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Review

Artificial intelligence, workers, and future of work skills

Sarah Bankins[1], Xinyu Hu[2,a] and Yunyun Yuan[3,a]

Abstract

Historically, the use of technology in organizations has reshaped the nature of human work. In this article, we overview how current waves of artificially intelligent (AI) technologies are following this trend, showing how its uses can both automate and complement human labor, alongside creating new forms of human work. However, AI can also generate both upsides and downsides for workers' experiences, which are dependent upon a range of factors such as how the technology is used and the support employees receive during digital transitions. We conclude by outlining how AI literacy and other human-centered skills will play an increasingly important role in future workplaces.

Addresses

[1] Department of Management, Macquarie Business School, Macquarie University, Wallumattagal Campus, Sydney, NSW, Australia

[2] School of Business, Renmin University of China, 59 Zhongguancun Street, Haidian District, Beijing, China

[3] School of Management, Beijing Institute of Technology, Zhongguancun, Beijing, China

Corresponding author: Bankins, Sarah (sarah.bankins@mq.edu.au)

[a] The second and third authors contributed equally to the paper and are listed in alphabetical order by surname.

Keywords

Artificial intelligence, AI and work, Future of work, AI and skills, AI literacy

Introduction

"It will change language and thought as writing did."

"(It) is likely to bring about an organizational revolution among white collar workers comparable in magnitude to that resulting from the introduction of the assembly-line in blue collar work."

"By 2038, computers will be alive …"

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You would be forgiven for thinking these quotes come from commentators today, talking about artificial intelligence (AI) and the next iteration of ChatGPT (at the time of writing, it is GPT-4o). These quotes are instead cited in an article on office automation [1], published over 40 years ago, and the technology referred to is not AI but microprocessors, the small chips inside computers for data processing.

Technology has been influencing the nature of human work for a long time and predictions of its effects span more pessimistic [2] to more optimistic [3] accounts. However, there is no simple answer to the question: "Will AI make work better or worse for employees?" The answer generally needs to start with "It depends …". Whether the benefits of AI use outweigh the costs for workers depends on many factors. These include what the AI is used for and other enabling or constraining individual, group, and organizational conditions [see 4 for an overview]. While research in this area is burgeoning, we aim to provide an overview of what AI is, how it affects work tasks, employees' responses to these changes, and the future of work skills this technology is generating.

Defining AI: capabilities and limitations

To understand how AI is impacting human workers, it is important to first understand its (current) capabilities and limitations. Artificial intelligence is an umbrella term that captures many different, but related, technologies. AI technologies can engage in problem-solving and learning and perform tasks that would otherwise require human thinking [5]. Such technologies include machine learning (which underpins predictive analytics), natural language processing (which involves interpreting and responding to spoken or written output), and image recognition [5]. Based on a user's prompts, Generative AI tools can also generate textual (e.g., ChatGPT; Claude), visual (e.g., DALL-E, Midjourney), audio (e.g., MusicLM), and video (e.g., Sora) content [6].

There are many and diverse types of AI systems, but these technologies are generally trained on large datasets in order to analyze and identify patterns in those datasets and formulate predictions to generate output [7]. To date, many AI applications in a work context have involved tasks requiring extensive analysis of some form of data [8]. The wide-ranging nature of AI applications means the technology can exist in narrower forms, where an AI can excel at specific tasks but cannot easily transfer those capabilities to other tasks the way that humans can, and broader forms through the advent of Generative AIs, given their broad training and adaptability to different tasks [9].

While the scope of many of AI's analytical capabilities surpass those of humans, these technologies have limitations, particularly in high-risk use contexts such as human resource management, healthcare, and judicial settings [10]. For example, various forms of *bias* in training data can lead to biased outputs [11], which has been exemplified in recruitment AIs that can generate discriminatory outcomes against groups such as women [12]. AI models can also be *blackbox systems*, meaning their end users (and even their designers) do not understand how they generate their output [13]. This is compounded by AI output potentially being *error-prone* in ways that may not be clear to the humans using it. For example, text-creating Generative AIs can 'hallucinate', meaning they generate false output that looks plausible [14]. Therefore, both the benefits and limitations of AI systems must be carefully evaluated before they are deployed into work processes.

How AI influences human work tasks

Broadly, technology impacts human work tasks via three channels: it can *replace* aspects of human work; it can *complement or augment* human workers, by providing insights or output that complements their skills; and it can *create new tasks* for workers [15,16]. As shown next, the three channels are not mutually exclusive, can interact in complex ways [17], and may all be experienced in a single job as a worker's tasks adapt to the integration of AI.

These three channels are evident in the three main ways that organizations are already extracting business value from AI [per [7,18]]. Reflecting the replacement channel, organizations are using AI for *process automation*, or automating tasks that can be characterized as repetitive, routine, and usually high-volume. This ranges from back-office administrative tasks to undertaking initial screening of job applications to generating software code.

Reflecting the complementarity channel, which may also be termed human-AI collaboration or human-AI symbiosis [3], AI can be used to generate *cognitive insights* into datasets and for *cognitive engagement*. Generating cognitive insights particularly leverages AI's pattern recognition and predictive capabilities, by processing vast amounts of data in ways that humans cannot. This use exists across a growing range of sectors and can augment, although it may also replace some aspects of, human decision making. Such uses can include in healthcare (e.g., analyzing diagnostic scans to support clinicians), finance (e.g., analyzing financial statements to support fraud detection), manufacturing (e.g., for predictive machine maintenance), and marketing (e.g., generating insights about customer behavior). AI used for *cognitive engagement* can both automate or support customer or other stakeholder engagement, such as by using chatbots to answer queries. This can triage and potentially resolve lower-level customer queries before escalating more complex ones to human workers, essentially replacing a repetitive task that they used to do to focus on higher-level work. When used appropriately [19], Generative AI tools can also assist with tasks like idea generation, first drafts of marketing copy, and brand-aligned presentation material. However, calibrating human-AI collaboration for optimal outcomes can be complex [20,21]. Doing so must account for factors such as automation bias (where people can overestimate technology's performance, leading to over-reliance), algorithm aversion (where people can be averse to a technology, even one with good capabilities) [22], and end user preferences for human or technological labor. The operation of these factors is also context dependent. For example, research suggests that algorithm aversion is more likely when an AI is undertaking subjective, compared to objective, tasks [23]. End users can also prefer human labor when seeking products with symbolic value to them [24], but can sometimes prefer interacting with an AI in embarrassing [25] or potentially stigmatizing [26] circumstances. Overall, such factors may shape how and whether complementarity or replacement channels are adopted.

How AI generates new tasks for workers may not become fully evident until it is more widely diffused; however, there is some evidence of the new types of roles it can create. For example, Wilson et al. [27] discuss the creation of trainer, explainer, and sustainer roles. *Trainer* roles require "human workers to teach AI systems how they should perform", in part to smooth their interactions with end users, and such roles will also likely involve data curation. *Explainer* roles will require technical and communication skills to translate and explain AI output for end users, helping to overcome the 'blackbox' issue mentioned earlier. *Sustainer* roles will help to ensure that organizational AI systems operate fairly, transparently, and in accordance with their design values in the longer term. Such roles may also include ongoing re- and up-skilling initiatives for employees, to support effective human-AI collaboration.

How AI influences the experience of work: upsides and downsides for workers

Given the scope of AI's uses, it is perhaps unsurprising that it elicits diverse responses from employees. These range from fears of replacement [28], to holding simultaneously positive (about how it may improve work) and negative (concerns about its decision making) views [29], to excitement and curiosity [30].

Understanding the potential upsides and downsides of AI use for workers can go some way to understanding the drivers of such responses.

In terms of upsides, workers will generally have better experiences of using AI when they trust it [31], when they perceive good system quality [32], and when they are skilled to use it effectively [33]. Employees generally reap benefits when AI is deployed in ways that improve their job design, such as by enhancing autonomy and job complexity [34] and easing role demands [35]. Workers' use of Generative AI tools, from call center staff to business consultants, can significantly enhance their productivity; however, the performance boost is higher for lower-skilled and lower-performing workers and can be reversed when the tool is used for tasks outside of the technology's capabilities [36,19]. Utilizing AI in ways that augment workers, such as through the complementarity channel, rather than in ways that replace important things that they do, can also enhance experiences of meaningful work [37] and support rather than threaten their sense of work identity [38]. These outcomes can be encouraged by supportive organizational climates and aligned work systems [39], alongside coaching forms of leadership [40].

The downsides for workers generally reflect the converse of the above. An interesting example of the contingent nature of AI's effects on workers comes from Meijer et al. [41]. They show how a similar AI system used in two different organizations led to very different outcomes for workers. Implementation within a more authoritarian organizational culture led to the AI becoming an "algorithmic cage" for workers, where they did not understand its value and viewed it as impeding their autonomy, heightening resistance. In the more collaborative organizational culture the AI became an "algorithmic colleague", with the system being a tool to support workers' decision making, reflecting the complementarity channel.

AI can also be used for the 'algorithmic management' of workers, for example to evaluate and monitor work and help make decisions about recruitment, promotion, and even termination [42]. Workers can now leave extensive digital trails, meaning companies can collect potentially large amounts of data on employees' work behaviors [43] and even their emotional states [44], leading to heightened "behavioral visibility" [45]. There is clearly an important line between utilizing AI in these ways to help workers do their jobs better, such as by providing helpful performance feedback [46], or using it in ways that could be perceived as invasive and controlling forms of surveillance that raise privacy concerns [47,48]. Such 'algorithmic management' deployments of AI can lead to worker stress and anxiety [49], the conditions for counterproductive work behaviors [50], and feelings of disrespectful treatment [51]. However, providing employees with some control over how monitoring occurs, ensuring clear and transparent reasons for such uses [43], and ensuring a fair workplace overall [50] can lead to more positive worker attitudes toward AI used in these ways.

Future of work skills in AI-enabled workplaces

Human-AI collaboration, in some way and to some extent, will be a feature of many workplaces. One component of future work skillsets will be AI literacy, or the "human proficiency in different subject areas of AI that enable purposeful, efficient, and ethical usage of AI technologies" [14]. This involves: technology-related capabilities (some degree of technical understanding); human-machine capabilities (understanding how to work effectively with AI, such as through appropriate task delegation); work-related capabilities (understanding ethical issues associated with AI use); and learning-related capabilities (a focus on lifelong learning) [52]. Other research suggests that employees will also need to become more comfortable working in multi-disciplinary teams to extract value from AI-driven insights [53]. The importance of soft skills such as those related to interpersonal skills, empathy, and social and emotional intelligence will also be critical as a new "feeling economy" emerges and workers focus more on tasks requiring these skills [54]. More generally, such skills will also continue to help people thrive in increasingly AI-enabled work environments [55].

Identifying, and helping workers to develop, these required skillsets is the responsibility of many stakeholders. For example, educational institutions and companies have a role in investing in learning programs that enhance prospective and current employees' understanding of AI technologies generally, as well as its occupation-specific applications. Moreover, policymakers play a crucial role in democratizing access to AI education, such as through offering publicly available programs to ensure equitable access to AI learning resources. Such initiatives are particularly vital for empowering disadvantaged groups, enabling them to participate more fully in AI-driven workplaces [52].

Conclusion

The increasing use of AI in organizations is, and will continue to, shape the nature of human work. How it does this depends on many factors like those canvassed in this overview, such as how the technology is utilized and what it is deployed to do, how it changes workers' job designs and how well they are re- and up-skilled to use it, and the type of organizational support provided during implementation. Keeping AI's effects on workers front-and-center in discussions of its use will help ensure the workforce remains supported and resilient in the AI era.

Credit authors' statement

The first author was involved in the conceptualization, writing – original draft, and writing – review and editing, project supervision and administration.

The second author was involved in the writing – original draft, writing – review and editing.

The third author was involved in the writing – original draft, writing – review and editing.

The second and third authors contributed equally to the manuscript.

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Declaration of competing interest

The authors declare no conflicts of interest.

Data availability

No data was used for the research described in the article.

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* of special interest
** of outstanding interest

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Further information on references of particular interest

4. ** This paper systematically reviews research focused on the implications of AI for workers' experiences. It identifies key themes in the evidence base, including the drivers and inhibitors of human-AI collaboration, workers' attitudes toward AI, and the implications of algorithmic management. The paper organizes these themes across individual, group, and organizational levels of analysis to specify the range of factors influencing workers' experiences of AI.

14. ** This paper systematically reviews existing, diverse research on AI literacy, a key future of work skillset. It identifies the formal and informal methods through which AI literacy can be developed, the

various dimensions of AI literacy, and how this literacy can lead to outcomes such as greater adaptability, trust in, and use of AI.

19. * This experimental study focuses on a cohort of knowledge workers (business consultants) and examines the performance outcomes of utilizing a Generative AI tool (GPT-4) for two types of tasks: an idea generation task and a business problem-solving task. The findings show how reliance on the technology for tasks outside its "capability frontier" can degrade worker performance, but the converse occurs when it is used for tasks inside this frontier. Lower-performing workers receive a higher performance boost from using the AI tool, suggesting that such technologies can minimize the performance gap between employees.

22. * This experimental study identifies conditions under which people will view AI decisions more or less favorably, compared to human decisions. It shows that end users tend to have less trust in AI decisions, compared to human decisions, particularly in high stakes contexts. The paper also discusses key mechanisms toward such outcomes, particularly automation bias and algorithm aversion.

40. * * This quantitative study reinforces the importance of supportive leadership in helping employees to navigate AI-induced change. It finds that coaching leadership can reduce the stressors felt by workers as a result of AI adoption, because such leadership focuses on employee mentoring, learning, and development.

43. * This systematic literature review examines the complex nature of electronic performance monitoring (EPM) and its effects on workers. It shows that different forms of EPM exist (from surveillance to developmental) and while workers can resist the use of technology for such purposes, this is not a universal finding. Personal (e.g., goal orientation), occupational (e.g., level of autonomy), and organizational (e.g., culture) characteristics influence employees' responses to EPM.