Situating Artificial Intelligence in Organization

A Human-machine Relationship Perspective

Li, Xin; Rong, Ke; Shi, Xinwei

ARTICLE IN PRESS

Journal of Digital Economy xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Digital Economy

journal homepage: www.keaipublishing.com/en/journals/journal-of-digital-economy

Situating Artificial Intelligence in Organization: A Human-machine Relationship Perspective

Xin Li [a], Ke Rong [b], Xinwei Shi [a,*]

[a] Newcastle University Business School, Newcastle University, 5 Barrack Road, Newcastle upon Tyne, NE1 4SE, UK
[b] Tsinghua University, Institute of Economics, Beijing, China

ARTICLE INFO

Keywords:
Artificial intelligence
Competitive advantages
Strategic management
Human-machine interaction
Digital economy

ABSTRACT

The increasing advancements in artificial intelligence (AI) technology have resulted in greater adoption of intelligent devices, such as industrial and service robots. Such context substantially influences the routine processes of operations, thereby promoting the ongoing evolutionary development of human-machine interaction. Here, we analyze an interesting article published in the Academy of Management Review (AMR) by Ayenda Kemp, who proposes the concept of situated AI for discussing AI-driven competitive advantages. In our alternative framework of situating AI in the organization, we identify three aspects of the human-machine relationship—cohesion, autonomy, and equality—and associate them with three redefined situating activities—anchoring, bounding, and calibrating, to bring the full potential of AI to an organization. We believe this defined framework can further contribute to relevant literature in the field of digital economy.

1. Introduction

The digital transformation of the economy is exerting a profound influence on the interconnectivity of individuals, the organizational frameworks of organizations, and the restructuring of industries in the era of the digital economy (Rong, 2022). AI undoubtedly is playing an irreplaceable role in the era of the digital economy and provides a significant opportunity for individuals and organizations who wish to improve their performance or competitiveness. According to an empirical study on socially shared regulation in learning, Jarvela et al. (2023) found that human-AI collaboration can achieve better performance in learning regulation. Yet, it also represents a great challenge to them due to its ethical and well-being impacts (Garibay et al., 2023). As it remains a question "whether the use of AI in management will turn out to be a blessing or a curse" (Raisch and Krakowski, 2021:203), there is a clear need for management research on AI. To date, not only computer scientists, roboticists, and engineers are studying AI (e.g., Raisch and Krakowski, 2021:203), management scholars are increasingly paying more attention to AI[1](e.g., Anthony, 2021; Gregory et al., 2021; Jia et al., 2023; Krakowski et al., 2022; Lebovitz et al., 2022; Raisch and Krakowski, 2021; Tang et al., 2022; Tong et al., 2021). Although existing empirical studies have found that human-AI collaboration can lead to positive performance in terms of decision-making decisions (e.g., Jarvela et al., 2023; Reverberi et al., 2022; Sharma et al., 2023), however, there is still a dearth of research related to how to clarify and differentiate the strategic role positions of humans (i.e., users) and AI-driven machines during the collaboration process.

* Corresponding author.
E-mail addresses: xin.li@newcastle.ac.uk (X. Li), r@mail.tsinghua.edu.cn (K. Rong), xinwei.shi@newcastle.ac.uk (X. Shi).

[1] Due to space limitations, we only included articles published in the top 5 generalist management journals on the UTD list, i.e., *Academy of Management Journal*, *Academy of Management Review*, *Administrative Science Quarterly*, *Organization Science*, and *Strategic Management Journal*.

https://doi.org/10.1016/j.jdec.2024.01.001
Received 12 November 2023; Received in revised form 3 January 2024; Accepted 6 January 2024

Please cite this article as: Li, X. et al., Situating Artificial Intelligence in Organization: A Human-machine Relationship Perspective, Journal of Digital Economy, https://doi.org/10.1016/j.jdec.2024.01.001

Against this backdrop, Kemp's (2023) article "Competitive advantages through artificial intelligence: Toward a theory of situated AI" is a timely and welcome contribution to our understanding of the management of AI in business organizations. We read with great interest Kemp's article and agree with the author that situating AI in organizations is strategically important for organizations to improve their competitiveness. Kemp's article touches on many important issues related to AI. However, there are three problems that render Kemp's theory of situated AI unconvincing. Yet, we find Kemp's framework of situating AI—grounding, bounding, and recasting—interesting and could be made more theoretically rigorous and practically useful with some revision or redefinition. In what follows, we first explain the three problems in Kemp's theory and then provide an alternative perspective on situating AI in organization that is centered on the human-machine relationship.

2. Three problems in Kemp's theory of SITUATED AI

Kemp's work focuses more on situated AI that, "AI whose agency is circumscribed in a firm's experiential, structural, and relational systems" (Kemp, 2023:3). Besides *situated* AI, we think that *basic* AI refers to elementary forms of AI that specifically involve simple tasks and rule-based systems or expert systems (e.g., deep learning systems) is also necessary for consideration. Basic AI is generally limited in its capacities and lacks the ability of learning from practical experiences. It is noteworthy that situated AI is likely not a concept specifically addressed by firms such as OpenAI. Thus, the first problem in Kemp's theory is that the author does not distinguish three broad types of firms in which AI is involved in different manners: (1) firms specialized in producing generalist or domain-free AI, such as OpenAI who owns ChatGPT, (2) firms not specialized in AI but having R&D capabilities on domain-specific AI, such as Bloomberg, and (3) firms that do not conduct R&D activities on AI but wish to adopt and therefore need to buy AI externally, such as many small and medium-sized enterprises (SMEs). The first two types of AI firms primarily engage in *basic* AI, whereas the third type corresponds to *situated* AI. Situated AI focuses not on how AI firms develop AI but on how already developed AI can be applied within firms. Hence, AI companies such as OpenAI are not the research scope of Kemp's work. In this paper, we think it is necessary to first identify the three types of firms and then point this out upfront in our critique of Kemp's theory. Accordingly, the relevance of the three situating activities—grounding, bounding, and recasting, as defined by Kemp—varies significantly among these three types of firms (see Table 1).

Grounding is defined by Kemp's (2023:14, italics added) as "the allocation of strategic attention and organizational resources to the process of selectively endowing AI with a historical sensibility", as such, it "focuses on strategically providing AI with experiences that shape its perspective on *a task or problem*". Apparently, grounding is largely irrelevant to specialized AI producers such as OpenAI, because these first-type firms often aim at producing general-purpose or domain-free AI products that can be applied to any industrial domain and task. For example, OpenAI's ChatGPT is a generative pre-trained transformer (GPT) model. The term pre-trained refers to the initial training phase of the model, which typically involves training the model on a vast amount of publicly available text data, such as books, articles, websites, and other textual sources. The pre-training enables the model to learn to capture statistical regularities and linguistic patterns present in the data and therefore effectively acquire a broad knowledge base.

Once the pre-training phase is completed, the model can be further trained or fine-tuned on a narrower dataset related to a specific domain or task. For example, Bloomberg developed its BloombergGPT™ that was "specifically trained on a wide range of financial data to support a diverse set of natural language processing (NLP) tasks within the financial industry" (Bloomberg, 2023). It is worth noting that while Bloomberg developed its BloombergGPT™ as both a general-purpose and a finance-specific AI, other firms of the second type—not specialized in AI but having R&D capabilities on domain-specific AI—could and might develop their own AI models in different ways, e.g., directly or purely based on domain-specific data. Therefore, it is a question whether grounding is relevant or not to all second-type firms. In comparison, for third-type firms that need to buy AI externally, grounding is necessary to let the AI buyers to train a generalist AI into a specialist AI.

Bounding, as defined by Kemp (2023:41), refers to activities aimed at the protection and monopoly of data that may cause competitors to incur opportunity and transaction costs in their efforts of developing AI. Such bounding activities include "enforcing confidentiality agreements", "signing data exclusivity deals", "investing in cyber-security innovations", and "capturing bottlenecks in computing or server management".

It remains a question whether bounding is necessary and possible for the specialized AI producers such as OpenAI, because these first-type firms train their general-purpose models on publicly available data. Notably, the publicly available data used by the first-type firms can be divided into two categories: (1) publicly available and directly useable data, such as textual data, and (2) publicly available but not directly useable data, such as graphics and videos. For those publicly available and directly useable data, there is no basis for data exclusivity. However, for those publicly available but not directly useable data, AI companies need to transform them into useable standardized data, and the transformed standardized data is still exclusive. Although enforcing confidentiality and investing in cyber-security is necessary, these are general IPR rather than AI-specific issues. While data exclusivity may be relevant for the second-type

Table 1
The relevance of Kemp's three situating activities to three types of firms.

Firm type	Description of the type of firms	Grounding	Bounding	Recasting
Type 1	Firms specialized in producing generalist or domain-free AI (e.g., OpenAI)	×	?	×
Type 2	Firms not specialized in AI but having R&D capabilities on domain-specific AI (e.g., Bloomberg)	?	✓	✓
Type 3	Firms that do not conduct R&D activities on AI but wish to adopt and therefore need to buy AI externally	✓	?	✓

Note: the symbol '√' denotes the corresponding activity is relevant to the corresponding type of firms. Accordingly, ' × ' denotes being not relevant or irrelevant; '?' denotes it remains a question whether the corresponding activity is relevant or appropriate to the corresponding type of firms.

firms who have in-house R&D capabilities on domain-specific AI, such as Bloomberg, it is a question whether signing data exclusivity deals is possible for the third-type firms who do not conduct R&D activities on AI and need to buy AI externally. Certainly, due to a lack of resources and market power, some small or medium-sized firms could and might not do many of the bounding activities identified by Kemp (2023).

Recasting, as defined by Kemp (2023:18, italic added), refers to "the adaptation of internal technologies and routines to *contextualize* AI in a firm's system of task, relational, and strategic interdependencies". Like grounding, recasting is also largely irrelevant to the first-type specialized AI producers as these firms often aim at producing domain-free—i.e., decontextualized—AI products that can be applied to any industrial domain and task. In contrast, recasting is relevant and necessary for the other two types of firms.

The second problem in Kemp's theory is that the three situating activities, as defined by the author, are on different levels, namely, grounding and recasting are intra-firm activities while bounding is an inter-firm issue. Such inconsistency in the level of analysis is problematic given the central question in Kemp's (2023:2) theorizing is "How can firms establish competitive advantages using artificial intelligence (AI)?". As competitive advantage is relational, i.e., in relation to one's competitor(s), intra-firm activities, such as grounding and recasting, may be necessary but not sufficient to bestow competitive advantage on the focal firm vis-à-vis its rival(s). On the other hand, bounding activities, though being inter-firm rather than intra-firm, is not sufficient either to render the focal firm more competitive than its rival(s) as the latter may do similar bounding activities against the former.

Above discussion leads to the third problem in Kemp's (2023) theory, that is, the author confounds the question of "how AI can be used to create unique value" (p.2) and that of "using AI to establish competitive advantages" (p.3). While both questions are of concern to many academics and practitioners, the issue of competitive advantage is often more complex than many people might have thought. Clearly, the sources of competitive advantage are different for the three types of firms. For the first-type specialized AI producers such as OpenAI, they compete on general-purpose AI products. There are four indispensable pillars of their competitive advantage: (A) algorithm, (B) brainpower—talented personnels who develop or/and use AI, (C) computing power, and (D) data (hence, the acronym ABCD). For the second-type firms who develop domain-specific AI systems internally, on top of the ABCD pillars, there is an additional pillar of the competitive advantage of their AI systems, i.e., (E) expertise or knowledge on a specific industrial domain or task. Unlike these two types of firms, for the third-type firms who need to buy external AI products to improve the performance of their products or services, the factors contributing to their competitive advantage might be very different.

There is a wide consensus that, competitive advantage, and especially sustainable competitive advantage, is the 'holy grail' of strategic management theory and practice. As the notion of (sustainable) competitive advantage is too elusive, Rita G. McGrath (2013), a world-leading expert on strategy has called for 'the end of competitive advantage'. In contrast, the issue of using AI to create unique value is a relatively more legitimate concern because it can be pursued on an intra-firm comparison basis, that is, to improve the focal firm's performance or competitiveness—instead of competitive advantage—by using AI, in relation to its own historical performance rather than its rivals'. In other words, a more robust theory can be made to address the question of how to use AI to achieve one's historical—rather than social—aspiration (March and Simon, 1958).

In the next section, we present such an alternative theoretical framework of situating AI that is centered on the human-machine relationship. As most firms are not of the first two types, we focus on the third type of firms who do not have in-house R&D resources and capabilities on AI and need to buy AI products or services externally, and hence the need for situating externally purchased AI in their organizations.

3. An alternative framework of situating AI

Kemp (2023) links the three situating activities—grounding, bounding, and recasting—to the "three strategic limitations of AI" (p.6), i.e., "the generic, explicit, and myopic nature of AI" (p.8).

First, as AI is generic, "the logic emerging from an AI algorithm is generally not unique to the user applying that algorithm" (p.6), hence grounding is needed. Through grounding activities, "firms *intentionally* orchestrate data collection and deployment to prioritize anchoring AI in their firm's unique knowledge", the result of which is that "AI becomes tethered to the firm's knowledge, histories, and beliefs" (p.15). One form of grounding is the process of fine-tuning used by OpenAI to enable "companies augment pre-trained models with their own custom data" (p.16).

Second, as AI is explicit, "AI manifests as a form of explicit knowledge" that "diffuses relatively quickly across organizational boundaries" (p.6), hence bounding is needed to protect AI-related data and knowledge and prevent from expropriation by rivals.

And third, AI is myopic because "AI algorithms lack *contextual* awareness of activities and events beyond the scope of their assigned tasks" (p.7, italic added) and "a sophisticated understanding of a firm's strategy" (p.8). To mitigate the myopia problem, Kemp (2023) argues that recasting is needed to "*contextualize* AI in a firm's system of task, relational, and strategic interdependencies" (p.18, italic added). Recasting activities include "*customizing* AI, restructuring links between AI different algorithms within a single conjoined routine, and promoting or demoting algorithms based on previously demonstrated alignment (or misalignment) with the firm's capabilities" (p.18, italic added).

While we see many insights in Kemp's framework, there are two defects that justify a revision of this framework. On the one hand, recasting, as defined by Kemp, has a very close relationship with grounding because both activities serve the same function, that is, to anchor a general-purpose AI in a firm's specific context including its history, knowledge, belief, structure, and strategy, etc. On the other hand, bounding as an inter-firm consideration is largely irrelevant to situating AI *within* a firm.

In our alternative framework of situating AI in organization, we shift our focus away from, without belittling the value and relevance of, the generic-explicit-myopic nature of AI to the human-machine relationship that is supposed to be altered and managed when a firm decides to situate AI in its organization. We identify three aspects of the human-machine relationship—cohesion, autonomy, and equality—and associate them with three *redefined* situating activities—anchoring, bounding, and calibrating (see Table 2). We posit that, to bring the full potential of AI to an organization, one needs to situate AI well in the organization by managing the human-machine relationship appropriately.

The first aspect of the human-machine relationship is cohesion, that is, how cohesively should the *externally* purchased AI be integrated within the organization to fit into its context including its history, knowledge, belief, structure, and strategy, etc. When an external AI product or service is purchased, it is naturally not aligned with the buying firm's contextual specifics. Without contextualization, an externally purchased AI can only think from an outsider or etic perspective, to use the anthropologic terminology. Anchoring as a situating activity helps contextualize or socialize AI-as-outsider into AI-as-insider to enable it to think from an insider or emic rather than etic perspective. Based on above discussion, we posit there are at least two forms of anchoring, i.e., specialization-oriented anchoring that corresponds to Kemp's (2023) notion of grounding and alignment-oriented anchoring that corresponds to Kemp's notion of recasting.

Specialization-oriented anchoring, such as OpenAI's fine-tuning process, enables an external general-purpose AI to gain specialist knowledge by training it with domain or task-specific data. After specialization-oriented anchoring, the grounded AI has both breadth and depth of knowledge; hence, we can call specialization-oriented anchoring as T-shape anchoring. Alignment-oriented anchoring aims to "contextualize AI in a firm's system of task, relational, and strategic interdependencies" (Kemp, 2023:18). After alignment-oriented anchoring, the recast AI's cognition and behavior will converge to those of the human actors within the organization; hence, we can call alignment-oriented anchoring V-shape anchoring.

The second aspect of the human-machine relationship is autonomy, that is, how autonomously should AI as *machine* be allowed to make decisions that may have impacts on human beings. AI as an intelligent machine is capable of making rational decisions efficiently. Existing literature suggests that there will be an emerging development of AI called super-intelligence, i.e., mock human emotion (e.g., Shi and Lei, 2021). Moreover, for instance, as conversational agents driven by large language models become increasingly similar to humans, consumers are beginning to perceive them as collaborators other than just assistants (Pataranutaporn et al., 2023). However, AI is non-human with little or no human oversight and lacks many capacities that humans have, such as emotions and feelings. Rational decisions made by AI may seem lack of affect and empathy and may have negative impacts on the well-being of affected humans. For example, in the experimental studies of human-AI collaboration, Westphal et al. (2023) found that explanations offered by the AI system may negatively affect user perceptions and compliance. In addition, AI may make decisions that are rational yet unethical. Bounding as a situating activity sets a boundary within which AI can make decisions that shall be bound by ethical and wellbeing considerations.

In an organization, there are many tasks and decisions that need to be done and made. Some of them are repetitive and have no or limited impacts on human beings. These tasks and decisions can easily be done and made by AI. Some other decisions, such as human resource management related, may have significant impacts on human wellbeing and hence need not to be made autonomously by AI. A case in point is Amazon.com Inc.'s use of AI algorithm to manage—hiring, monitoring, rating, and firing—its contract drivers. A Bloomberg (2021) report reveals that "Amazon knew delegating work to machines would lead to mistakes [...] but decided it was cheaper to trust the algorithms than pay people to investigate mistaken firings so long as the drivers could be replaced easily". As negative news reports drew criticisms, Amazon had to emphasize that "[its] workforce management technology supports and enhances the experience of job candidates and employees. It's not meant to replace managers, but to aid their decision-making with data and information" (Mearian, 2021).

The third aspect of the human-machine relationship is equality, that is, how equally should AI as a *human-made* actor be treated within organization as technologies evolve over time. People are divided in their views on the future of AI development. Some optimist people believe that AI may never surpass humans because it is a creation of humans and humans as the creator have control on AI. Other people are less optimistic but insist that there is a long way for AI to go before it can catch up with human intelligence. Still others wonder or worry whether AI may outcompete humans on all forms of intelligence given the recent acceleration of technological advancement.

Calibrating as a situating activity addresses the equality issue in the human-machine relationship. Drawn from the dynamic capability perspective (Teece et al., 1997), how to combine the actual resources and capabilities of the firm to cope with the uncertain and ever-demanding external environment determines whether the firm can fully utilize its AI potential. Hence, while currently AI is still in its early stage of maturity, it is better for humans to start to think about the need for dynamically adjusting the status of AI vis-à-vis humans within the organizational hierarchy. While we might have taken AI as a technological tool or servant for granted, with the rapid development of AI technologies, maybe we should consider treating AI as a copilot in the future. The practical implication is that if we treat AI as an assistant or servant, it will be adopted as a plug-and-play module in the organization as a platform. However, if we treat AI as a copilot, we might think about restructuring the entire organization in which a future powerful AI acts as an organizing platform

Table 2
Three aspects of human-machine relationship and three situating activities.

Aspect of Relationship	Explanation of the aspect	Situating activities	Goal/outcome
Cohesion	How cohesively should the *externally* purchased AI be integrated within the organization to fit into its context	Anchoring	To socialize AI-as-outsider into AI-as-insider to enable it to think from an emic rather than etic perspective
Autonomy	How autonomously should AI as *machine* be allowed to make decisions that may have impacts on human beings	Bounding	To set a boundary within which AI can make decisions that are bound by ethical and wellbeing considerations
Equality	How equally should AI as a *human-made* actor be treated within organization as technologies evolve over time	Calibrating	To dynamically adjust the status of AI vis-à-vis humans by considering treating AI as servant or copilot

while all other elements or functions of the business organization become modules to be plugged into the artificially intelligent platform. Only time will tell if this will be the reality!

4. Conclusion

This study examines an intriguing article by Ayenda Kemp (2023), which introduces the notion of situated AI to explore competitive advantages driven by AI. Within our alternative framework for situating AI into an organization, we recognize three key elements of the human-machine: cohesion, autonomy, and equality. We link these elements to three redefined activities: anchoring, bounding, and calibrating. This approach aims to fully leverage the capabilities of AI within an organization to achieve strategic competitive advantage from a long-term dynamic lens. This study can guide future research on underlying solutions for firms to address three elements of the human-machine relationship in order to leverage AI-driven capabilities to realize organizations' dynamic competitive advantages.

The initial facet of the human-machine connection is cohesion, which refers to the level of integration required for externally acquired AI to seamlessly fit into the organization's context, encompassing its history, knowledge, beliefs, structure, and strategy. Cohesion pertains to the assimilation of externally acquired AI into an organization. This integration entails synchronizing the AI system with the organization's past circumstances, collected knowledge, beliefs, framework, and strategic goals. It is essential to comprehend the extent to which AI may be integrated into the structure of an organization in order to optimize its usefulness and guarantee smooth interaction with current systems and procedures.

The second dimension of the human-machine interaction is autonomy, namely, the extent to which AI machines should be granted the ability to independently make decisions that could potentially affect human beings. Achieving an optimal equilibrium between human supervision and machine independence is a crucial factor to take into account. This entails examining the allocation of decision-making power to AI, ascertaining suitable degrees of autonomy, and implementing measures to reduce possible hazards or ethical problems arising from machine-driven decisions impacting humans.

The third dimension of human-machine interaction pertains to the concept of equality, which prompts significant inquiries regarding the appropriate treatment of AI within an organization as technology progresses. To ensure fairness and equitable treatment of AI systems, it is necessary to comprehend the consequences of advancing technologies on organizational dynamics, the collaboration between humans and AI, and the prospective effects on employment structures. Additionally, it entails tackling ethical concerns pertaining to prejudice and discrimination and guaranteeing that AI is implemented and supervised in a way that adheres to principles of fairness and equality.

Overall, the characteristics of cohesion, autonomy, and equality offer a thorough framework for analyzing and comprehending the complex nature of the human-machine relationship while addressing organizations' strategic management issues in the era of the digital economy. As organizations increasingly incorporate AI into their operations, it is crucial to address these issues to fully utilize the promise of AI while managing related challenges and guaranteeing ethical and fair practices.

CRediT authorship contribution statement

Xin Li: Writing – review & editing, Writing – original draft, Conceptualization. **Ke Rong:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Xinwei Shi:** Writing – review & editing, Writing – original draft, Project administration, Conceptualization.

Declaration of competing interest

Xinwei Shi is an Editorial Board Member and Ke Rong is the Editor-in-Chief for the *Journal of Digital Economy* and were not involved in the editorial review or the decision to publish this article. All the authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Anthony, C., 2021. When knowledge work and analytical technologies collide: the practices and consequences of black boxing algorithmic technologies. Adm. Sci. Q. 66 (4), 1173–1212.

Bloomberg, 2021. Fired by Bot at Amazon: 'It's You against the Machine'. Online article, available at: https://www.bloomberg.com/news/features/2021-06-28/fired-by-bot-amazon-turns-to-machine-managers-and-workers-are-losing-out.

Bloomberg, 2023. Introducing BloombergGPT, Bloomberg's 50-billion Parameter Large Language Model, Purpose-Built from Scratch for Finance. Online news report, 30 March 2023, available at: https://www.bloomberg.com/company/press/bloomberggpt-50-billion-parameter-llm-tuned-finance/.

Garibay, O.O., Winslow, B., Andolina, S., Antona, M., Bodenschatz, A., Coursaris, C., et al., 2023. Six human-centered artificial intelligence Grand challenges. Int. J. Hum. Comput. Interact. 39 (3), 391–437.

Gregory, R.W., Henfridsson, O., Kaganer, E., Kyriakou, H., 2021. The role of artificial intelligence and data network effects for creating user value. Acad. Manag. Rev. 46 (3), 534–551.

Jarvela, S., Nguyen, A., Hadwin, A., 2023. Human and artificial intelligence collaboration for socially shared regulation in learning. Br. J. Educ. Technol. 54, 1057–1076.

Jia, N., Luo, X., Fang, Z., Liao, C., 2023. When and how artificial intelligence augments employee Creativity. Acad. Manag. J. https://doi.org/10.5465/amj.2022.0426 published online on 28 Mar 2023.

Kemp, A., 2023. Competitive advantages through artificial intelligence: toward a theory of situated AI. Acad. Manag. Rev. https://doi.org/10.5465/amr.2020.0205 published on online on 27 April 2023.

Krakowski, S., Luger, J., Raisch, S., 2022. Artificial intelligence and the changing sources of competitive advantage. Strat. Manag. J. 44 (6), 1425–1452.

Lebovitz, S., Lifshitz-Assaf, H., Levina, N., 2022. To engage or not to engage with AI for critical judgments: how professionals deal with opacity when using AI for medical diagnosis. Organ. Sci. 33 (1), 126–148.

March, J.G., Simon, H.A., 1958. Organizations. wiley, New York.

McGrath, R.G., 2013. The End of Competitive Advantage: How to Keep Your Strategy Moving as Fast as Your Business. Harvard Business Review Press, Boston, MA.

Mearian, L., 2021. The Rise of Digital Bosses: They Can Hire You—And Fire You. ComputerWorld available at: https://www.computerworld.com/article/3646234/the-rise-of-ai-based-managers-they-now-play-a-big-role-in-hiring-training-and-firing.html.

Pataranutaporn, P., Liu, R., Finn, E., Maes, P., 2023. Influencing human-AI interaction by priming beliefs about AI can increase perceived trustworthiness, empathy and effectiveness. Nat. Mach. Intell. 5, 1076–1086.

Raisch, S., Krakowski, S., 2021. Artificial intelligence and management: the automation–augmentation paradox. Acad. Manag. Rev. 46 (1), 192–210.

Reverberi, C., Rigon, T., Solari, A., Hassan, C., Cherubini, P., , Gi Genius CADx Study Group, Cherubini, A., 2022. Experimental evidence of effective human-AI collaboration in medical decision-making. Sci. Rep. 12, 14592.

Rong, K., 2022. Research agenda for the digital economy. Journal of Digital Economy 1 (1), 20–31.

Sharma, A., Lin, I.W., Miner, A.S., Atkins, D.C., Althoff, T., 2023. Human-AI collaboration enables more empathic conversations in text-based peer-to-peer mental health support. Nat. Mach. Intell. 5, 46–57.

Shi, X., Lei, J., 2021. Breakthroughs in information technology and their implications for Education and health. In: A. Hooke. Technological Breakthroughs and Future Business Opportunities in Education, Health., and Outer Space. IGI Global.

Tang, P.M., Koopman, J., McClean, S.T., Zhang, J.H., Li, C.H., De Cremer, D., Ng, C.T.S., 2022. When conscientious employees meet intelligent machines: an integrative approach inspired by complementarity theory and role theory. Acad. Manag. J. 65 (3), 1019–1054.

Teece, D.J., Pisano, G., Shuen, A., 1997. Dynamic capabilities and strategic management. Strat. Manag. J. 18 (7), 509–533.

Tong, S., Jia, N., Luo, X., Fang, Z., 2021. The Janus face of artificial intelligence feedback: deployment versus disclosure effects on employee performance. Strat. Manag. J. 42 (9), 1600–1631.

Westphal, M., Vossing, M., Satzger, G., Yom-Tov, G.B., Rafaeli, A., 2023. Decision control and explanations in human-AI collaboration: improving user perceptions and compliance. Comput. Hum. Behav. 144, 107714.