IBIMA Publishing
Communications of International Proceedings
https://ibimapublishing.com/p-articles/47ISM/2026/4727126/
Vol. 2026 (7), Article ID 4727126

Understanding AI Integration Intensity in HR Practices and Its Implications for Employee Satisfaction: A Socio-Technical Perspective*

Hervé DJIOWOU YOUMBI, Daniel TOMIUK AND Jérémie KATEMBO

Université du Québec à Montréal, Montreal, Canada

Correspondence should be addressed to: Daniel TOMIUK, tomiuk.daniel@uqam.ca

*Presented at the 47th IBIMA International Conference, 29-30 June 2026, Madrid, Spain

Abstract

AI is increasingly being integrated into HR. This has important implications for HR processes, employee interactions, and decision-making. Research on AI in HR management has focused mostly on whether organizations adopt AI, how they use it, or on specific HR applications. This paper takes a different angle. It looks at the intensity of AI integration in HR practices. This distinction is important because two organizations may both adopt AI while integrating it into HR work systems at very different levels of depth, breadth, and autonomy. We conceptualize AI integration intensity through five dimensions: functional scope, decision-making influence, employee-AI interaction intensity, algorithmic sophistication, and algorithmic autonomy. Drawing on a socio-technical perspective, we develop a conceptual model in which HR analytics mediates the relationship between AI integration intensity and employee satisfaction, while AI governance moderates this relationship. Furthermore, we propose a quantitative survey design using partial least squares structural equation modeling (PLS-SEM) to test the model and assess AI integration intensity as a reflective-formative hierarchical construct. Our model suggests that the integration of AI within HR processes may impact employee satisfaction through the organization's ability to transform the data generated by AI into useful HR analytics, as well as through employees' perceptions of the fairness, transparency and trustworthiness of AI-supported HR practices. The paper contributes to the literature on AI in HR by distinguishing limited or narrow AI adoption from deeper forms of AI integration that reshape HR processes, interactions, and decisions.

Keywords: AI in HRM; AI integration intensity; HR analytics; AI governance; employee satisfaction

Introduction

Increasingly, organizations use AI to assist HR management. It can improve recruitment and help with talent management and training. Performance appraisals can now be performed by AI as well as workforce planning. AI promises not only to improve efficiency but also change how HR decisions are produced and justified (Gelbard et al., 2023). Some companies have even delegated decision-making to data-driven systems (Boudoumi, 2024). Importantly, AI has also affected labour relations. It can reshape employees' perceptions of autonomy and control (Kellogg et al., 2020).

Employee well-being is often measured using job satisfaction (Judge et al., 2001). However, the relationship between AI adoption in HR and employee satisfaction is not well-understood. AI can improve work conditions

---

Cite this Article as: Hervé DJIOWOU YOUMBI, Daniel TOMIUK AND Jérémie KATEMBO Vol. 2026 (7) " Understanding AI Integration Intensity in HR Practices and Its Implications for Employee Satisfaction: A Socio-Technical Perspective " Communications of International Proceedings, Vol. 2026 (7), Article ID 4727126, https://doi.org/10.5171/2026.4727126

and career paths for employees through such things as skill matching and improved career development through better personalization. It also offers higher-quality decisions through HR analytics. For example, AI helps organizations identify employee who possess particular capabilities. It can also anticipate workforce needs. Such uses can lead to greater satisfaction and stronger commitment given that employees perceive AI as useful, fair, and supportive (Minbaeva, 2018).

AI has also generated employee concerns. Such worries as job surveillance and a sense of loss of control over one's job are rising. Some employees even believe that AI can lead to dehumanization in the workplace. When an employee feels that (s)he is being monitored or evaluated using some opaque AI system, the employee-organization relationship can deteriorate. As such, whereas AI-supported HR can undoubtedly improve many aspects of HR, it can also weaken the employees' sense of autonomy and trust in their organization (Kellogg et al., 2020).

Another employee concern is algorithmic bias and how this can affect workplace justice. Unfortunately, AI-based HR decisions can reproduce existing forms of discrimination in the organization and even amplify them. This is because models used to train the AI may rely on biased historical data. Such practices can undermine employees' perceptions of fairness and lead them to question the legitimacy of AI (Raghavan et al., 2020; Naoum et al., 2026). For this reason, AI governance has become especially important to quell such possibilities. AI governance refers to mechanisms the organization puts in place to regulate AI applications. It usually means ensuring transparency and accountability of algorithmic decisions. Through AI governance, organizations can maintain employee trust and satisfaction in AI-enabled HR environments (Floridi et al., 2018).

Although existing research on AI adoption in HR has generated important insights, it has paid less attention to the varying degree to which AI is structurally embedded in HR work systems by different organizations. Two organizations may both be described as AI adopters, even though their use of AI can differ substantially. Compare one organization that uses AI only for limited administrative support to another which relies on AI across multiple HR functions, supporting employee interactions at many levels, and has deeply embedded AI into its decision processes. Treating both of these organizations simply as AI adopters can seriously obscure important differences in how each has integrated AI into its HR.

In this paper, we address this limitation. Instead of simply considering adoption, we consider the intensity of AI integration in HR practices. We define this concept as the *degree to which AI is embedded in its HR activities, decision-making, and interactions.* We argue that it varies across five dimensions: functional scope, decision-making influence, employee-AI interaction intensity, algorithmic sophistication, and algorithmic autonomy.

Furthermore, we propose a socio-technical model which links the intensity of AI integration in HR to employee satisfaction. In this model, HR analytics plays a mediating role through which AI integration influences employee outcomes. Moreover, AI governance acts as a moderating variable that helps shape whether employees experience AI-supported HRP as being fair, transparent, and trustworthy. Our model treats employee satisfaction as the central dependent variable. Organizational commitment is also positioned as a related attitudinal consequence of satisfaction.

Literature Review and Theoretical Framework

AI and the Transformation of HR Management

AI in HR should not be treated as a single, homogeneous phenomenon. AI integration varies in terms of how broadly and deeply AI is incorporated into HR and how autonomously it functions. Dima et al. (2024) argues that AI affects numerous HR activities in multiple ways. It is used for automation and improving data analysis. It can also transform the social and relational dimensions of work. On a spectrum, AI in HR can vary from providing simple support to complete human replacement across a multitude of activities including recruitment, workforce planning, talent management, training, and performance assessments. Across organizations, this transformation has neither been uniform nor always positive because of its possible implications on employee experiences. Soulami et al. (2024) show that AI can have ambivalent effects. On the positive side, AI can improve autonomy and innovation which can lead to greater employee satisfaction. On the negative side, some employees report increased levels of stress and insecurity when employees feel monitored or that they are being evaluated by opaque systems which they have little control over. Many report having a fear of technological substitution.

Intensity of AI Integration in HR Practices

Intensity of AI integration in HR practices (HRP from now on) is *the extent to which AI becomes embedded in HR functions, the interactions with employees, and the organization's decision-making*. Low-intensity can involve simple use of AI for such tasks as basic automation. High-intensity usually means strong influence in decision-making or even substitution (e.g., AI-conducted recruitment and training; automated employee performance evaluations). This intensity distinction goes beyond simply considering whether AI is present or not. The concept of *Intensity of AI integration in HRP* aims to capture how broadly and deeply AI is incorporated into HR and how autonomously it functions.

Intensity can be understood through three broad axes: scope (or breadth), depth, and agency. Scope/breadth refers to *the extent to which AI is deployed across different HR functions*. Depth is *the extent to which AI is embedded into the various HR decisions, employee interactions, and work processes of an organization*. Agency taps into to *the technical capabilities of the AI in HRP and the level of autonomy it has been delegated*.

These three axes are derived from IS research which distinguishes between initial IT adoption from deeper IT incorporation into work systems and organizational processes (see Cooper & Zmud, 1990; Zmud & Apple, 1992). It is also consistent with scientific literature on AI in HR that distinguishes between AI as augmentation vs. AI as automation/substitution. The former treats AI as supportive, assistive and even augmentative while the latter in interested more in its ability to replace or bypass human judgment (Dima et al., 2024; Kellogg et al., 2020; Nguyen & Elbanna, 2025; Raisch & Krakowski, 2021).

We operationalize intensity of AI integration across these three axes through five complementary dimensions: functional scope, decision-making influence, employee-AI interaction intensity, algorithmic sophistication, and algorithmic autonomy. Functional scope captures the breadth of AI deployment across HR functions. These dimensions (presented in the following sections) are conceptually distinct. Consequently, we conceptualize the AI integration intensity construct formative rather than reflective meaning that these dimensions jointly shape the overall intensity of integration. They are not necessarily interchangeable and are not necessarily strongly correlated.

Dimension 1 - Functional Scope

Functional scope is *the breadth of AI deployment across HR activities*. It captures breadth. Some organizations can use AI only in a limited number of HR activities. Others will choose to integrate AI more extensively across HR operations. Importantly, this dimension does not capture the AI's technical sophistication or decision-making influence as relatively simple AI tools can have broad organizational implementation if they are used across many HR activities while some very advanced AI applications may have limited functional scope if they are used in very specific functions in confined ways.

Dimension 2 - Decision-Making Influence

Decision-making influence refers to *the extent to which AI outputs (i.e., recommendations, predictions, or analyses) shape HR decisions*. It's the weight given to AI-generated information in HR decisions. Influence is low when AI plays a peripheral or advisory role and high when AI outputs strongly influence organizational decisions. In low-influence conditions, HR managers can consult AI-generated information while retaining substantial decisional discretion. In high-influence conditions, AI outputs may become central to decision-making even though humans still retain final authority.

Dimension 3 - The Intensity of Employee-AI Interactions

Employee-AI interaction intensity taps into *how direct are interactions between employees and AI systems within HRP.* In high-intensity situations, direct interactions with AI are frequent (not only through formal, up-down channels but also through repeated, personal and direct experiences with the AI). The more direct the interactions, the more frequent, visible, and central these interactions between employees and AI are in everyday HR experiences. The intensity of employee-AI interactions is high when there are frequent exchanges between employees and automated support systems, recommendation systems and chatbots, or AI-enabled communication platforms. In low-intensity situations, AI will operate mostly in the background with little to no direct visibility by employees.

Dimension 4 - The Sophistication of AI Algorithmic Capabilities

Algorithmic sophistication is *the level of complexity, adaptability, and learning capability of the AI integrated into HRP*. It captures the AI's technical properties (e.g., processing, predicting capabilities). Some organizations adopt simple, static automated systems. Others opt for very advanced AI capable of learning from historical data and generating context-specific recommendations. Some AI can even learn and adapt to individuals through user interactions and patterns of use, rather than offering generic interfaces and analytical models.

Dimension 5 - The Level of Autonomy of Algorithmic Systems

Algorithmic autonomy is defined as *the degree to which the organization delegates action, coordination, or decision-making authority to AI in HRP*. The higher this autonomy, the more directly AI influences how employees are managed (i.e., evaluated, monitored). Two clarifications should be made at this point.

First, algorithmic autonomy does not necessarily correlate significantly with dimension 2 (decision-making influence) across organizations. Autonomy is the extent to which AI can act or trigger decisions *without* human intervention (i.e., a substitutive role). Influence is about how much AI outputs affect human decisions (i.e., a supportive role). Influence is about the weight given to AI advice whereas autonomy is about the degree of delegation provided to the AI. Autonomy is low in organizations where AI only provide recommendations to decision-makers. It is high when AI is allowed to initiate HR actions without checks or final human verification (e.g., triggering alerts, flagging performance issues).

Second, autonomy should be distinguished from sophistication. Some organizations with very sophisticated AI can have its outputs and actions monitored tightly by humans (i.e., for final approval). Others may implement simpler AI but give them considerable leeway in triggering actions and making decisions.

Employees will not necessarily perceive autonomy as deleterious. If AI is perceived as supportive and fair and its reasoning transparent, it is very likely that autonomy will be seen as improving efficiency and workplace experience. However, concerns about surveillance and injustice may arise when AI is perceived as opaque and unchallengeable in its authority.

Employee Satisfaction in an AI Context

When investigating how employees may respond to technological change, job satisfaction is a useful variable. Employees can react positively to AI when it is perceived as helpful. They can become dissatisfied when AI affects decisions about them in ways they do not understand or trust and feel unable to control. Recent studies on AI and employee well-being evidences such ambivalence. Soulami et al. (2024) show that AI can support satisfaction and innovation when it reduces repetitive tasks and improves efficiency. AI can also increase stress and uncertainty if employees associate it with surveillance and potential job loss (Chuang et al., 2025). Thus, the relationship between AI and employee satisfaction is unlikely to be direct or automatic and we therefore seek to identify mechanisms through which AI impacts employee satisfaction.

HR Analytics as a Mediating Capability

Following Marler and Boudreau's (2017) review, HR analytics can be understood as *the systematic use of HR-related data, metrics, and analytical techniques to support evidence-based HR decision-making*. We distinguish HR analytics from AI's algorithmic sophistication. Sophistication is a technical property of AI. HR analytics is an organization's capability to make use of HR-generated data in meaningful ways (Marler & Boudreau, 2017; Minbaeva, 2018). We propose that HR analytics mediates the relationship between the intensity of AI integration in HRP and employee satisfaction. More intensive AI integration may increase HR-related data (in terms of quantity, speed, and granularity).

AI sophistication alone will not ensure that employees will experience AI as beneficial. It is through organizational transformation that AI-generated output will become useful, relevant, and supportive. An organization with AI but without adequate HR analytics will have access to powerful AI outputs but without the ability to use them effectively.

AI Governance and Organizational Acceptability

The organizational effects of AI are also likely to depend on governance. As AI become increasingly embedded within HR processes, interactions, and decisions, issues related to those AI systems. When AI starts influencing recruitment, performance evaluation, promotion, termination risk, etc. employees naturally want to know how decisions are made and what data are used. They also want to know how to contest or correct the AI when they perceive it as unfair and whether there's still a real person they can turn to for help. AI governance is *the set of mechanisms that organizations use to regulate the development and use of AI systems*. These include the principles that the organization puts into place related to such things as transparency, explainability, human oversight, data security, etc. (Malin et al., 2025). AI governance is likely to moderate the relationship between AI integration and employee satisfaction.

Theoretical Frameworks Used

We adopt a socio-technical perspective grounded in Social Exchange Theory (Cropanzano et al., 2017) given that AI integration in HRP is not only a technological issue. Social Exchange Theory sheds light on how employees are likely to respond to AI; positive reactions when AI is perceived as personally useful, fair, transparent, and supportive and negative reactions when AI is perceived as opaque, controlling, or unjust. This also helps explain why employee satisfaction and organizational commitment may depend not only on the intensity of AI integration but on the way AI-generated outputs are used and governed as well.

The Job Demands-Resources model also helps make sense of the ambivalent effects of AI on employees. AI is likely to be seen as a resource when employees perceive direct benefits (e.g., reducing repetitive tasks, improving decision quality, personalizing support) and also as a demand when it increases negative perceptions (i.e., surveillance, loss of control, job insecurity).

Conceptual Model and Hypotheses

Model Logic

The proposed model investigates the impact that the integration of AI into HRP can have upon employee satisfaction and commitment. HR analytics (an organizational capability) is the way that the data from AI systems is interpreted and used to make it useful to HR decisions. AI governance shapes how employees interpret AI integration. As such, similar intensities of AI integration in HRP in two different organizations can be interpreted as clear and legitimate in one and as opaque and intrusive in the other. Satisfaction from the employees is the central element of this model. Commitment from the employees is thought to be impacted as a result of their satisfaction with the AI. Commitment from employees relates to their feelings of attachment to and identification with their organization (Mowday et al., 1979; Meyer & Allen, 1991).

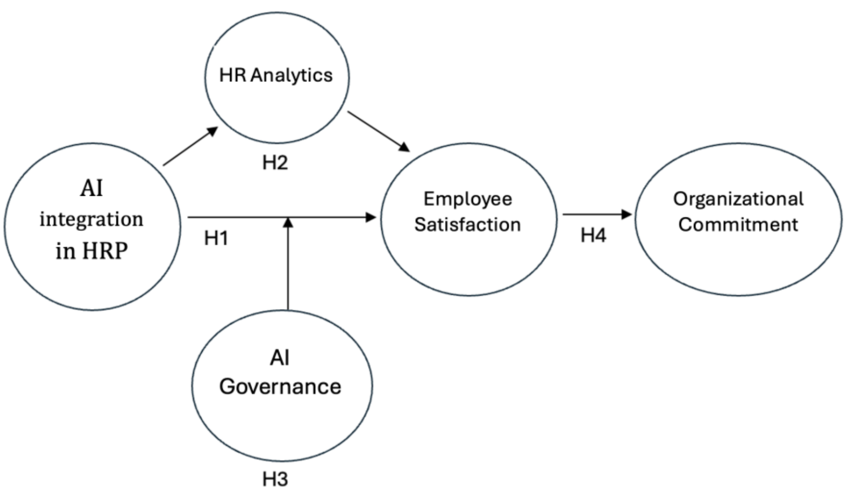

Figure 1 – Conceptual Model

Hypotheses

Intensive integration of AI into HRP can impact employee satisfaction in a variety of ways. For instance, it may lead to positive impacts on employee satisfaction if integration allows HR to take better decisions, provide more personalization, and improve access to information. However, it can also reduce employee satisfaction if employees associate AI with increased surveillance, lack of individual control, and the belief that AI reduces HR's ability to apply sound judgment. AI integration may be positive in some contexts, but negative in others. For these reasons, the following non-directional hypothesis is made:

H1. The intensity of AI integration into HRP is associated with employee satisfaction.

Increased integration of AI into HRP should enable HR departments to gain access to potentially useful data regarding HR practices. However, data alone does not have inherent value; the value of those data is dependent upon HR analytics (i.e., how well the organization can capitalize on it to make better decisions within their HRP.

H2. HR analytics will mediate the relationship between the intensity of AI integration into HR practices and employee satisfaction.

AI governance is expected to impact the relationship between the intensity of AI integration in HRP and employee satisfaction. When HR departments have strong AI governance in place (e.g., granting employees more control over their data, protecting that data from misuse, increased transparency, human oversight) then intensive integration of AI into HRP will be positively associated with employee satisfaction whereas weak governance of AI is more likely to lead to negative effects on employee satisfaction.

H3. AI governance will moderate the relationship between the intensity of AI integration into HR practices and employee satisfaction such that the relationship is positive if AI governance is strong.

Finally, employees that are more satisfied with their organization's AI integration in HRP, are more likely to feel committed to that organization.

H4. Employee satisfaction has a positive influence on organizational commitment.

Methodology

Conceptualization of Constructs

We conceptualize intensity of AI integration in HRP as a second-order hierarchical construct composed of five dimensions. These dimensions are distinct components that together form the overall intensity of AI integration. For this reason, intensity of AI integration in HRP is conceptualized as formative. Jarvis, MacKenzie, and Podsakoff (2003) discuss the difference between reflective and formative constructs in relation to measurement models. Formative constructs are those in which the indicators or dimensions jointly form a construct, rather than reflect an underlying latent variable. Formative dimensions are not expected to be correlated.

Furthermore, each dimension is conceptualized as a reflective construct. The indicators associated with each dimension are therefore treated as observable manifestations of the same underlying concept, consistent with latent variable modeling logic (Bollen, 1989). For example, items measuring algorithmic autonomy should reflect the same underlying idea and should therefore be strongly correlated.

Overall, the proposed measurement structure corresponds to a 'reflective-formative hierarchical component model'. This is consistent with prior work on hierarchical component models in PLS-SEM used to represent complex multidimensional constructs composed of conceptually distinct lower-order dimensions (Becker, Klein, & Wetzels, 2012).

We will use a quantitative survey design targeting employees and managers working in organizations where AI technologies are used in HRP. PLS-SEM is commonly used to estimate complex models involving formative constructs and hierarchical component structures (Hair et al., 2014). The combination of mediation and moderation analysis allows the study to examine not only whether AI integration intensity is related to employee satisfaction, but also through which mechanisms and under which organizational conditions this relationship can occur (Hayes, 2018).

Questionnaire Development and Sample Size

Questionnaire development will occur in several stages. Items for each of the main constructs will first be identified from the literature on AI in HR. When possible, items from validated questionnaires will be adapted. However, because there is no validated measure of the intensity of AI integration in HRP, new items will likely have to be developed for this study to assess each of the five dimensions of AI integration in human resources. All items will be content validated by experts in the field in human resource management and those who are experts in AI.

Prior to the distribution of the questionnaire to the targeted populations, a pre-test will be performed to determine the clarity, comprehensibility, and relevance of all items included in the questionnaire. All items will be measured using Likert-type scales.

Target respondents will be employees working in organizations that have implemented AI-enabled technologies in one or more HRP. Sample size will be estimated through a priori power analysis. Target power will be .80 with a significance level of .05 (Cohen, 1992; Faul et al., 2009). We will also ensure that sample size is adequate by using methods specific to PLS-SEM (e.g., Kock and Hadaya, 2018).

Discussion and Conclusion

Overall, this paper argues that the organizational consequences of AI in HR cannot be fully understood by asking whether AI has been adopted. A more useful question is how intensively AI is integrated into HR work systems, and under what conditions this integration supports or undermines employee attitudes. By conceptualizing AI integration intensity as a multidimensional construct and linking it to employee satisfaction through HR analytics and AI governance, this paper provides a foundation for future empirical research on the socio-technical transformation of HR practices.

As discussed, the ability of AI to create useful data for HR departments does not automatically translate into positive effects for the employees of those organizations. The organization must utilize HR analytics in ways that are perceived as beneficial by employees. Another way in which AI can contribute to the HR departments is through the use of adequate AI governance to legitimize those practices. As HR departments become more and more digitized, employees may begin to feel as if their rights are being disregarded or that HR departments lose their humanity. Good governance should help mitigate employee concerns. Alternatively, poor or lack of governance is likely to contribute to employees' negative attitudes toward the AI and lower their commitment to the organization.

One limitation with our proposed study is that AI is continuously evolving and the construct of AI integration is still emerging. As AI adapts to HR practices and vice versa, the dimensions of AI integration within HR departments may need to be refined. Finally, the effects of AI integration within HR departments may differ by sector and industry. Future studies can investigate the effect of AI integration within specific groups of organizations. Future studies can investigate whether the five dimensions of AI integration that were proposed in this paper are sufficient to reflect the level of integration of AI within HR departments.

Acknowledgment

The authors used generative AI tools, specifically ChatGPT 5.5, to support editing, language refinement, and the identification of grammatical and semantic issues. AI tools were used to improve the language and presentation of the manuscript, but not to generate or alter the study's core ideas, research design, or scholarly contribution. The authors reviewed and approved all AI-assisted revisions and remain fully responsible for the manuscript's content.

References

Becker, J.-M., Klein, K. and Wetzels, M. G. M. (2012) 'Hierarchical latent variable models in PLS-SEM: guidelines for using reflective-formative type models', *Long Range Planning*, 45(5–6), pp. 359–394. https://doi.org/10.1016/j.lrp.2012.10.001

Bollen, K. A. (1989) *Structural Equations with Latent Variables*. Wiley.

Boudoumi, M. (2024) *L'impact de l'intelligence artificielle sur les processus décisionnels en entreprise*. Maîtrise en relations industrielles, Faculté des arts et des sciences, Université de Montréal, Canada.

Chuang, Y.-T., Chiang, H.-L. and Lin, A.-P. (2025) 'Insights from the Job Demands–Resources model: AI's dual impact on employees' work and life well-being', *International Journal of Information Management*, 83, Article 102887. https://doi.org/10.1016/j.ijinfomgt.2025.102887

Cohen, J. (1992) 'A power primer', *Psychological Bulletin*, 112(1), pp. 155–159. https://doi.org/10.1037/0033-2909.112.1.155

Cooper, R. B. and Zmud, R. W. (1990) 'Information technology implementation research: a technological diffusion approach', *Management Science*, 36(2), pp. 123–139. https://doi.org/10.1287/mnsc.36.2.123

Cropanzano, R., Anthony, E. L., Daniels, S. R. and Hall, A. V. (2017) 'Social exchange theory: a critical review with theoretical remedies', *Academy of Management Annals*, 11(1), pp. 479–516. https://doi.org/10.5465/annals.2015.0099

Dima, J., Gilbert, M.-H., Dextras-Gauthier, J. and 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, Article 1360401. https://doi.org/10.3389/fpsyg.2024.1360401

Faul, F., Erdfelder, E., Buchner, A. and Lang, A.-G. (2009) 'Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses', *Behavior Research Methods*, 41(4), pp. 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V. et al. (2018) 'AI4People—an ethical framework for a good AI society: opportunities, risks, principles, and recommendations', *Minds and Machines*, pp. 689–707. https://doi.org/10.1007/s11023-018-9482-5

Gelbard, R., Ramon-Gonen, R. and Carmeli, A. (2023) 'HR analytics and organizational performance: a systematic review', *Human Resource Management Review*, 33(2), 100912. https://doi.org/10.1016/j.hrmr.2022.100912

Hair, J. F. Jr., Hult, G. T. M., Ringle, C. M. and Sarstedt, M. (2014) *A primer on partial least squares structural equation modeling (PLS-SEM)*. SAGE Publications.

Hayes, A. F. (2018) *Introduction to mediation, moderation, and conditional process analysis*. Guilford Press.

Jarvis, C. B., MacKenzie, S. B. and Podsakoff, P. M. (2003) 'A critical review of construct indicators and measurement model misspecification in marketing and consumer research', *Journal of Consumer Research*, 30(2), pp. 199–218. https://doi.org/10.1086/376806

Judge, T. A., Thoresen, C. J., Bono, J. E. and Patton, G. K. (2001) 'The job satisfaction–job performance relationship: a qualitative and quantitative review', *Psychological Bulletin*, 127(3), pp. 376–407. https://doi.org/10.1037/0033-2909.127.3.376

Kellogg, K. C., Valentine, M. A. and Christin, A. (2020) 'Algorithms at work: the new contested terrain of control', *Academy of Management Annals*, 14(1), pp. 366–410. https://doi.org/10.5465/annals.2018.0174

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

Malin, C., Fleiß, J. and Thalmann, S. (2025) ‘Stakeholder-specific adoption of AI in HRM: workers’ representatives’ perspective on concerns, requirements, and measures’, *Frontiers in Artificial Intelligence*, 8. https://doi.org/10.3389/frai.2025.1561322

Marler, J. H. and Boudreau, J. W. (2017) ‘An evidence-based review of HR analytics’, *International Journal of Human Resource Management*, pp. 1–26. https://doi.org/10.1080/09585192.2016.1244699

Meyer, J. P. and Allen, N. J. (1991) ‘A three-component conceptualization of organizational commitment’, *Human Resource Management Review*, 1(1), pp. 61–89. https://doi.org/10.1016/1053-4822(91)90011-Z

Minbaeva, D. B. (2018) ‘Building credible human capital analytics for organizational competitive advantage’, *Human Resource Management*, 57(3), pp. 701–713. https://doi.org/10.1002/hrm.21848

Mowday, R. T., Steers, R. M. and Porter, L. W. (1979) ‘The measurement of organizational commitment’, *Journal of Vocational Behavior*, 14(2), pp. 224–247. https://doi.org/10.1016/0001-8791(79)90072-1

Naoum, R. F., Szakadáti, T. and Balogh, G. (2026) ‘Artificial intelligence (AI) in human resource management (HRM): a systematic review of its dual impact on diversity, equity, and inclusion (DEI)’, *Management Review Quarterly*, 1–72. https://doi.org/10.1007/s11301-025-00580-y

Nguyen, T. and Elbanna, A. (2025) ‘Understanding human–AI augmentation in the workplace: a review and a future research agenda’, *Information Systems Frontiers*. https://doi.org/10.1007/s10796-025-10591-5

Raisch, S. and Krakowski, S. (2021) ‘Artificial intelligence and management: the automation–augmentation paradox’, *Academy of Management Review*, 46(1), pp. 192–210. https://doi.org/10.5465/amr.2018.0072

Raghavan, M., Barocas, S., Kleinberg, J. and Levy, K. (2020) ‘Mitigating bias in algorithmic hiring: evaluating claims and practices’, in *Proceedings of the Conference on Fairness, Accountability, and Transparency*, pp. 1–13. https://dl.acm.org/doi/pdf/10.1145/3351095.3372828

Soulami, M., Benchekroun, S. and Galiulina, A. (2024) ‘Exploring how AI adoption in the workplace affects employees: a bibliometric and systematic review’, *Frontiers in Artificial Intelligence*, 7, Article 1473872. https://doi.org/10.3389/frai.2024.1473872

Zhou, X., Xiong, Q., Wang, M., Huang, L. and Zhong, M. (2025) ‘Employees’ perception of digital human resource management changes and proactive behavior: the mediating role of work engagement and moderating effect of person–organization fit’, *Frontiers in Psychology*, 16, Article 1623702. https://doi.org/10.3389/fpsyg.2025.1623702

Zmud, R. W. and Apple, L. E. (1992) ‘Measuring technology incorporation/infusion’, *Journal of Product Innovation Management*, 9(2), pp. 148–155. https://doi.org/10.1111/1540-5885.920148