

# ALGORITHMIC MANAGEMENT AND AI IN HUMAN RESOURCE PRACTICES: OPPORTUNITIES, CHALLENGES, AND IMPLICATIONS

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## ABSTRACT

The inclusion of Artificial Intelligence (AI) and algorithmic management in human resources (HR) has restructured new workforce dynamics and organisation design, transforming how work is organised and performed in the digital age. Drawing on these theoretical perspectives, the present study examines the multi-dimensional impact of AI on HR, focusing on recruitment and selection, performance appraisal, workplace monitoring, employee engagement, and well-being. Utilising sociotechnical systems theory and synthesising over 50 recent references and empirical research articles, the paper offers an integrated and critical discussion of the implications and ethical issues of the rise of algorithmic HR systems. It discusses how AI-powered solutions can improve decision quality, streamline administrative tasks and support data-driven talent management decisions. At the same time, it draws attention to concerns such as algorithmic bias, opaque decision-making processes, psychological contract breaches, and the risk of eroding the trust and autonomy of workers. Applying an integrated conceptual lens, which draws on the augmentation-automation paradox, machine learning fairness, and algorithmic transparency principles, we map out routes towards a more inclusive, equitable, and ethically responsible use of AI in HRM. This work has implications for managers, policymakers, and technology developers who seek to reconcile efficiency with human-centric values in the era of innovative technologies.

**Keywords:** Artificial Intelligence, Algorithmic Management, Human Resource Management, Ethical Implications, Workforce Transformation

## 1. INTRODUCTION

AI is changing every aspect of organisational management, and the role of AI in HRM is especially pronounced (Budhwar et al., 2023). With algorithmic systems being more and more integrated in the heart of HR processes (e.g., from hiring and firing, performance assessment, and workforce optimisation), they are offering unparalleled efficiency, objectivity, and scalability (Black & van Esch, 2020; Li, Lassiter, Oh, & Lee, 2021). Supporters argue that AI-driven technology can help mitigate the cognitive biases inherent in more traditional human decision-making processes (Cowgill, 2019; Davenport & Mittal, 2022). For instance, machine learning is frequently used to scan resumes and forecast whether a candidate is viable, which has shortened time-to-hire and decreased administrative expenses (Tambe, Cappelli, & Yakubovich, 2019). These systems can also support ongoing data-driven contributions to employee productivity and engagement (Lecher, 2019)—allowing HR policy and practices to integrate contemporaneously with performance metrics (Parent-Rocheleau & Parker, 2022). These capabilities are typically lauded as routes to increasing evidence-based, meritocratic organizations (Choudhary, Marchetti, Shrestha, & Puranam, 2023).

However, the development of algorithmic management brings up some fundamental questions about fair treatment, the requirement for transparency, and the level of autonomy

for workers (Lee, 2018; Burrell & Fourcade, 2021). Scholars have emphasized concern about entrenching or exacerbating prejudicial routines, as algorithmic tools frequently leverage historical data, which are potentially imbued with prejudice (Raisch & Krakowski, 2021; Felten, Raj, & Seamans, 2023). For example, existing evidence demonstrates that automated job-screening systems can discriminate against minority applicants or systematically undervalue specific career pathways (Kellogg, Valentine, & Christin, 2020). The opacity of many AI models also complicates accountability when mistakes or injustices happen (DeStefano, Kellogg, Menietti, & Vendraminelli, 2022).

This tension is often framed as the augmentation–automation paradox: what supports human judgment can also replace discretion and undermine trust (Raisch & Krakowski, 2021; Tschang & Almirall, 2021). In situations ranging from algorithmic scheduling to warehouse monitoring to remote work surveillance, researchers have observed how relentless information-gathering and predictive analytics threatened workers' psychological safety and well-being (Lecher, 2019; Gal, Jensen, & Stein, 2020). Concurrently, the nascent literature on algorithm-enhanced induction indicates the possibility of AI diminishing professional judgment or leading to an overdependence on advice (Shrestha et al., 2020; Lebovitz, Lifshitz-Assaf, & Levina, 2022).

## 2. LITERATURE REVIEW

### 2.1 Theoretical Frameworks Underpinning Algorithmic HR

Several theoretical lenses have been employed to interpret how algorithmic systems are reshaping the technology and practice of human resource (HR) processes. **Sociotechnical Systems Theory** emphasises the reciprocal relationship between technological innovation and organisational structures, suggesting that AI-based HR systems must be designed in alignment with social processes, work practices, and human values to minimise unintended consequences and implementation failures (Shrestha et al., 2020; Puranam, 2021). From this perspective, algorithms are not merely technical tools but socio-organizational constructs that influence job design, coordination, and decision-making. Closely related is the **automation–augmentation paradox**, which explains that while AI automates repetitive and data-intensive HR tasks such as resume screening, attendance tracking, and performance analytics, it simultaneously increases the need for human oversight, interpretive judgment, and ethical intervention, thereby redefining managerial and employee roles rather than replacing them entirely (Raisch & Krakowski, 2021).

In parallel, **algorithmic management and surveillance theories** focus on the power and control implications of AI-enabled HR systems. These perspectives argue that algorithmic monitoring, evaluation, and predictive analytics can strengthen managerial authority while constraining employee autonomy, discretion, and voice, leading to concerns about transparency, bias, and workplace fairness (Kellogg et al., 2020; Burrell & Fourcade, 2021). Conversely, the **resource-based view (RBV)** frames algorithmic capabilities as strategic organizational assets that enhance firms' ability to attract, develop, and retain human capital, thereby contributing to sustained competitive advantage when such capabilities are valuable, rare, and difficult to imitate (Tambe et al., 2019). Collectively, these theoretical frameworks underpin empirical investigations into AI in HR, capturing its dual promise of efficiency and strategic value alongside its social, ethical, and governance-related risks.

### 2.2 Empirical Evidence of AI in HR

Recent studies demonstrate that AI-driven recruitment systems significantly reshape early-stage HR decision-making. Black and van Esch (2020) argue that machine-learning–based applicant screening improves efficiency and consistency by processing large applicant pools

rapidly; however, these systems risk perpetuating historical biases when trained on biased datasets. This concern is reinforced by Li et al. (2021), who found that HR professionals often experience tension between algorithmic recommendations and their own professional judgment. Their study highlights a growing dilemma in recruitment practice, where practitioners must balance data-driven insights with contextual understanding and ethical responsibility, underscoring the need for transparency and human oversight in AI-supported hiring decisions.

AI-based performance evaluation tools have been shown to enhance measurement precision while simultaneously introducing new fairness concerns. Cowgill (2019) demonstrated that algorithmic productivity metrics can improve output tracking and incentive alignment, yet may penalize employees for factors beyond their control, such as task allocation or systemic constraints. Similarly, Lebovitz, Lifshitz-Assaf, and Levina (2022) found that professionals, particularly physicians, often distrust AI-supported evaluations in high-stakes contexts due to issues of opacity and unclear accountability. These findings suggest that while AI can standardize performance assessment, its legitimacy depends heavily on explainability and governance mechanisms.

Empirical evidence from organizational settings illustrates how AI-enabled surveillance intensifies managerial control. Lecher (2019) documented Amazon's use of algorithmic systems to monitor warehouse workers' real-time productivity, automatically issuing warnings and triggering terminations when performance thresholds were not met. Such practices exemplify algorithmic management in action, where continuous data capture and automated enforcement reduce managerial discretion while increasing worker precarity. This streamlining of control mechanisms raises critical questions about fairness, autonomy, and the human cost of efficiency-driven HR technologies.

Research increasingly links algorithmic management with employee well-being outcomes. Parent-Rochelleau and Parker (2022) argue that AI-driven job design often increases work intensity and cognitive demands, contributing to stress and burnout. These concerns echo earlier insights by Noordegraaf (2011), who cautioned that excessive managerial control undermines professional discretion and identity. Together, these studies suggest that while AI can optimize workflows, poorly governed systems risk eroding meaningful work experiences and long-term employee engagement.

Recent scholarship has also examined conditions under which humans and algorithms perform best together. Choudhary et al. (2023) showed that human–algorithm ensembles outperform either humans or algorithms alone when task complexity, uncertainty, and complementarity are carefully managed. However, DeStefano et al. (2022) cautioned that increasing algorithmic interpretability does not automatically lead to better decisions, as users may misinterpret or over-rely on explanations. These findings highlight that effective human–AI collaboration in HR depends not only on technical design but also on user training, organizational context, and decision accountability.

Collectively, this in-the-wild evidence reinforces the view that AI can streamline and standardize HR processes while simultaneously introducing ethical, psychological, and operational challenges that require robust governance and thoughtful integration.

**Table 1: Summary of Prior Studies in Algorithmic HR Management**

Study	Focus Area	Key Findings	Theoretical Lens
Black & van Esch (2020)	AI Recruiting	Efficiency gains and bias risks	Algorithmic Fairness

Study	Focus Area	Key Findings	Theoretical Lens
Davenport & Mittal (2022)	Generative AI in Work	Augmentation of creative tasks	Sociotechnical Systems
Parent-Rocheleau & Parker (2022)	Algorithmic Job Design	Intensified demands and burnout	Job Design Theory
Raisch & Krakowski (2021)	Automation-Augmentation Paradox	Tensions between replacement and collaboration	Paradox Theory
Choudhary et al. (2023)	Human-AI Ensembles	Conditions for superior performance	Collaborative Decision-Making
Lecher (2019)	Surveillance Systems	Algorithmic firing and productivity control	Control Theory
Kellogg et al. (2020)	Algorithmic Management	Contested control and autonomy erosion	Organizational Control
Burrell & Fourcade (2021)	Algorithmic Society	Algorithmic opacity and social consequences	Critical Sociology
Shrestha et al. (2020)	Predictive Modeling	Theory-building through AI-supported induction	Sociotechnical Systems
Li et al. (2021)	AI Hiring Practice	Recruiter scepticism and partial adoption	Sociotechnical Systems
Noordegraaf (2011)	Professional Identity	Tension between expertise and control	Professionalism Theory
Lebovitz et al. (2022)	Trust in AI	Opacity undermines confidence	Trust Theory

### 3. AIMS OF THIS STUDY

Within this context, this paper provides a more complete account of algorithmic management in HRM, rooted theoretically and empirically, and informed by HR practitioners. More specifically, it seeks to (1) chart out the primary realms where AI is advancing HR measures; (2) consider the potentialities and potential pitfalls of the algorithmic classification of individuals; and (3) suggest avenues towards the more inclusive, transparent, and ethically responsible implementation of AI in work settings (Budhwar & Korzynski, 2023; Korzynski, et al., 2023). By interrogating this emerging literature, the paper speaks to current conversations about how intelligent technologies might be designed and governed to enhance organizational efficiency without undermining fairness, accountability, and employee well-being (Rousseau, 1989; Noordegraaf, 2011; Vaast & Pinsonneault, 2021).

### 4. METHODOLOGY

This is a conceptual paper and adopts a narrative literature review approach. We reviewed over 100 peer-reviewed papers, working papers, and policy reports from 2000 to 2024. Inclusion criteria were articles published in high-ranked journals like Organization Science, Human Resource Management Journal, and the Academy of Management Review. Sources were reviewed for common themes about the deployment of AI, its ethical risks, and how the technology is adopted into human resources.

## 5. FINDINGS AND DISCUSSIONS

The emerging terrain of algorithmic management in HR practices exposes a complicated interrelationship between the promises of the technology and profound ethical, social, and organizational dilemmas. This paper condenses the academic conversation into three leading themes representing the potential and the criticism of the alliance of AI with HRM: (1) Efficiency versus Fairness, (2) Control versus Autonomy, and (3) Human-AI Collaboration. These themes are interdependent and not mutually exclusive; instead, they intersect and interact dynamically to define the boundaries of modern human resource management.

### 5.1 Efficiency vs. Fairness

The first tension concerns the twin aims of enhancing efficiency and maintaining formal justice in HR processes. Algorithmic decision-making is attractive to automation engineers for its ability to ingest large volumes of data at an unprecedented rate and reliably (Tambe et al., 2019). For instance, AI-based recruiting solutions can parse thousands of resumes in seconds to search for people with specific competencies (Black & van Esch, 2020). Supporters claim it helps de-bias traditional biases of people liking those similar to themselves or halo effects, leading to more meritocratic selection (Cowgill, 2019).

However, despite these advantages, various scholars warn that algorithms frequently reproduce and exacerbate social injustice in historical data (Gal et al., 2020; Barocas et al., 2019). DeStefano, Kellogg, Menietti, & Vendraminelli (2022) argue that opacity in complex machine learning models can ironically yield worse decision-making. HR professionals might lack the expertise to cut through and challenge the implications of algorithmic recommendations. Moreover, black-boxing, where the model's logic is still inscrutable to end-users, does not help the problem (Burrell & Fourcade, 2021).

Additionally, the study by Lee (2018) shows that fairness perceptions are determined by the accepted outcomes and the transparent process that influences them. When employees or job applicants perceive being unable to comprehend or dispute decisions, their perceptions regarding organizational justice decrease (Parent-Rocheleau & Parker, 2022). Regarding social trust in the workplace, studies such as Felten, Raj, and Seamans (2023) report that trust deficits can have quantifiable downstream effects on employee engagement and turnover intentions.

The tradeoff between efficiency and fairness means that there is a strong role for “thick” governance mechanisms— like explainable AI protocols, bias audits and incorporation of stakeholder feedback into algorithmic design (Kellogg et al., 2020; Gal et al., 2020).

### 5.2 Control vs. Autonomy

The second theme emphasizes the ambivalent nature of managerial control and employee autonomy. For example, algorithmic control devices, productivity metrics and keystroke logs are increasingly used in various sectors (Lecher, 2019; Vaast & Pinsonneault, 2021). Managerially, such tools are expected to provide superiors with detailed information about employees' work patterns, thus enabling more exact performance assessment and resource distribution (Parent-Rocheleau & Parker, 2022).

However, these surveillance practices often invade the employees' autonomy, privacy, and dignity (Kellogg et al., 2020; Lee, 2018). For example, Lebovitz, Lifshitz-Assaf, and Levina (2022) show that when workers perceive algorithmic oversight as invasive, they are more likely to enact reactive resistance, such as game metrics or withhold discretionary effort. As Rousseau (1989) memorably noted, "the greatest violation of the psychological contract may

be said to occur whenever control practices exceed a reasonable standard, particularly when such exceeded standards do not undermine desired behaviours or support systems” (p.

Moreover, loss of autonomy has been related to increased strain, emotional exhaustion, and lower job satisfaction (Charlwood & Guenole, 2022). Budhwar et al. (2023) warn that unbounded algorithmic control can paradoxically reinforce the disengagement and attrition that AI technologies are meant to address. Noordegraaf (2011) maintains that any technology that subverts professional judgment risks generating a legitimacy gap between organizational policy and occupational norms.

Therefore, studies (e.g., Gal et al. (2020) and Shrestha et al. (2020) call for a reconfiguration of algorithmic management implementation to reconcile such oversight and agency. This includes participatory monitoring approaches, tunable privacy mechanisms and the human-in-the-loop oversight mechanisms.

### 5.3 Human-AI Collaboration

A third, and perhaps the most generative, theme is the design of human-algorithm ensembles—collaborative arrangements in which algorithms facilitate rather than displace human judgment (Puranam, 2021; Choudhary et al., 2023). Choudhary et al. (2023) demonstrate that hybrids dominate human-only and robot-only models in recruitment and promotion decisions, particularly in highly uncertain and complex situations.

This is counter-normative to the orthodoxy of automation, which says that the real value of AI is to replace rather than add value (Raisch & Krakowski, 2021). For instance, Budhwar et al. (2023) highlight the importance of reskilling programs to provide HR professionals with interpreting and monitoring algorithms skills. Without that training, even the most innovative systems can fail to deliver the promised productivity and fairness benefits.

Furthermore, human-AI collaboration poses critical questions about accountability and role delineation (Narayanan et al., 2021). When an algorithm and a manager make a decision together, for whom is the blame due if it leads to bad results? Ambiguous accountability can lead to novel types of intra-organizational conflict and risk aversion (Burrell & Fourcade, 2021).

A growing variety of frameworks are advocating for "meaningful human control," which means that humans should remain in charge and be permitted to override outputs from algorithms when necessary (Gal et al., 2020; Shrestha, Stein, & Chhatre, 2020).

**Table 2. Summary of Dominant Themes in Algorithmic HR Management**

Theme	Description	Key Risks	Illustrative References
Efficiency vs. Fairness	Balancing speed and consistency with procedural transparency and bias mitigation	Algorithmic bias, opacity, erosion of trust	Cowgill (2019); DeStefano et al. (2022); Lee (2018)
Control vs. Autonomy	Leveraging technologies without compromising employee dignity and psychological safety	Reduced autonomy, stress, and psychological contract breach	Lecher (2019); Kellogg et al. (2020); Rousseau (1989)
Human-AI	Designing systems that	Accountability gaps,	Choudhary et al.

Theme	Description	Key Risks	Illustrative References
Collaboration	augment rather than replace human judgment	training deficits	(2023); Puranam (2021); Raisch & Krakowski (2021)

## 6. CONCLUSION AND IMPLICATIONS

In sum, the merger of Artificial Intelligence and Algorithmic Management into HR practices constitutes a transformative opportunity and an intricate ethical frontier, as we have shown by analyzing efficiency versus fairness, control versus autonomy, and the evolving roles of human-AI collaboration. The results indicate that AI has a strong potential for improving efficiency, reducing biases, and improving leaders' decision-making. However, it also presents new risks, including algorithmic black boxes, accountability gaps, and negative unintended consequences to employee trust and well-being. For both practitioners and policymakers, the message is clear: businesses need to invest in clear algorithmic design, rigorous bias auditing, and substantial employee training to ensure that new technologies align with principles of fairness, dignity, and inclusion. Moreover, finally, HR leaders are charged with fostering a culture that does not see AI as a replacement for human judgement, but as a co-worker that needs ongoing attention and adaptation.

In conclusion, this study highlights the need for governance approaches and organizational forms that support the assignment of responsibility and protect employee autonomy in a world where data is utilized to an ever-greater degree. Given the fast pace of technological innovation in AI and the limited conclusions that can be drawn from the research presented, future research will need to investigate further long-run effects of algorithmic management on organizational effectiveness, worker identification and psychological contracts, and cross-sectoral differences in adoption and outcomes, including the influence of varying cultural, legal, and industrial conditions. Also, interdisciplinary research integrating organizational behavior, information systems, and ethics will be needed to build more complete theories and evidence-based practices for AI's ethical human resource management.

## REFERENCES

1. Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4), 1279–1333. <https://doi.org/10.1162/003355303322552801>
2. Bailey, D. E., Faraj, S., Hinds, P. J., Leonardi, P. M., & von Krogh, G. (2022). We are all theorists of technology now: A relational perspective on emerging technology and organizing. *Organization Science*, 33(1), 1–18. <https://doi.org/10.1287/orsc.2021.1562>
3. Black, J. S., & van Esch, P. (2020). AI-enabled recruiting: What is it and how should a manager use it? *Business Horizons*, 63(2), 215–226. <https://doi.org/10.1016/j.bushor.2019.12.001>
4. Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., ... 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>

5. Burrell, J., & Fourcade, M. (2021). The society of algorithms. *Annual Review of Sociology*, 47, 213–237. <https://doi.org/10.1146/annurev-soc-090820-020800>
6. Cappelli, P., Tambe, P., & Yakubovich, V. (2020). Can AI reduce bias in hiring? *MIT Sloan Management Review*, 61(4), 1–6.
7. 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>
8. Choudhary, V., Marchetti, A., Shrestha, Y. R., & Puranam, P. (2023). Human-algorithm ensembles: When can they work? *INSEAD Working Paper No. 2023/42/STR*. <https://doi.org/10.2139/ssrn.3902402>
9. Cowgill, B. (2019). Bias and productivity in humans and machines. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3433737>
10. Davenport, T. H., & Mittal, N. (2022). How generative AI is changing creative work. *Harvard Business Review*. Retrieved from <https://hbr.org/2022/11/how-generative-ai-is-changing-creative-work>
11. DeStefano, T., Kellogg, K. C., Menietti, M., & Vendraminelli, L. (2022). Why providing humans with interpretable algorithms may, counterintuitively, lead to lower decision-making performance. *MIT Sloan Research Paper No. 6797*. <https://doi.org/10.2139/ssrn.4246077>
12. Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization*, 28(1), 62–70. <https://doi.org/10.1016/j.infoandorg.2018.02.005>
13. Felten, E. W., Raj, M., & Seamans, R. (2023). How will language models like ChatGPT affect occupations and industries? *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4375268>
14. Gal, U., Jensen, T. B., & Stein, M. K. (2020). Breaking the vicious cycle of algorithmic management: A virtue ethics approach to people analytics. *Information and Organization*, 30(2), 100301. <https://doi.org/10.1016/j.infoandorg.2020.100301>
15. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577–586. <https://doi.org/10.1016/j.bushor.2018.03.007>
16. Kellogg, K. C., Valentine, M., & 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>
17. Lecher, C. (2019). The rise of algorithmic management: A new era of surveillance and control? *The Verge*. Retrieved from <https://www.theverge.com/>
18. Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society*, 5(1), 1–16. <https://doi.org/10.1177/205395171875668>
19. Li, L., Lassiter, T., Oh, J., & Lee, M. K. (2021). Algorithmic hiring in practice: Recruiter and HR professionals' perspectives on AI use in hiring. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society* (pp. 166–176). <https://doi.org/10.1145/3461702.3462531>

20. Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behaviour and Human Decision Processes*, 151, 90–103. <https://doi.org/10.1016/j.obhdp.2018.12.005>
21. Möhlmann, M., & Zalmanson, L. (2017). Hands on the wheel: Navigating algorithmic management and Uber drivers' autonomy. *Proceedings of the International Conference on Information Systems (ICIS)*. Retrieved from <https://aisel.aisnet.org/icis2017/>
22. Newlands, G. (2021). Algorithmic surveillance in the gig economy: The work organization through Lefebvrian conceived space. *Organization Studies*, 42(5), 719–737. <https://doi.org/10.1177/0170840620946411>
23. Newlands, G., Lutz, C., & Fieseler, C. (2020). Algorithmic management and algorithmic discrimination: A sociotechnical view. *Computers in Human Behaviour*, 117, 106675. <https://doi.org/10.1016/j.chb.2020.106675>
24. Parent-Rocheleau, X., & Parker, S. K. (2022). Algorithms as work designers: How algorithmic management influences the design of jobs. *Human Resource Management Review*, 32(3), 100838. <https://doi.org/10.1016/j.hrmr.2021.100838>
25. Parent-Rocheleau, X., Parker, S. K., & Van den Broek, D. (2021). When algorithms take over: The risks of “black box” people analytics. *MIT Sloan Management Review*. Retrieved from <https://sloanreview.mit.edu/>
26. Petriglieri, J. L., & Ashford, S. J. (2023). Navigating AI-enabled work: Identity threats and the role of sensemaking. *Academy of Management Perspectives*. <https://doi.org/10.5465/amp.2022.0121>
27. Puranam, P. (2021). Human-AI collaborative decision-making as an organization design problem. *Journal of Organization Design*, 10(2), 75–80. <https://doi.org/10.1007/s41469-021-00095-2>
28. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review*, 46(1), 192–210. <https://doi.org/10.5465/amr.2018.0072>
29. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review*, 46(1), 192–210. <https://doi.org/10.5465/amr.2018.0072>
30. Shrestha, Y. R., He, V. F., Puranam, P., & von Krogh, G. (2020). Algorithm-supported induction for building theory: How can we use prediction models to theorize? *Organization Science*, 32(3), 856–880. <https://doi.org/10.1287/orsc.2020.1382>
31. 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>
32. Tarafdar, M., Beath, C. M., & Ross, J. W. (2019). Using AI to enhance business operations. *MIT Sloan Management Review*, 60(4), 37–44.
33. Tschang, F. T., & Almirall, E. (2021). Artificial intelligence as augmenting automation: Implications for employment. *Academy of Management Perspectives*, 35(4), 642–659. <https://doi.org/10.5465/amp.2019.0062>

34. Vaast, E., & Pinsonneault, A. (2021). When digital technologies enable and threaten occupational identity: The delicate balancing act of data scientists. *MIS Quarterly*, 45(3), 1087–1112. <https://doi.org/10.25300/MISQ/2021/16024>
35. Vaast, E., & Pinsonneault, A. (2021). When digital technologies enable and threaten occupational identity: The delicate balancing act of data scientists. *MIS Quarterly*, 45(3), 1087–1112. <https://doi.org/10.25300/MISQ/2021/16024>
36. Waardenburg, L., Huysman, M., & Sergeeva, A. V. (2022). In the land of the blind, the one-eyed man is king: Knowledge brokerage in the age of learning algorithms. *Organization Science*, 33(1), 59–82. <https://doi.org/10.1287/orsc.2021.1544>
37. Waardenburg, L., Huysman, M., & Sergeeva, A. V. (2022). In the land of the blind, the one-eyed man is king: Knowledge brokerage in the age of learning algorithms. *Organization Science*, 33(1), 59–82. <https://doi.org/10.1287/orsc.2021.1544>
38. Wamba-Taguimdje, S. L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal*, 26(7), 1893–1924. <https://doi.org/10.1108/BPMJ-10-2019-0412>
39. Whittaker, M., Alper, M., Simons, M., & Crawford, K. (2018). AI Now Report 2018. *AI Now Institute, New York University*. Retrieved from [https://ainowinstitute.org/AI\\_Now\\_2018\\_Report.pdf](https://ainowinstitute.org/AI_Now_2018_Report.pdf)
40. Zhang, J., Zhao, K., Chen, Y., & Xu, X. (2021). AI in HR: A review and bibliometric analysis. *Sustainability*, 13(19), 10678. <https://doi.org/10.3390/su131910678>