
Generative Artificial Intelligence and the Future of Work: A Human–AI Collaboration Capability Framework for Employee and Organizational Outcomes

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Abstract: Generative Artificial Intelligence (GenAI) is quickly evolving as disruptive technology able to generate text, images, code, summaries, recommendations and other kinds of content. While classical artificial intelligence technologies were mainly used for predictive purposes, GenAI technology allows employees to interact with artificial intelligence using natural language and embed AI into knowledge-intensive tasks. Such technology implies certain consequences regarding productivity, employee learning, creativity, human resources management and organizational performance. But access to GenAI does not mean automatic creation of value by organizations. Results achieved from GenAI use depend on capabilities of employees, nature of tasks, organizational preparedness, control of human over processes and responsible governance. In this conceptual paper, a Human–Generative AI Collaboration Capability (H-GAICC) framework is developed to explore ways of translating GenAI capabilities into employee and organizational outcomes. Using Resource-Based View, Socio-technical Systems Theory, Automation-Augmentation Approach, Job Demands–Resources Theory and Dynamic Capabilities Theory, the paper argues that GenAI capability, AI literacy of employees and organizational preparedness determine quality of human-AI collaboration. Collaboration effectiveness has an impact on productivity, creativity, learning, and employee experience and therefore can have a bearing on organizational performance. Trust, responsible AI governance, task complexity, and human supervision are put forward as moderating factors. Twelve propositions are formulated for the purpose of guiding further empirical work. This paper makes a contribution to the growing GenAI literature by directing the focus away from mere AI adoption to its organizational configuration with humans.

Keywords: Generative artificial intelligence; human–AI collaboration; AI literacy; employee experience; productivity; organizational performance; responsible AI; human resource management

Introduction

From specialized analytical tools to increasingly general-purpose applications, artificial intelligence has evolved. Previous AI was largely used in prediction, classification, recommendations, and automation. The generative artificial intelligence is a step further, since it can produce something new according to natural-language prompts. Large language models can generate documents, summarization, software code, ideation, and facilitate communication. There are major organizational implications from this development. Staff will be able to engage with GenAI without any programming knowledge. As a result, GenAI will not only become important for technology-oriented companies but also for human resources management, education, finance, marketing, consulting, and public administration. Empirical research proves there are productivity gains from GenAI. According to Noy and Zhang (2023), ChatGPT significantly decreased the time needed to perform professional writing tasks and improved the quality of their results on average. Brynjolfsson et al. (2025) using data of more than 5,000 customer support representatives have discovered productivity gains in staff who used an AI assistant.

However, technological capability does not necessarily lead to organizational effectiveness. AI tools may provide erroneous information, reproduce biases, pose privacy concerns and foster overreliance on technology.

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Dell'Acqua et al. (2026) show that the capabilities of generative AI vary from one task to another, implying that proper implementation would involve knowledge about what AI is good at and what requires human skills. The body of literature on AI in human resource management stresses that implementation cannot be done solely by acquiring new technology. Tambe et al. (2019), Chowdhury et al. (2023), Malik et al. (2023), and Prikshat et al. (2023) all underline the necessity of organization capability, skillset of employees, governance, and interaction between human and AI. Despite this expanding body of literature, the research remains fragmented. Productivity studies concentrate on task-level outcomes, HRM studies deal with particular applications in organization, and responsible AI research centers on risks and governance. There is a need for comprehensive theoretical explanation of how technological capability turns into organizational and employee value.

This research paper will fill this gap by addressing the following research question:

- How can organizations transform GenAI capability into sustainable organizational and employee outcome by means of human-AI interaction?

The paper proposes that GenAI should not be treated simply as an independent variable influencing performance. Rather, organizational value emerges through a process:

GenAI capability → Human–AI collaboration → Employee/task outcomes → Organizational outcomes.

Generative AI and the Future of Work

In contrast to traditional automation, generative AI has the ability to take part in cognitive and knowledge-based processes. Autor (2015) says that technological advancement needs to be studied based on task-level and not occupational level. An occupation normally contains multiple tasks, and technology may substitute for some while complementing others.

This logic is particularly relevant to GenAI. A human resource manager may use GenAI to draft a job description, summarize employee feedback or prepare training content while retaining responsibility for evaluation and decision-making.

Therefore, three categories of work can be distinguished:

1. **Tasks suitable for automation**
2. **Tasks suitable for human–AI augmentation**
3. **Tasks requiring predominantly human judgment**

The appropriate balance depends on task complexity, ambiguity, sensitivity and consequences.

Raisch and Krakowski (2021) describe this as the automation–augmentation paradox. AI may simultaneously substitute for some human activities and complement others. The organizational challenge is therefore not to choose between "humans" and "AI" but to determine how their respective capabilities should be combined.

Generative AI and Human Resource Management: HRM is particularly relevant to GenAI because HR activities contain both routine information-processing tasks and high-context human decisions.

Potential applications include:

Recruitment: GenAI can support job descriptions, recruitment communication, interview questions and candidate information summaries. However, high-stakes selection decisions require human oversight because algorithmic systems may reproduce historical bias.

Training and development: GenAI can generate personalized learning content, simulations, case studies and feedback. It can therefore support individualized learning at scale.

Performance management: Managers can use GenAI to organize performance information and prepare feedback drafts. Nevertheless, contextual and interpersonal judgments should remain human responsibilities.

Employee services: AI assistants can provide rapid responses to routine HR queries, improving accessibility and reducing administrative workload.

HR analytics: Natural-language interfaces can make analytics more accessible to managers.

However, generated interpretations require verification because fluent AI responses can contain factual or analytical errors.

Existing research supports the view that AI-HRM implementation is fundamentally socio-technical. Chowdhury et al. (2023) conceptualize AI capability as involving technological and human resources, while Malik et al. (2023) propose an extended strategic framework for AI-assisted HRM. Priksat et al. (2023) similarly emphasize the organizational assimilation of AI rather than simple technological adoption.

GenAI expands these issues because employees themselves can become direct users of AI systems.

Theoretical Foundations

Resource-Based View: The Resource-Based View suggests that organizations achieve competitive advantage by developing valuable and difficult-to-imitate resources.

Mikalef and Gupta (2021) conceptualize AI capability as involving technological resources, human skills and organizational resources.

Access to the same GenAI model may therefore produce different outcomes across organizations. Competitive advantage may arise from the ability to combine:

AI technology + employee skills + organizational knowledge + data + governance.

Thus, GenAI itself may be less strategically valuable than the organizational capability to deploy it effectively.

Socio-Technical Systems Theory: Socio-technical Theory places emphasis on the joint optimization of both social and technical systems. According to Makarius et al. (2020), organizations should look at the relationship between people and AI systems instead of seeing AI as a standalone technology. This implies that the application of GenAI is characterized by change in the workflow, jobs, and decision structures.

Automation–Augmentation Perspective: Raisch & Krakowski (2021) point out that organizations need to find a balance between automation and augmentation.

GenAI augmentation may turn out to be especially significant for knowledge work as human employees participate in it:

- Contextual understanding;
- Ethical reasoning;
- Interpersonal judgment;
- Organizational knowledge;
- Accountability.

Job Demands–Resources Theory: The JD-R perspective suggests that GenAI may simultaneously operate as a job resource and a job demand.

It can reduce:

- Repetitive work;
- Information-search burden;
- Documentation workload.

But it may also increase:

- Technological learning requirements;
- Output-verification demands;
- Performance expectations;
- Technological uncertainty.

Therefore, employee outcomes depend on how GenAI is introduced and managed.

Proposed Human–Generative AI Collaboration Capability Framework: The central contribution of this paper is the **Human–Generative AI Collaboration Capability (H-GAICC)** framework.

The model proposes three antecedents:

1. **GenAI capability**
2. **Employee AI literacy**
3. **Organizational readiness**

These influence:

4. **Human–GenAI collaboration quality**

Which produces:

5. **Task and employee outcomes**

And ultimately:

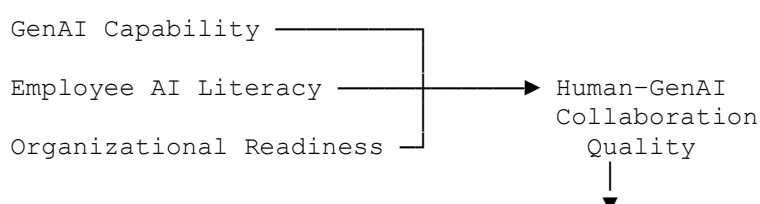
6. **Organizational outcomes**

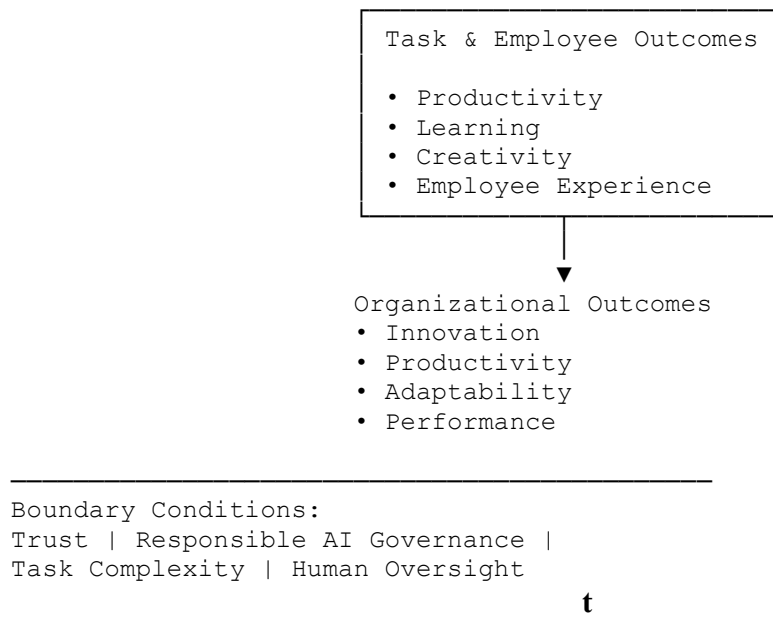
The relationships are conditioned by:

- a. Trust;
- b. Responsible Ai Governance;
- c. Task Complexity;
- d. Human Oversight.

Figure 1. Proposed Conceptual Framework

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Core Constructs

GenAI Capability: GenAI capability refers to the organization's ability to acquire, integrate, deploy and govern generative AI.

It includes:

- Technological infrastructure;
- Data readiness;
- System integration;
- Technical expertise;
- Governance;
- Organizational learning.

Employee AI Literacy: AI literacy involves more than prompt-writing ability.

It includes:

- Understanding AI capabilities;
- Recognizing AI limitations;
- Prompt and interaction competence;
- Evaluating outputs;
- Ethical awareness;
- Domain-specific application.

An employee who can generate an AI response but cannot determine whether it is accurate has limited practical AI literacy.

Organizational Readiness: Organizational readiness includes:

- Leadership support;
- Digital culture;

- Employee preparedness;
- Financial and technological resources;
- Change-management capability.

Technology implementation is unlikely to produce sustainable value when employees and organizational systems are unprepared.

Human–GenAI Collaboration Quality: Human–AI collaboration quality is the central mediating construct.

It includes:

Task allocation: Determining which activities should be performed by humans and AI.

Interaction: Providing appropriate context and instructions.

Verification: Checking AI outputs before implementation.

Complementarity: Combining AI's information-processing capabilities with human judgment.

Learning: Improving work practices through repeated human–AI interaction.

The framework therefore argues that **AI use frequency is less important than AI collaboration quality**.

Propositions

P1: GenAI capability is positively associated with GenAI-enabled work integration.

Organizations possessing stronger technological and governance capabilities are expected to integrate GenAI more effectively.

P2: Employee AI literacy is positively associated with human–GenAI collaboration quality.

Employees with stronger AI literacy should be better able to allocate tasks, formulate instructions and verify outputs.

P3: Organizational readiness positively moderates the relationship between GenAI capability and human–GenAI collaboration quality.

P4: Human–GenAI collaboration quality is positively associated with task productivity.

P5: Human–GenAI collaboration quality is positively associated with employee learning.

P6: Human–GenAI collaboration quality is positively associated with employee creativity.

P7: Human–GenAI collaboration quality is positively associated with employee experience when GenAI reduces unnecessary cognitive and administrative workload.

P8: Human–GenAI collaboration quality mediates the relationship between GenAI capability and employee productivity.

P9: Employee AI literacy mediates the relationship between GenAI exposure and employee performance.

P10: Responsible AI governance positively moderates the relationship between human–GenAI collaboration and organizational outcomes.

P11: Task complexity moderates the relationship between human–GenAI collaboration quality and productivity.

P12: Human oversight is positively associated with the quality of outcomes produced by GenAI in high-stakes organizational decisions.

GenAI, Productivity and Employee Experience: Recent empirical evidence provides support for the productivity potential of GenAI.

Noy and Zhang (2023) found substantial productivity effects in professional writing tasks. Brynjolfsson et al. (2025) found productivity improvements among customer-support workers using generative AI.

However, productivity should not be treated as synonymous with organizational value.

Suppose GenAI reduces the time required to produce a report by 40 percent. If the report contains inaccurate information requiring substantial correction, the actual productivity gain may be much smaller.

Consequently, organizations should measure:

- Completion time;
- Output quality;
- Error rates;
- Employee learning;
- Customer outcomes;
- Employee experience.

The employee dimension is particularly important.

GenAI can reduce routine work, but organizations may respond by increasing performance expectations. Employees may consequently experience both greater efficiency and greater pressure.

Therefore, the relationship between GenAI and employee well-being should not be assumed to be universally positive or negative.

Creativity and Innovation:

- GenAI can influence creativity by rapidly producing alternative ideas, structures, examples and perspectives.
- Haefner et al. (2021) argue that AI can influence innovation management by extending organizational information-processing capabilities.
- Mariani and Dwivedi (2024) similarly identify GenAI as an important emerging domain for innovation research.
- However, excessive reliance on similar AI systems may also result in convergence of ideas.

Therefore, a useful organizational principle is:

AI for idea expansion; humans for contextual evaluation.

Gen-AI May generate many possibilities, while human experts evaluate:

- Originality;
- Strategic relevance;
- Ethical implications;
- Feasibility;
- Contextual appropriateness.

Responsible AI Governance: Responsible governance is essential because GenAI can produce:

- Biased outputs;
- Inaccurate information;
- Privacy risks;
- Intellectual-property concerns;
- Inappropriate recommendations.

Governance should therefore include:

1. Transparency;
2. Accountability;
3. Privacy;
4. Security;
5. Fairness;
6. Human oversight;
7. Auditability.

An important concept is **calibrated trust**. Employees should neither blindly trust nor automatically reject AI. They should learn: **when to rely on AI, when to verify AI and when not to use AI**. This is especially important in HRM, where decisions can affect employment, careers and employee rights.

Managerial Implications:

The framework provides several practical implications.

First, organizations should redesign tasks rather than eliminate jobs automatically.

Managers should identify which activities are suitable for automation, augmentation and human judgment.

Second, AI literacy should become a formal organizational capability.

Training should cover prompting, verification, bias, privacy, hallucination and responsible use.

Third, HR should become a designer of human–AI work systems.

HR professionals can contribute to:

- Job redesign;
- Reskilling;
- Ai competency frameworks;

- Employee communication;
- Ai governance;
- Performance-management redesign.

Fourth, AI governance should be risk-based: Routine drafting may require limited oversight, whereas recruitment, disciplinary and employment decisions require significantly stronger human involvement.

Fifth, organizations should measure employee outcomes alongside productivity: GenAI implementation should be evaluated through:

Productivity + Quality + Learning + Innovation + Employee Experience.

Future Research Agenda: Future empirical research can examine the proposed framework through several approaches.

Individual-level studies: Researchers can investigate:

- AI literacy;
- Trust;
- AI anxiety;
- Cognitive offloading;
- Creativity;
- Employee engagement.

Team-level studies: Research can examine:

- AI-supported teamwork;
- Knowledge sharing;
- Team creativity;
- Coordination.

Organizational studies: Research can investigate:

- GenAI capability;
- Organizational Readiness;
- Oovernance;
- Organizational Innovation;
- Performance.

Longitudinal studies: Longitudinal designs can determine whether initial productivity gains persist and whether employees develop new capabilities over time.

Experimental research: Researchers can manipulate AI availability, AI literacy, human oversight and task complexity to establish causal effects.

Cross-cultural research: Studies comparing different countries and institutional environments can determine whether GenAI outcomes vary according to culture, regulation, education and digital infrastructure.

Conclusion

GenAI stands for a major evolution in the interplay between technology and work. The importance of GenAI lies not only in its potential to automate work but also in its direct involvement in knowledge-based activities. The key idea of this study can be stated as follows: the use of GenAI in itself does not bring about organizational value. Value results from the combination of technological skills and workers' GenAI literacy. Hence, the proposed H-GAICC framework suggests a paradigm shift in academic research away from the question:

"Will GenAI replace humans?" towards the question:

"How can humans and GenAI be configured to complement each other?"

Based on the theoretical model, the relationships between GenAI capability and AI literacy on one hand and productivity, learning and creativity on the other hand, are moderated by responsible AI governance, trust, complexity and human oversight. The key theoretical contribution to literature in this regard lies in the development of human–GenAI collaboration capability as a mediator through which technological assets can be leveraged for business value creation. In terms of future empirical studies, the proposed framework can be tested through structural equation modelling, multilevel analysis, longitudinal studies and field experiments. Therefore, the future of work needs to be studied not as a competition between humans and artificial intelligence, but rather as a design of human–technology synergies.

References

- Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3), 3–30. <https://doi.org/10.1257/jep.29.3.3>
- Basu, S., Majumdar, B., Mukherjee, K., Munjal, S., & Palaksha, C. (2023). Artificial intelligence–HRM interactions and outcomes: A systematic review and causal configurational explanation. *Human Resource Management Review*, 33(1), 100893. <https://doi.org/10.1016/j.hrmr.2022.100893>
- Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 610–623. <https://doi.org/10.1145/3442188.3445922>
- Brynjolfsson, E., Li, D., & Raymond, L. R. (2025). Generative AI at work. *The Quarterly Journal of Economics*, 140(2), 889–942. <https://doi.org/10.1093/qje/qjae044>
- Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Cooke, F. L., Decker, S., DeNisi, A., Dey, P. K., Guest, D., Knoblich, A. J., Malik, A., Paaauwe, J., Papagiannidis, S., Patel, C., Pereira, V., Ren, S., Rogelberg, S., Saunders, M. N. K., Tung, R. L., & 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>
- 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>

- Cui, K. Z., Demirer, M., Jaffe, S., Musolff, L., Peng, S., & Salz, T. (2026). The effects of generative AI on high-skilled work: Evidence from three field experiments with software developers. *Management Science*. <https://doi.org/10.1287/mnsc.2025.00535>
- Dell'Acqua, F., Ayoubi, C., Lifshitz-Assaf, H., Sadun, R., Mollick, E., Mollick, L., Han, Y., Goldman, J., Nair, H., Taub, S., & Lakhani, K. R. (2026). The cybernetic teammate: A field experiment on generative AI and teamwork. *Organization Science*. <https://doi.org/10.1287/orsc.2025.20702>
- Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., et al. (2023). “So what if ChatGPT wrote it?” Multidisciplinary Perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642. <https://doi.org/10.1016/j.ijinfomgt.2023.102642>
- Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering*, 66, 111–126. <https://doi.org/10.1007/s12599-023-00834-7>
- Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting and Social Change*, 162, 120392. <https://doi.org/10.1016/j.techfore.2020.120392>
- Jatobá, M. N., Ferreira, J. J., Fernandes, P. O., & Teixeira, J. P. (2023). Intelligent human resources for the adoption of artificial intelligence: A systematic literature review. *Journal of Organizational Change Management*, 36(7), 1099–1124. <https://doi.org/10.1108/JOCM-03-2022-0075>
- Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., Stadler, M., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274. <https://doi.org/10.1016/j.lindif.2023.102274>
- Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, 120, 262–273. <https://doi.org/10.1016/j.jbusres.2020.07.045>
- 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>
- Mariani, M., & Dwivedi, Y. K. (2024). Generative artificial intelligence in innovation management: A preview of future research developments. *Journal of Business Research*, 175, 114542. <https://doi.org/10.1016/j.jbusres.2024.114542>
- Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3), 103434. <https://doi.org/10.1016/j.im.2021.103434>

- Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, 381(6654), 187–192. <https://doi.org/10.1126/science.adh2586>
- Pereira, V., Hadjielias, E., Christofi, M., & Vrontis, D. (2023). A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. *Human Resource Management Review*, 33(1), 100857. <https://doi.org/10.1016/j.hrmr.2021.100857>
- Peres, R., Schreier, M., Schweidel, D., & Sorescu, A. (2023). On ChatGPT and beyond: How generative artificial intelligence may affect research, teaching, and practice. *International Journal of Research in Marketing*, 40(2), 269–275. <https://doi.org/10.1016/j.ijresmar.2023.03.001>
- Prikshat, V., Malik, A., & Budhwar, P. (2023). AI-augmented HRM: Antecedents, assimilation and multilevel consequences. *Human Resource Management Review*, 33(1), 100860. <https://doi.org/10.1016/j.hrmr.2021.100860>
- 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>
- 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>
- Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *The International Journal of Human Resource Management*, 33(6), 1237–1266. <https://doi.org/10.1080/09585192.2020.1871398>