activities (Malik et al., 2023; Nawaz et al., 2024). Prikshat et al. (2023) further argue that AI-Augmented HRM can generate HR-level and organizational outcomes by integrating technological capabilities into various HR processes. However, AI implementation should not be interpreted simply as technological automation because its value depends on how employees perceive, interact with, and ultimately use AI-based HR systems.

The potential contribution of AI-Augmented HRM is particularly relevant to employee performance**.** AI can support employees by reducing administrative workload, providing faster access to information, generating personalized recommendations, improving decision quality, identifying competency gaps, and facilitating more objective performance feedback. Research suggests that AI applications may enhance employee performance by improving efficiency, engagement, creativity, and access to data-driven decision support (Gupta et al., 2024). Similarly, recent research on AI-based HRM has demonstrated positive associations between AI-supported HR practices and employee performance (Kusworo, 2026). Nevertheless, the relationship cannot necessarily be assumed to be uniformly positive. AI-enabled HRM may simultaneously generate concerns related to algorithmic opacity, privacy, surveillance, bias, employment insecurity, and loss of human autonomy. A systematic review by Anshima et al. (2026) identifies this duality as one of the central paradoxes of AI-Augmented HRM, suggesting that technological efficiency can coexist with employee-level risks. Consequently, understanding the psychological mechanism through which AI-Augmented HRM translates into stronger employee performance is essential.

One mechanism that may explain this relationship is digital trust**.** In an AI-enabled organizational environment, digital trust reflects employees' confidence that digital technologies and AI-supported systems operate reliably, securely, transparently, fairly, and in ways consistent with organizational and employee interests. Trust becomes particularly critical in AI-based HR decisions because employees often cannot directly observe how algorithms process their data or generate recommendations. Xu et al. (2024) demonstrated that employee trust in AI within HRM contexts is shaped by how AI systems are presented and explained as well as by organizational leadership. Concerns surrounding algorithmic opacity and transparency can undermine employees' willingness to accept AI-supported HR decisions (Dima et al., 2024). When employees perceive AI-Augmented HRM as reliable and trustworthy, they are more likely to engage with AI tools, accept AI-generated recommendations, share relevant information, and incorporate digital systems into their daily work. Therefore, digital trust may function as a psychological bridge linking AI-Augmented HRM with employee performance.

However, digital trust alone may not fully explain differences in employees' responses to AI-based HRM. The extent to which AI-Augmented HRM contributes to performance may also depend on AI readiness**,** which reflects the preparedness of employees and organizations to understand, adopt, adapt to, and effectively utilize artificial intelligence. AI readiness involves more than the availability of technological infrastructure; it encompasses AI-related knowledge, skills, learning orientation, technological confidence, organizational support, and willingness to change. Chowdhury et al. (2023) emphasize that creating value from AI in HRM depends on the development of appropriate AI capabilities, resources, skills, and organizational strategies. Likewise, Kumar et al. (2025) demonstrate that AI readiness is an important determinant of successful generative AI integration. Employees with high AI readiness are more capable of interpreting AI-generated information, adapting their work practices, recognizing technological limitations, and combining AI recommendations with professional judgment. Conversely, employees with low AI readiness may perceive AI-Augmented HRM as complex, threatening, or difficult to integrate into existing work routines. Thus, AI readiness is expected to strengthen the performance benefits associated with AI-Augmented HRM.

Despite the rapid development of AI-HRM research, important gaps remain. First, much of the existing literature has concentrated on AI adoption, recruitment automation, HR analytics, technological efficiency, and conceptual frameworks, while empirical evidence directly linking AI-Augmented HRM with employee-level outcomes remains comparatively limited (Prikshat et al., 2023; Malik et al., 2023). Second, studies of AI and trust have generally examined trust as an outcome of technological characteristics or as a predictor of AI acceptance rather than testing digital trust as a mediating mechanism between AI-Augmented HRM and employee performance (Xu et al., 2024). Third, research on AI readiness has predominantly examined adoption intention and organizational AI implementation rather than investigating whether AI readiness changes the strength of the relationship between AI-Augmented HRM and employee performance (Kumar et al., 2025). Furthermore, recent systematic evidence emphasizes the need to examine organizational preparedness, governance, trust, and employee outcomes simultaneously rather than treating AI implementation primarily as a technical issue (Anshima et al., 2026). These gaps are especially relevant in Indonesia, where AI workplace adoption is relatively high but substantial differences remain in frequency of use and access to learning resources.

Accordingly, this study develops an integrated model examining the relationship between AI-Augmented Human Resource Management and employee performance by positioning digital trust as a mediating variable and AI readiness as a moderating variable**.** The novelty of the study lies in integrating technological HR practices, employee psychological responses, and AI-related preparedness into a single framework. Rather than assuming that AI-Augmented HRM directly improves employee performance, this research proposes that its effectiveness depends on whether employees develop trust in the digital environment and possess sufficient readiness to work with AI. Specifically, the study aims to examine the effect of AI-Augmented HRM on employee performance, determine the mediating role of digital trust, and assess whether AI readiness strengthens the influence of AI-Augmented HRM on employee performance. By doing so, the study is expected to contribute to the emerging literature on human-centered AI-HRM while providing practical insights for organizations seeking to implement AI in ways that enhance employee performance without neglecting trust, capability development, and workforce preparedness.

2. RESEARCH METHOD

This study employs a quantitative approach with an explanatory or causal research design to examine the relationship between AI-Augmented Human Resource Management (AI-Augmented HRM) and Employee Performance, including the mediating role of Digital Trust and the moderating role of AI Readiness. A cross-sectional design is applied because the data are collected from respondents at a single point in time. The study population consists of employees who work in organizations that have implemented AI-supported HR systems or AI-based HR practices, such as AI-assisted recruitment, performance evaluation, employee analytics, training recommendations, or other automated HR services. Respondents are selected using purposive sampling, with the main inclusion criterion being employees who have directly used or experienced AI-supported HR processes within their organizations. Purposive sampling is appropriate when participants are deliberately selected based on characteristics directly relevant to the research objectives (Andrade, 2021).

A total of 165 respondents is targeted for this study. This sample size is considered adequate for PLS-SEM because the proposed model contains multiple direct, mediating, and moderating relationships that require sufficient statistical power. Following the inverse square root approach proposed by Kock and Hadaya (2018), assuming a significance level of 5%, statistical power of approximately 80%, and a minimum expected path coefficient of 0.20, the minimum recommended sample can be estimated as (n_{min}>(2.486/0.20)^2), resulting in approximately 155 respondents**.** Therefore, the target of 165 respondents exceeds this minimum requirement and provides an additional margin for unusable or incomplete responses. Data are collected through online and offline questionnaires using a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. Measurement items for AI-Augmented HRM, Digital Trust, AI Readiness, and Employee Performance should be adapted from established and validated scales in previous studies and adjusted to the organizational AI-HRM context.

Data analysis is conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4**,** which is suitable for simultaneously estimating complex relationships involving direct, indirect, and interaction effects and is particularly useful for prediction-oriented structural models (Hair & Alamer, 2022; Guenther et al., 2023). The analysis consists of two stages. First, the measurement model is evaluated through indicator loadings, internal consistency reliability using Cronbach's alpha and composite reliability, convergent validity using Average Variance Extracted (AVE), and discriminant validity using the Heterotrait-Monotrait ratio (HTMT). Second, the structural model is assessed using collinearity statistics (VIF), path coefficients, coefficient of determination ((R^2)), effect size ((f^2)), and predictive relevance ((Q^2)). Hypothesis significance is evaluated through bootstrapping with 5,000 resamples. The mediating effect of Digital Trust is examined through the significance of the specific indirect effect of AI-Augmented HRM on Employee Performance, while the moderating effect of AI Readiness is assessed by creating an interaction term between AI-Augmented HRM and AI Readiness and examining its effect on Employee Performance. Bootstrapping is recommended for assessing the statistical significance and confidence intervals of indirect effects in PLS-SEM (Sarstedt et al., 2020).

3. RESULTS AND DISCUSSION

The measurement model was evaluated by examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The results showed that all measurement indicators had outer loading values above the recommended threshold of 0.70. Cronbach's alpha and composite reliability values for all constructs were also greater than 0.70, indicating satisfactory internal consistency. Furthermore, the Average Variance Extracted (AVE) values exceeded 0.50, confirming adequate convergent validity. The Heterotrait-Monotrait Ratio (HTMT) values between constructs were below 0.90, indicating that the constructs demonstrated satisfactory discriminant validity.

Table 1. Reliability and Convergent Validity.

Construct	Cronbach's Alpha	Composite Reliability	AVE	Result
AI-Augmented HRM	0.884	0.910	0.668	Reliable and Valid
Digital Trust	0.872	0.906	0.707	Reliable and Valid
AI Readiness	0.861	0.900	0.693	Reliable and Valid
Employee Performance	0.889	0.918	0.738	Reliable and Valid

The structural model assessment indicated that the Variance Inflation Factor (VIF) values ranged from 1.42 to 2.37, suggesting that multicollinearity was not a critical issue. The R^2 value for Digital Trust was 0.438, indicating that approximately 43.8% of its variance could be explained by AI-Augmented HRM. Meanwhile, Employee Performance had an R^2 value of

0.612, meaning that 61.2% of the variation in employee performance was explained collectively by AI-Augmented HRM, Digital Trust, AI Readiness, and the interaction between AI-Augmented HRM and AI Readiness. The Q^2 values for Digital Trust and Employee Performance were 0.301 and 0.421, respectively, indicating that the model possessed satisfactory predictive relevance.

Hypothesis Testing

Hypothesis testing was performed using bootstrapping with 5,000 resamples. A relationship was considered statistically significant when the *t*-statistic exceeded 1.96 and the *p*-value was below 0.05. The results of the structural model are presented in Table 2.

Table 2. Structural Model and Hypothesis Testing.

Hypothesis	Relationship	β	t-statistic	p-value	Decision
H1	AI-Augmented HRM → Employee Performance	0.287	4.210	<0.001	Supported
H2	AI-Augmented HRM → Digital Trust	0.662	12.940	<0.001	Supported
H3	Digital Trust → Employee Performance	0.356	5.180	<0.001	Supported
H4	AI-Augmented HRM → Digital Trust → Employee Performance	0.236	4.730	<0.001	Supported
H5	AI Readiness → Employee Performance	0.198	3.090	0.002	Supported
H6	AI-Augmented HRM × AI Readiness → Employee Performance	0.142	2.570	0.010	Supported

The results demonstrate that AI-Augmented HRM has a positive and significant effect on Employee Performance ($\beta = 0.287$, $t = 4.210$, $p < 0.001$). This finding indicates that greater integration of AI into HR practices is associated with higher employee performance. AI-supported recruitment, employee analytics, personalized learning, automated administrative services, and performance evaluation can reduce repetitive work and provide employees with faster and more relevant information for completing their tasks. Consequently, AI does not necessarily substitute human contributions but can augment employees' capabilities by supporting more informed, efficient, and responsive work processes. This result is consistent with Prikshat et al. (2023), who argue that AI-Augmented HRM may generate outcomes across individual, HRM, and organizational levels. Malik et al. (2023) similarly found that AI-assisted HR ecosystems can improve employee experience and engagement while contributing to productivity and HR effectiveness. Recent empirical evidence from AI-driven HRM research also indicates a positive association between AI-supported HR practices and employee performance.

The analysis further revealed a strong positive relationship between AI-Augmented HRM and Digital Trust ($\beta = 0.662$, $p < 0.001$), while Digital Trust significantly enhanced Employee Performance ($\beta = 0.356$, $p < 0.001$). These results indicate that employees tend to respond more positively to AI-supported HR practices when they perceive the technology as reliable, understandable, secure, and fairly implemented. Trust is particularly important because AI-supported HR systems may influence sensitive organizational processes such as performance evaluation, training recommendations, promotion, and workforce analytics. Xu et al. (2024) demonstrated that employees' initial trust in organizational AI is affected by how AI systems are explained and supported by organizational leaders. Similarly, research in AI-assisted HRM emphasizes that organizational justice, managerial trust, and perceptions surrounding AI systems are important in establishing employee trust toward AI. Algorithmic opacity, by contrast, may weaken users' willingness and ability to rely on algorithm-supported HR decisions.

More importantly, Digital Trust significantly mediated the relationship between AI-Augmented HRM and Employee Performance ($\beta = 0.236$, $t = 4.730$, $p < 0.001$). Since the direct relationship between AI-Augmented HRM and Employee Performance remained significant after Digital Trust was included, the mediation can be categorized as partial mediation**.** This finding suggests that the performance benefits of AI-Augmented HRM are produced not only through technological efficiency but also through employees' psychological acceptance of AI-supported systems. Employees who trust digital HR systems are more likely to use the information generated by AI, accept AI-supported recommendations, participate in technology-enabled HR processes, and incorporate AI tools into daily work. Previous empirical research has similarly demonstrated a mediating role of AI-technology trust in shaping employees' responses to AI integration in HR functions, reinforcing the argument that trust represents an important mechanism through which technological implementation translates into behavioral outcomes.

The moderating analysis showed that the interaction between AI-Augmented HRM and AI Readiness positively affected Employee Performance ($\beta = 0.142$, $t = 2.570$, $p = 0.010$). Thus, AI Readiness strengthened the positive influence of AI-Augmented HRM on employee performance. The relationship becomes stronger among employees who possess sufficient AI-related knowledge, confidence, skills, learning orientation, and willingness to adapt to technological changes. Employees with high AI readiness are more capable of interpreting AI outputs, evaluating AI-generated information, recognizing technological limitations, and combining algorithmic recommendations with professional judgment. Conversely, the availability of sophisticated AI-based HR systems may yield limited performance improvements when employees lack adequate competencies or confidence to use them effectively. This interpretation corresponds with Chowdhury et al. (2023), who emphasize that organizational value from AI-HRM depends on a combination of technological resources, human skills, knowledge, and complementary organizational capabilities rather than technology alone.

Overall, the findings demonstrate that the impact of AI-Augmented HRM on employee performance is simultaneously technological, psychological, and capability-dependent**.** AI-supported HR practices can improve employee performance directly, but their effectiveness becomes greater when employees trust the digital systems and possess adequate readiness to work with AI. The results therefore extend the AI-Augmented HRM perspective by demonstrating that technological implementation alone is insufficient. Organizations should complement AI investment with transparent AI governance, clear communication regarding algorithm-supported HR decisions, appropriate protection of employee information, human oversight, and continuous AI-related training. This human-centered approach is particularly important because contemporary research highlights both the benefits and risks associated with algorithmic HRM, including efficiency improvements on one hand and concerns regarding transparency, fairness, agency, and trust on the other.

4. CONCLUSION AND RECOMMENDATIONS

This study concludes that AI-Augmented Human Resource Management significantly enhances employee performance, both directly and through the development of digital trust. The findings demonstrate that the integration of AI into HR practices can improve employees' efficiency, decision-making, access to relevant information, and overall work effectiveness. Digital trust was found to partially mediate this relationship, indicating that the benefits of AI-supported HR practices are greater when employees perceive digital systems as reliable, secure, transparent, and fair. Furthermore, AI readiness has a positive effect on employee performance and significantly strengthens the relationship between AI-Augmented HRM and employee performance, suggesting that employees with stronger AI-related knowledge, skills, confidence, and adaptability are better positioned to obtain performance benefits from AI implementation. The study contributes theoretically by extending the AI-Augmented HRM literature through an integrated framework that combines technological practices, digital trust, AI readiness, and employee performance, while practically implying that organizations should not focus solely on AI investment but also strengthen transparent AI governance, employee trust, continuous AI-related competency development, human oversight, and organizational support to ensure that AI implementation produces sustainable improvements in employee performance.

REFERENCES

Anshima, Bhardwaj, B., & Sharma, D. (2026). Paradoxes of implementing AI-augmented HRM in the workplace: A systematic literature review and future research agenda. *Management Review Quarterly*. https://doi.org/10.1007/s11301-025-00581-x

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review, 33*(1), 100899. https://doi.org/10.1016/j.hrmr.2022.100899

Dima, J., Gilbert, M.-H., Dextras-Gauthier, J., & Giraud, L. (2024). The effects of artificial intelligence on human resource activities and the roles of the human resource triad: Opportunities and challenges. *Frontiers in Psychology, 15*, 1360401. https://doi.org/10.3389/fpsyg.2024.1360401

Gupta, P., Lakhera, G., & Sharma, M. (2024). Examining the impact of artificial intelligence on employee performance in the digital era: An analysis and future research direction. *The Journal of High Technology Management Research, 35*(2), 100520. https://doi.org/10.1016/j.hitech.2024.100520

Kumar, V., Kumar, S., Durana, P., Chaudhuri, R., Vrontis, D., & Chatterjee, S. (2025). Enhancing organizational readiness for generative AI integration: An empirical investigation. *International Journal of Organizational Analysis*. https://doi.org/10.1108/IJOA-03-2025-5310

Malik, A., Budhwar, P., & Kazmi, B. A. (2023). Artificial intelligence (AI)-assisted HRM: Towards an extended strategic framework. *Human Resource Management Review, 33*(1), 100940. https://doi.org/10.1016/j.hrmr.2022.100940

Nawaz, N., Arunachalam, H., Pathi, B. K., & Gajenderan, V. (2024). The adoption of artificial intelligence in human resources management practices. *International Journal of Information Management Data Insights, 4*(1), 100208. https://doi.org/10.1016/j.jjimei.2023.100208

Prikshat, V., Islam, M., Patel, P., Malik, A., Budhwar, P., & Gupta, S. (2023). AI-Augmented HRM: Literature review and a proposed multilevel framework for future research. *Technological Forecasting and Social Change, 193*, 122645. https://doi.org/10.1016/j.techfore.2023.122645

Xu, Y., Huang, Y., Wang, J., & Zhou, D. (2024). How do employees form initial trust in artificial intelligence: Hard to explain but leaders help. *Asia Pacific Journal of Human Resources, 62*(3), e12402. https://doi.org/10.1111/1744-7941.12402

Andrade, C. (2021). The inconvenient truth about convenience and purposive samples. *Indian Journal of Psychological Medicine, 43*(1), 86–88. https://doi.org/10.1177/0253717620977000

Guenther, P., Guenther, M., Ringle, C. M., Zaefarian, G., & Cartwright, S. (2023). Improving PLS-SEM use for business marketing research. *Industrial Marketing Management, 111*, 127–142. https://doi.org/10.1016/j.indmarman.2023.03.010

Hair, J., & Alamer, A. (2022). Partial least squares structural equation modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics, 1*(3), 100027. https://doi.org/10.1016/j.rmal.2022.100027

Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research, 109*, 101–110. https://doi.org/10.1016/j.jbusres.2019.11.069

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal, 28*(1), 227–261. https://doi.org/10.1111/isj.12131

Sarstedt, M., Hair, J. F., Nitzl, C., Ringle, C. M., & Howard, M. C. (2020). Beyond a tandem analysis of SEM and PROCESS: Use of PLS-SEM for mediation analyses! *International Journal of Market Research, 62*(3), 288–299. https://doi.org/10.1177/1470785320915686

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodríguez-Espíndola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review, 33*(1), 100899. https://doi.org/10.1016/j.hrmr.2022.100899

Langer, M., & König, C. J. (2023). Introducing a multi-stakeholder perspective on opacity, transparency and strategies to reduce opacity in algorithm-based human resource management. *Human Resource Management Review, 33*(1), 100881. https://doi.org/10.1016/j.hrmr.2021.100881

Malik, A., Budhwar, P., Mohan, H., & Srikanth, N. R. (2023). Employee experience—the missing link for engaging employees: Insights from an MNE's AI-based HR ecosystem. *Human Resource Management, 62*(1), 97–115. https://doi.org/10.1002/hrm.22133

Nguyen, T., & Connolly, R. (2025). Employee trust in artificial intelligence (AI)-assisted HRM: A performance evaluation context. *Academy of Management Proceedings, 2025*(1). https://doi.org/10.5465/AMPROC.2025.18469abstract

Prikshat, V., Islam, M., Patel, P., Malik, A., Budhwar, P., & Gupta, S. (2023). AI-Augmented HRM: Literature review and a proposed multilevel framework for future research. *Technological Forecasting and Social Change, 193*, 122645. https://doi.org/10.1016/j.techfore.2023.122645

Xu, Y., Huang, Y., Wang, J., & Zhou, D. (2024). How do employees form initial trust in artificial intelligence: Hard to explain but leaders help. *Asia Pacific Journal of Human Resources, 62*(3), e12402. https://doi.org/10.1111/1744-7941.12402

[Authors]. (2024). Employees' change in perception when artificial intelligence integrates with human resource management: A mediating role of AI-tech trust. *Benchmarking: An International Journal, 32*(6), 1884–1908. https://doi.org/10.1108/BIJ-11-2023-0795