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ALTERNATIVE FORMAT

Aligning Artificial Intelligence with Worker Health, Well-Being, and Safety: An Occupational Health Psychology Agenda

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Abstract

Artificial Intelligence technologies (AI) are rapidly transforming the nature of jobs and work. While much of the discussion around AI concerns its capabilities, this set of compiled commentaries argues that AI also has profound implications for workers' health, safety, and well-being. The commentaries explore these implications across a range of topics, including technostress, human health, flourishing, job and occupational insecurity, algorithmic management, ethics, and training needs for future occupational safety and health professionals. Together, the commentaries suggest that AI's potential impacts are neither inherent nor inevitable. In a world where AI's effects are still a consequence of human decisions, the frameworks and values of occupational health psychology hold promise for understanding and shaping a future of work where worker health, safety, and well-being are paramount.

Keywords Artificial intelligence · Technology · Occupational health psychology · Worker well-being · Algorithmic management

Introduction

Prognostications regarding the impact of artificial intelligence (AI) on the workers of today and tomorrow continue to challenge AI system designers, economists, and all involved in the enterprise of work. In part, this is due to exponential increases in AI capabilities that far outpace even expert predictions from just a few years ago (Maslej et al., 2025) leading many to conclude that the dawn of artificial general intelligence is no longer within the realm of the far-off distant future, but rather a fast-approaching reality (Dilmegani & Ermut, 2026). Regardless of whether and when

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such forecasts materialize, the rapid adoption of AI across numerous industry sectors represents a structural transformation of the organization of work.

While much focus has been on AI as a potential productivity multiplier, the increased integration of AI-enabled, -mediated, and -directed systems into core organizational processes has profound implications for occupational health, safety, and well-being. AI is reshaping job design, task allocation, decision authority, and skill requirements with direct and indirect downstream impacts on employee safety, psychological well-being, stress, autonomy, meaning of work, and dignity at work.

Given this, our intent in this collection of commentaries is to showcase the leading role that occupational health psychology (OHP) can play in shaping the Fourth Industrial Revolution (Schwab, 2016). OHP is uniquely positioned to address both the challenges and opportunities arising from the adoption of AI because of our field's inherent emphasis on worker health and well-being. Whereas other disciplines might focus on whether and how AI can enhance efficiency, productivity, or performance, OHP centers the human consequences of these systems and the conditions under which such technological advancement preserves or even enhances - rather than undermines - worker health and safety.

As such, we shift the conversation from what is technologically feasible to the more pressing question of what is most sustainable and optimal for the workers interacting with these systems. A major point of discussion in the field of AI safety concerns the issue of alignment (Yudkowsky, 2016), i.e., ensuring that the goals, behaviors, and outputs of AI systems are consistent with intended human values, interests, ethical principles, and societal norms. Yet, what is often lost in that discussion is *whose* interests should be prioritized, and *which* values are embedded within the design and deployment of AI systems. We argue that *our role as OHP researchers and practitioners is to ensure that AI systems are aligned with the occupational safety*, *health and well-being interests of workers*. As such, OHP offers a critical framework for evaluating the extent to which AI-enabled, -mediated, and -directed systems are aligned with this goal.

Toward this end, we offer the below commentaries as an initial step toward articulating a research and practice agenda at the intersection of AI and occupational health. Not only do these commentaries provide insights regarding AI's impact for OHP, but they also position OHP as a discipline that offers a set of values and methodologies as well as a lens through which to inform broader discussions in support of such alignment. While academic discourse has sometimes mirrored the popular polarization of AI's potential effects (e.g., breathless fears of an impending job apocalypse [Fore, 2025] and the creation of surveillance states [Tokson, 2025], on the one hand, and utopian dreams of liberation from the need to work at all, on the other [Musk, 2025]), the commentaries move beyond such a binary narrative by inviting diverse perspectives from leading OHP scholars regarding the promises and perils of AI. In doing so, we aim to provide a more nuanced and empirically and theoretically grounded discussion regarding AI's potential impact on occupational health, safety, and well-being.

In recognition of the multi-level systems approach that is foundational to OHP, the contributing authors examine processes unfolding at the individual, interpersonal, organizational, and macro-contextual levels. Across these levels, contributors

explore how AI might influence experiences of technostress (Dragano), human health (Jetha) and flourishing (Tay), job and occupational insecurity (Selenko & van den Broek), and workplace relationships (Tang & Koopman), implications of algorithmic management (Behrend) for ethical organizational governance (Bankins), and the workforce training needs of future occupational safety and health professionals (Vietas) in increasingly automated work environments.

Looking Beyond Efficiency: The Ethical Imperative for Ensuring Occupational Health and Safety in an AI-Enabled World

Sarah Bankins

Ethical AI refers to the "fair and just development, use, and management of AI technologies" (Bankins & Formosa, 2021, p. 60). The design and deployment of an increasingly wide array of AI technologies generates diverse ethical implications. A particular set of ethical concerns relate to AI's impact on our experience of work. This means centrally positioning the occupational safety and health (OSH) implications of these technologies as a core set of ethical criteria that guide their design and deployment. To truly "invent a future where artificial intelligence extends what humans can do to improve organizations and the world" (Locke, 2025), actions toward these ends must ensure that workers, their health, and their safety are at the forefront of those conversations, not approached as afterthoughts. From a socio-technical perspective, ensuring that such ethical criteria are set and met to support physical and psychosocial safety at work requires the actions of multiple stakeholders: from the companies that create these technologies, to the organizations adopting them, the employees using them, and the policymakers that can influence design and deployment trajectories.

For many of us over our life course, work can offer intrinsic benefits by providing sources of meaning, the ability to develop and exercise our skills, capabilities, and agency, to work in environments that are fair and preserve our dignity, and by providing opportunities to form important connections with others, as well as extrinsic benefits such as income, promotions, and other tangible rewards. Access to safe, dignified, decent, and meaningful work is held to be important across various ethical theories (Bankins & Formosa, 2023). Ensuring the ethical deployment of AI generally entails identifying, weighing, and managing the trade-offs that it generates through its capacity to both enhance or diminish physical and psychosocial aspects of work (see Jarota, 2023 for an overview).

AI-enabled technologies, such as sensors and wearable devices, can make work safer through continuous safety and environmental monitoring, hazard identification, risk assessment, and facilitating more proactive approaches for safeguarding workers (El-Helaly, 2024; Shah & Mishra, 2024). Examples include predictive analytics to identify equipment malfunctions, AI-driven exoskeletons and personal protective equipment (Horner, 2024), and 'emotion AI' tools that monitor employees' mental wellbeing (Roemmich et al., 2023). However, the way that AI technologies collect, combine, and use employee data for such purposes also raises privacy and data security concerns. Relatedly, the potential for 'scope creep' of these technologies, whereby

they are designed and deployed for one purpose, such as safety management, but then have their use expanded, such as for more explicit worker surveillance, also leads to worries about potential harms they could generate for feelings of competence, security, and autonomy at work (see Bankins, 2021; Behrend's commentary in this article; Parent-Rocheleau & Parker, 2022; Ravid et al., 2020).

Where AI acts in a truly augmentative capacity, and where workers are skilled in its use and have the autonomy to use it in ways that are helpful to them, it can also generate opportunities for higher-value human work while reducing the more demanding aspects of jobs (Bankins & Formosa, 2023). For example, where AI technologies are used to automate 'dull dirty, and dangerous' work, this reflects enhanced job design (Parker et al., 2025). AI is also changing the nature of "deskless jobs" across manufacturing, construction, and cleaning sectors through requiring more active collaboration with AI-driven tools, driving more complex job tasks, and enhancing remuneration for higher-level work (Zielinski, 2025). However, these technologies are also generating new forms of poorly paid, poor quality, often precarious, and invisibilized "ghost work", such as data labelling, content moderation, and more (Gray & Suri, 2019). Companies claiming AI-powered outcomes, but where the work is undertaken by humans, represent more extreme forms of deeply invisibilizing such workers to tout unrealized technological capabilities (see Bitter, 2024; Morris, 2025).

AI technologies also have the potential to create new types of challenging and interesting work and roles that foreground and amplify critical human skills (Locke, 2025), while generating opportunities for more interesting and complex forms of human problem solving and decision making. However, these benefits are tempered when AI technologies malfunction, are deployed in ways that apply time pressure to workers (Jarota, 2023), are used to generate AI workslop that complicates work processes (Niederhoffer et al., 2025), or lead to employees having their competence judged negatively when they use AI tools (Acar et al., 2025). As work accountabilities become more distributed and potentially opaque across socio-technical systems (i.e., across both automated systems and humans), workers also risk being placed in "moral crumple zones" (Elish, 2016, p. 40) whereby ethical blame for unintended outcomes lands with a human even when that outcome is outside their control.

So how can we navigate the ethical trade-offs and tensions that AI use generates and ensure ethical AI deployment that supports safe and healthy workplaces? Although which outcomes are felt more or less by which workers are dependent on many contingencies (Bankins et al., 2026), a range of stakeholders, as noted earlier, each play an important role in centrally positioning OSH considerations across the AI lifecycle: from technology designers (what are we designing for?), to organizational leaders (to what ends are we deploying AI?), employees (how are we using AI?), and policymakers (what guardrails are needed in the AI ecosystem?). Several practice and research priorities offer good starting points.

Embed Ethics in AI Roadmaps

Various forms of ethical AI principles exist (e.g., Department of Industry, Science And Resources, 2025; Floridi et al., 2018), but they generally coalesce around the need for AI systems to be used in ways that maximize community benefit, are fair, just

and inclusive, safeguard human autonomy, ensure data security and privacy protections, have clear chains of accountability and contestability regarding their outputs, and that the systems themselves are reliable and safe and appropriately transparent and explainable. From an OSH perspective, this can mean ensuring assessments of physical and psychosocial risks to workers prior to deployment and prioritizing the use of AI to enhance job design. These principles are made real when organizations develop their AI roadmaps, leaders communicate them well, and decisions are truly guided by them: ethical AI deployment requires bringing each of the aforementioned aspects into those conversations.

Avoid AI Fear of Missing Out, Act with Care

Organizations can feel pressure to adopt AI quickly to keep up with technological changes. But ethical AI deployment is grounded in weighing up benefits and costs and recognizing that deployment decisions often entail trade-offs (Bankins & Formosa, 2023). These deliberations demand care and time. From an OSH perspective, this can mean adopting change management practices that provide avenues for employees' voices to be heard prior, during, and after deployment, to ensure ongoing evaluation and management of any unintended or emerging physical, cognitive, or psychosocial risks. For example, engaging with stakeholders to inform impact assessments (Thomas & Uminsky, 2022) and thinking carefully about where AI capabilities are truly value-adding in a given context (Anand & Wu, 2025; Furr et al., 2025) are important. Listening to workers about where they see AI automation being helpful, such as for freeing up time for more valuable tasks, reducing repetitive tasks, and improving the quality of their work (Shao et al., 2025) can not only help support ethical AI adoption, but also build trust and reduce fear in these technologies (Lynch, 2025). Benefits and costs then need to be weighed: if automating a range of work processes will generate cost efficiencies, are those efficiencies being purchased by degrading job design, adding stress to workers, and dehumanizing decision making? Are those trade-offs ethically defendable? Are other paths available? Such deliberations help translate ethical AI principles into practice.

Developing an 'Epidemiology' of AI-Mediated and -Enabled Work

For researchers, documenting and tracking the occupational health outcomes of AI-enabled, -mediated, and -managed work will be important for mapping its ethical implications. AI-enabled work reflects tasks that are completed with the use of AI, through augmenting or complementing the human worker. AI-mediated work refers to tasks where the technology acts as the interface through which work is completed, shaping how interactions occur, such as knowledge sharing (Malik et al., 2021). AI-managed work, also termed algorithmic management, occurs when AI is used to direct or evaluate the work of a human, as can occur on gig work platforms. From an OSH perspective, efforts to quantify the effects of each type of work would better pinpoint trade-offs and tensions, benefits and costs. Such measures could include cognitive load and fatigue, perceived skill atrophy, and self-efficacy (AI-enabled work); extent of social interaction, technostress, and information overload (AI-mediated work);

and moral injury, sense of autonomy, and surveillance-induced stress (AI-managed work).

Overall, the use of AI technologies can generate new and emerging forms of physical and psychosocial benefits and risks in the workplace and these carry ethical implications. It is important to proactively surface and discuss these, determine if they can be managed, and chart a path forward that fairly balances multiple priorities.

Algorithmic Management and Surveillance

Tara Behrend

The use of artificial intelligence to support performance management is now common. Human managers may rely on AI-supported metrics for decision-making, or in more extreme cases managers may be fully replaced by AI. This latter case, often referred to as algorithmic management, is popular in work ranging from platform work (e.g., gig drivers) to hospitality, retail, logistics and warehouse work, and manufacturing. In these contexts, schedules, routes, work assignments, and performance quotas are determined by algorithm and then communicated to workers via technological means. For this kind of algorithmic management to be possible, workers must also be digitally tracked and monitored at all times, so their behavior can be compared against these metrics, and the algorithms can be updated.

Research on the topic of electronic work surveillance has clearly demonstrated that workers experience this surveillance as a stressor. Early ergonomic and occupational stress studies established that computer-based monitoring is associated with increased anxiety, tension, and fatigue (Carayon, 1993; Smith et al., 1992). More recent meta-analytic work has confirmed that monitoring does indeed increase stress (Ravid et al., 2023), not only due to increased attentional demands, but due to worry and fear that data captured from monitoring will be used for punishment.

Perversely, algorithmic management practices which are often meant to improve efficiency have shown no demonstrated effect on productivity (Ravid et al., 2023). Instead, they may incentivize dangerous and counterproductive behaviors. Algorithmic management increases job demands by creating faster production expectations, implementing real-time scheduling changes, and increasing performance pressure, while simultaneously reducing resources by restricting autonomy, and limiting feedback and social support (Parent-Rocheleau & Parker, 2022, see also Dragano's commentary, this article). These pressures lead to predictable consequences. For example, a driver in Georgia was filmed driving on a busy sidewalk to avoid a traffic jam, presumably so their delivery speed metrics would not be affected by the slowdown (FOX 5 Atlanta Digital Team, 2024). Warehouse workers continue to work past the point of severe dehydration rather than step away from their work and be penalized for falling behind (Oxfam, 2024). In this way, both psychological harms, from stress and uncertainty, and physical harms, from time pressure and workload, are directly tied to algorithmic management.

It is possible to imagine that ubiquitous monitoring may actually protect worker health by identifying unsafe work conditions, for example, or providing unbiased

documentation to protect workers from bullying or harassment (see Jetha's commentary, this article). Truck drivers are frequently outfitted with in-vehicle monitoring software that alerts them to signs of fatigue. The success of these tools depends entirely on how the data are used. If that fatigue data is transmitted to a supervisor who uses it to punish the driver, it is inevitable that the driver will find ways around the technology, creating conditions that are even more unsafe. It is also the case that pervasive monitoring creates a workplace characterized by lower trust and shared responsibility, making it less likely that workers will put in extra effort to speak up about potential dangers (Yost et al., 2019).

Some emerging evidence has pointed to possible interventions that can lessen the negative impacts of algorithmic management on workers. For example, Nilsson et al. (2025) report that four tactics may be beneficial, based on observational data comparing companies with different approaches to algorithmic management: (1) involving workers in the design and implementation of algorithmic management functions; (2) explicit consideration of algorithmic management in the occupational health and safety management process; (3) adoption of systems that offer relatively more worker control; and (4) using algorithmic management as a supplement instead of replacement for human judgment. Recent evidence from police officers who are monitored via body worn cameras suggests that officers in departments with officer-supportive policies (e.g., officers have discretion about muting personal conversations) have more favorable attitudes about cameras and less emotional labor and exhaustion (Ravid et al., 2025). No systematic experimental evidence has established, however, the effectiveness of these tactics in improving either short term or long term health outcomes for workers.

It is essential that future research in this area avoids technological determinism, acting as if technology progress is out of human control (Behrend et al., 2024) and instead focuses on organizational responsibilities and actions. Technologies such as those used in digital surveillance do not have fixed properties, and research that compares "human" and "technology" conditions in a vacuum is not ideal for understanding health and safety effects. Research must explicitly focus on how the technologies are used in context, with an eye toward adoption and implementation decisions and their downstream consequences. Research that identifies misuses and misunderstandings of data that arise from algorithmic management will be especially needed in fully understanding its emergent effects.

There are clear policy gaps in the US that leave workers vulnerable to harmful surveillance. Many countries have data protection laws that apply to employee personal data, requiring notice, consent, and access/rectification rights. In Europe, the General Data Protection Regulation (GDPR; https://gdpr-info.eu/) has stated that monitoring of employees violates data protection, right to privacy, and data minimization principles. For example, France has fined Amazon for "excessively intrusive" monitoring of workers in warehouse settings under GDPR grounds (AP, 2024). In the US, however, no comprehensive federal statute regulates workplace monitoring or algorithmic surveillance of employees. In fact, the Federal Wiretap Act (Electronic Communications Privacy Act of 1986) specifically excludes monitoring that takes place as part of the normal course of business from its prohibition on intercepting electronic communication without consent, and it also excludes tracking devices and

biometric monitoring in its scope. Several state laws provide varying protections, but many issues remain legally ambiguous; state laws vary widely in whether they regulate consent for recording telephone conversations, biometric data usage, notification of monitoring, and privacy rights.

A 2025 report from the U.S. Government Accountability Office (GAO, 2025) indicates that currently, the Equal Employment Opportunity Commission (EEOC), National Labor Relations Board (NLRB), and Occupational Safety and Health Administration (OSHA) have the ability to investigate claims that involve digital surveillance. They note, however, that "several federal agencies have also provided guidance or resources to employers about the use of digital surveillance but *have either rescinded these prior efforts or are reassessing their alignment with the current administration's priorities.(p.2)"* Policymakers and regulators need to urgently reprioritize the establishment of standards for transparency, data minimization, worker consent, and disclosure regarding the purposes, metrics, and data ownership for monitoring technologies. To do so, they need high-quality evidence from the research community to guide their decision-making.

Artificial Intelligence and Technostress at Work

Nico Dragano

Work-related stress and its health consequences are a core topic of occupational safety and health. Since the 1980s, digital technologies have been examined as a source of stress, and today there is extensive research and practical experience on technology-induced stress (i.e., technostress) at work. Until recently, AI was only a marginal topic in this context, as it was neither widely adopted nor applied beyond specialized domains. This has changed with the emergence of new, mass-market products such as large language models. In view of this rapid development, it is important to assess the role of AI as a possible trigger of stress — or, framed positively, as a potential tool for stress reduction. Therefore, it seems appropriate and resource-saving to draw upon established concepts for assessing technology-induced stress when evaluating possible consequences of AI for occupational health and safety. This commentary provides a brief assessment of when and whether such a transfer is reasonable, what the current state of research is, and where a simple continuation of known technostress approaches may not be sufficient.

The technostress framework has evolved over the past decades in response to the rapid proliferation of digital technologies in the workplace (Marsh et al., 2022; Nastjuk et al., 2023; Tarafdar et al., 2019). However, it is not a coherent theory but rather an umbrella term for different approaches that attempt to conceptualize different ways in which the use of digital tools influences health via a psychobiological stress response (Dragano & Lunau, 2020). Correspondingly, it encompasses various models which focus on different forms of stressors. The most popular concept in this regard is a taxonomy of five so-called 'technostress creators' (Tarafdar et al., 2007). These are namely 'techno-overload' (e.g., due to multitasking, information overload), 'techno-complexity' (e.g., high cognitive demands), 'techno-insecurity' (fear

of job loss due to technology; see also Selenko's commentary in this article), 'techno-invasion' (spillover of digital work into other areas of life), and 'techno-uncertainty' (volatile digital work environments). A sixth more recently considered core form of technostress is 'techno-unreliability' (Kalischko et al., 2020). This is an immediate reaction to being confronted with defective, non-ergonomic or unreliable digital technology. In addition, a number of other technostressors have been identified that are related to specific applications of technology. Examples include the restriction of autonomy through digital surveillance, a general cognitive overload due to digital input, or digital bullying (Kalischko & Riedl, 2021; Korte, 2020; Yan et al., 2025).

The strength of existing technostress models lies in their solid theoretical grounding and in the fact that there is extensive empirical research for many of them—particularly for the technostress creators—demonstrating that they indeed have health effects and are relevant for OSH (Borle et al., 2021; La Torre et al., 2019). In addition, and this is important for the question of applicability to new technologies, most models are relatively open with regard to the triggering technology. Apart from some exceptions, previous attempts to conceptualize technostress have not been tailored to specific technologies, resulting in largely generic understandings of technology-induced stress (Ayyagari et al., 2011; Marsh et al., 2022). Thus, it is known that, for example, techno-overload can be associated with the use of very different information and communication technologies (ICT) (e.g., e-mail or enterprise resource planning software) (Bhatt & Paras Kothari, 2022). In many cases, it therefore seems that it is less the specific technology itself than its specific field of application (e.g., communication, collaboration, documentation) that is decisive for the emergence of particular forms of technostress.

In this respect, the existing models are in principle suitable for capturing potential strain arising from new digital technologies. Whether this also applies specifically to AI applications, and whether certain forms of technostress will play a particular role, remains to be discussed. If one first seeks to draw on empirical evidence, the options are currently limited, as there are only very few studies that explicitly examine AI in relation to technostress, and these studies have considerable methodological limitations (e.g., small and non-representative samples, lack of health-related outcomes). However, individual findings at least suggest that technostress-like reactions may occur when working with AI (Chang et al., 2024; Cram et al., 2022; Di Stefano et al., 2025; Litan, 2025; Zhang et al., 2025). For example, Di Stefano and colleagues report, based on a survey of radiologists, an increased occurrence of individual technostress creators when working with AI was perceived as problematic (Di Stefano et al., 2025). Other studies provide at least indirect indications of stress-related strain in the context of working with AI, although without explicit reference to technostress concepts. For instance, associations between AI use and burnout (Liu et al., 2024), or anxiety related to AI use (AI anxiety) have been observed (Li & Huang, 2020).

At present, more than an "informed speculation" about the relationships between AI use and individual forms of technostress is not possible. With a certain degree of plausibility, it can be expected that techno-insecurity, in particular, may occur more frequently. It is currently widely assumed that organizations will use AI to replace human labor (Kaaria, 2024). As a result, employees in occupations with high automation potential may develop concerns about their own job security, thereby contribut-

ing to the development of chronic stress (Sharif et al., 2025). In a more moderate form, established ways of working are also being called into question in many occupations, such that work tasks may fundamentally change through the use of AI (Jetha et al., 2023), which could promote both techno-insecurity and techno-uncertainty. With regard to the category of techno-overload, various scenarios are conceivable. On the one hand, AI—like other digital technologies before it—could act as a driver of work intensification. At the same time, however, relief is also conceivable, for example if well-designed AI applications improve work organization or if psychologically demanding tasks are entirely taken over by AI (Sharma, 2024). Opposing effects can also be assumed for the technostressors of techno-complexity and techno-unreliability. On the one hand, AI may reduce complexity by making large volumes of data and complex processes manageable, identifying patterns, and summarizing complex issues (Cram et al., 2022; Jetha et al., 2023). On the other hand, increasing black-box situations may arise, as employees may find it difficult or even impossible to understand how AI outputs are generated, thereby potentially increasing perceived complexity (Issa et al., 2024). Techno-unreliability, that is, stress resulting from interaction with faulty technologies, may likewise either increase or decrease, depending on the reliability and stability of the technology in use.

These assessments are intended to be merely illustrative and are meant to demonstrate that an evaluation along established technostressors can be useful for anticipating strain related to AI applications. In the case of AI as a disruptive technology, however, this will likely not be sufficient. Researchers have already argued, in the context of the rapid digitalization of work, that the entire sociotechnical work environment—with its multiple tools, norms governing technology use, and the organizational embedding of technologies—is crucial for the emergence of strain (Marsh et al., 2022). According to current assessments, the consistent use of AI has the potential to fundamentally transform entire work systems and even whole labor markets (OECD, 2022). That this will also have complex consequences for employees' mental health is at least likely. Accordingly, it will be necessary to examine the effects of AI on entire work systems.

In addition, it must be discussed whether idiosyncratic characteristics of AI exist that produce specific strains that are not comparable to the effects of other technologies and therefore cannot be adequately described using established forms of technostress. What these characteristics might be is currently the subject of initial research. For example, Issa et al. propose "techno-unpredictability" as a new stressor in the context of AI (Issa et al., 2024). This refers to stress triggered by the unpredictability and lack of transparency of AI responses. Examples include concerns about erroneous decisions made by diagnostic AI tools in medical contexts (Liu et al., 2022). Another such aspect is the combination of AI and robotics, which gives rise to entirely new forms of human–machine interaction that may pose psychological challenges in their own specific ways (Beer & Mulder, 2020).

Despite the strong focus on risks, it should also not be overlooked that digital technologies can have positive effects on mental health. For example, they can relieve workers of routine tasks, improve productivity, or facilitate knowledge acquisition (Sharma, 2024). Research on AI and stress should therefore also consider opportunities for health promotion; see also Jetha in this article. Initial indications of such

potentials already exist, for example in studies in which AI facilitated workers' emotional regulation during stressful workdays (Henkel et al., 2020).

In sum, it appears that the technostress framework is in principle suitable for assessing potential psychological strain in the context of working with AI. This suggests a pragmatic approach for both research and practice, in which established concepts are adopted. Examples include the adaptation of existing technostress questionnaires by instructing respondents to refer their answers specifically to work with AI (Litan, 2025). At the same time, however, rapid and targeted research is desirable to identify potential AI-specific strains that go beyond established technostressors.

The AI Unknown: Exploring How Intelligent Machines Could Reshape Working Conditions and Worker Health

Arif Jetha

A great deal of media attention has been directed to the threat AI poses to the employment of human workers. Yet, in its current, narrowly applied form, fears of mass job losses attributed to AI have been overstated. Instead, research shows that AI is being used in a complementary role and redistributing job roles between human workers and machines (Agrawal et al., 2018; Brynjolfsson & Mitchell, 2017; Chen et al., 2025). In this role, AI is enhancing the efficiency, precision and speed of job performance while also substantially transforming workplaces (Milanez, 2023). Despite productivity gains, our understanding of the impact of AI on worker health remains limited (Jetha et al., 2023). So too are enforceable legislations on AI that can protect workers. Drawing on a small body of research and scholarship led by the Partnership on AI and Quality of work (PAIQ) at the Institute for Work & Health in Canada (IWH, 2025), this commentary presents potential positive and negative implications of AI on working conditions to bring to light direct and indirect impacts of the technology on the health and well-being of workers.

AI may change working conditions in ways that are beneficial to worker health. AI systems can be adopted in the workplace to automate strenuous and psychologically demanding job tasks such as those that require repetitive processing or sustained attention (e.g., data entry tasks) (Brynjolfsson et al., 2023; Brynjolfsson & Mitchell, 2017). AI-related automation may partially or fully remove workers from the most hazardous situations to minimize workplace injury or illness. While AI can take on codifiable tasks, humans can focus on high value tasks such as those that involve creativity, strategic thinking, interpersonal communication) thus improving perceived job satisfaction (Brynjolfsson et al., 2023; Chen et al., 2025). AI systems may also ensure fair and safe allocation of human resources. For instance, AI-informed scheduling systems for nurses in a large hospital can minimize multiple back-to-back and overnight shifts to improve patient care and job satisfaction (Kang et al., 2025).

When used to support the performance of physically demanding job tasks, AI may minimize the physical and ergonomic strain that is placed on workers. For instance, one study in the United States showed that a rise in robot exposure was associated with a 16% lower total-case injury rate over a six-year period (Gihleb et al., 2022).

While this study wasn't specifically focused on AI-enabled robots, it provides evidence of the role advanced technology can play in creating safer working conditions.

At the same time, studies signal potential adverse changes to working conditions and worker health that could emerge when AI is deployed within workplaces. Workers exposed to intelligent and highly productive machines may feel pressure to increase the speed and intensity of their work which may contribute to unsafe behaviors. The intensification of work can increase job demands, emotional strain, stress and burnout for human workers who are required to work alongside AI (Hai et al., 2025). Employers who turn to AI may raise their expectations of human workers to produce more outputs and take on more responsibilities without reducing overall workloads (Milanez, 2023; Monahan & Burlacu, 2024).

Some studies suggest that the integration of AI is contributing to a dehumanization of work where workers feel like their employers are treating them as a piece of machinery and where they have less autonomy and skill discretion (Kim & Lee, 2024). Interestingly, the dehumanization of work has the potential for workers to unsafely cut corners to complete a task (Hai et al., 2025). Moreover, an overreliance on automated technology at work could create a false sense of security among workers and delay human intervention if a health and safety risk emerges (Kim et al., 2025).

Decisions made in design and deployment of AI systems may impact working conditions and worker health. AI systems require large amounts of different training data to learn and operate with independence. Ongoing data collection and the constant surveillance of workers can be a source of stress. Ongoing data collection may also provide real-time feedback to workers which may promote safety behaviors or may alert a worker to a workplace hazard. Yet, recent systematic reviews show that there is a minimal measurable impact of AI-powered health and safety systems on worker injury or illness outcomes (Jetha et al. 2025a, b, c). The lack of transparency regarding the role of an AI system at work and the reasons for ongoing data collection can be associated with a feeling of powerlessness among workers and may reduce trust in employers and the technology (Azzi & Papandrea, 2025).

Changes to working conditions and worker health emerging from AI may be patterned according to occupational and worker characteristics in ways that may differ from previous periods of technological adoption. Studies suggest that workers in occupations characterized by better job quality (e.g., higher wages, permanent contracts) and greater job skill and educational requirements are more likely to be exposed to AI when compared to precariously employed workers or those in jobs with lower job skill requirements (Eloundou et al., 2024). Interestingly, workers most exposed to AI may be those who have been previously sheltered from the impact of new technologies. Some groups of workers, including women or young workers, may be more likely be employed in occupations impacted by AI (Brynjolfsson et al., 2025; Jetha et al. 2025a, b, c). In the short-term, these groups of workers may benefit from AI-related productivity gains while also directly experiencing positive and negative impacts of the technology on their working conditions.

In the long-term, as AI grows in intelligence, workers highly exposed to the technology may face more significant disruptions to their employment, working conditions and health. In particular, the promise of artificial general intelligence (AGI), AI that

may understand, learn, and apply knowledge across a diverse tasks at a level comparable to human intelligence, could significantly disrupt the relationship between work and health. AGI is expected to exceed human abilities including those that involve problem solving and creative or abstract thinking without human intervention, or may exhibit greater self-awareness and emotion (Restrepo, 2025). AGI may result in a more drastic transformation of occupational structures, redefine the very nature of human productivity, and disrupt the fundamental role of human workers.

Recommendations for Occupational Health and Safety Research

1. ***Expand Transdisciplinary Research On AI, Work, And Health***

Empirical studies are required to examine how AI at work can affect various working conditions and the physical and mental health of workers, both positively and negatively (Jetha et al., 2023). Research within the workplace is needed to elaborate on how the design and adoption of AI can impact the working lives of different groups of workers. Research should bring together expertise from different disciplines including occupational health, computer science and engineering, management sciences and policy to unpack complexity in this domain. Please see Vietas's commentary in this article on related recommendations for improving education and training for OHS professionals.

2. ***Develop Research Approaches That Keep Up with The Pace of Change***

Studies should be implemented that track the ongoing impact of AI advancements on different aspects of work and investigate how more advanced and independent AI systems may impact the role human workers play at work including their autonomy, well-being and safety (Jetha et al. 2025a, b, c). There is also a critical need to understand health and safety risks for workers exposed to emerging AI systems.

3. ***Build Evidence to Strengthen Worker Protections Related to AI Adoption at Work***

Workers based in different occupations are likely to experience positive and negative impacts associated with the adoption of AI at work. In the absence of widespread legislative protections, there is an important need to build an applied evidence base to directly inform targeted policies and protections that ameliorate AI-related risks and enhance the benefits of the technology.

AI Changes and Their Effect on Job and Occupational Insecurity

Eva Selenko & Antonius van den Broek

Job insecurity has long been acknowledged as a core stressor in occupational health. Commonly defined as the perceptions and worry of losing one's job and valued job features, job insecurity has been found to lead to diminishing psychological health, reduced job performance and even to affect people's wider life in society (Klug et al., 2024). Recent speculation about AI's effect on future employment is reigniting interest in job insecurity research, with some even speaking of a "jobpocalypse" (Financial Times, 2025) to reflect the fear that AI will replace jobs on a mass scale. Others praise the job-generating potential of AI technology, highlighting the World Economic Forum's estimate of 170 million newly created jobs (WEF, 2025). These extreme positions on AI in work settings show urgency on the matter yet provide little help in understanding its impact on job insecurity.

Our commentary will look at three aspects, (1) we explore how we can understand exposure to AI; (2) we look at empirical data connecting exposure to employment decline and (3) we connect these observations with our insights into the broader job insecurity literature and emerging research on occupation insecurity (see also Dragano's commentary in this article discussing techno-insecurity as a component of technostress).

To get a better handle on the effect of AI on jobs, it helps to understand jobs and occupations as bundles of tasks. Rather than affecting occupations or jobs as a whole, AI technology is affecting specific job tasks. While there is a consensus that almost every occupation will have *some* tasks that can be replaced by AI, few, if any, occupations, will have *all* tasks replaced. Indeed, occupations and job roles differ to the degree they consist of tasks that are 'suitable for machine learning' and are hence exposed to AI automation or augmentation (Brynjolfsson et al., 2018, p. 43).

The extent to which an occupation is exposed to AI, and hence how much AI can take over job tasks, has been measured in two ways. One approach assesses an occupation's O*NET tasks and estimates the machine-learning potential and Large Language Model (LLM) exposure for each task. Doing so shows that only 1.86% of all tasks across all occupations are fully automatable without human oversight, but 71% of all tasks have at least some components that an LLM could plausibly complete (with help) (Eloundou et al., 2024). Note that these are predictions of exposure – not real job impact yet.

A second approach analyzes real worker-LLM interactions, maps them against O*Net tasks, and then links these tasks to occupations (Handa et al., 2025). This evidence suggests that AI is currently being used largely for augmentation (57%) rather than automation (43%) of human tasks. However, since these data come from early adopters, more observation is needed to gauge AI's true impact on work.

While these two measures may help identify AI exposure, their link to actual job loss is complex. Mapping the employment data of 25 million US workers across 7000 occupations against predicted AI exposure, Brynjolfsson and colleagues (2025) found that employment loss hinges on (1) whether AI augments or automates labor and (2) the age of workers in the exposed occupation. Entry level employment declined

in occupations where AI primarily automated work, but interestingly, employment grew in professions where AI was primarily used for augmentation. They further found that the effect of AI exposure on job loss was moderated by experience: in highly exposed jobs early-career workers' (aged 22–25) employment declined, yet the decline was much lower and not significant in slightly older groups and there was even a slight growth in the midcareer and senior group. The authors suggest that this might be due to accumulated tacit knowledge that older workers possess, and AI cannot easily accommodate for. Associating these findings with knowledge from job insecurity literature leads to interesting predictions.

For younger workers and those entering the labor market, the situation is not easy – particularly in professions exposed to AI. Their biggest challenge will be career-entry worries – the concern of not finding a foothold in a career that corresponds to one's education (Ebner et al., 2021) or liking. This is problematic, as unemployment at a young age has been found to lead to dramatic health consequences (Paul & Moser, 2009), and delays and failures to land a suitable job at a young age can have long term scarring effects in terms of economic inactivity (Ralston et al., 2022).

For older and more experienced workers, job security and salaries are likely to remain stable (if AI changes to jobs are managed well) – but this does not mean that they will be unaffected. Even if they may be objectively speaking safe (for now), mid-career and senior workers are not an island – but will be affected by the job insecurity of younger others (e.g., Shoss et al., 2023).

Radical changes to core functions of jobs and valued job features due to AI are likely to induce qualitative job insecurity (aka the fear of potentially losing valued job aspects, such as colleagues or working conditions). Moreover, the tasks that change may not remain localized to the current holder and job-role - but threaten fundamental features of the occupation more broadly. Roll and colleagues (2023, 2025) recently proposed occupational insecurity to describe this broader worry about the disappearance of one's occupation (general occupational insecurity) and the worry of substantial changes of occupational job tasks (content occupational insecurity) due to technological changes, which they could relate to automaton risk as well as burnout (Roll et al., 2023, 2025). The more these AI-affected features are intertwined with people's self-understandings (as it is often the case with more experienced people) the more threatened people will feel by these changes (Probst, 2000; Selenko et al., 2022).

On a more positive note, most tasks and occupations still require human involvement or oversight, even if AI is heavily used – and if it is used to augment, it can quickly lift juniors' work outputs to the level of more senior colleagues (Strich et al., 2021). We also note that most task-focused AI research implicitly suggests that doing tasks well would be the only performance facet of value. However, successful performance requires many other task-unspecific facets, like citizenship (e.g., showing conscientious initiative), proactivity (e.g. taking charge) or team member proficiency (e.g., providing help to coworkers when needed) (see Griffin et al., 2007). These performance dimensions are intricately interwoven with doing tasks but more difficult to "datafy" and hence automate with AI technology – and still of value to organizations.

Workers start to recognize this too. Our own research with workers in a heavily exposed profession (digital creative designers) shows, for example, that while people

are aware of the impact of AI on their profession, and wary of job losses around them, they themselves do not feel threatened (van den Broek & Selenko, 2025). They attribute this to their human capabilities, like empathy, that machines cannot take over. Whether that is a coping mechanism or a reflection of their seniority or indeed an emerging recognition of the value of performance dimensions not covered by AI is up for further research. However, what this indicates is that the road between job exposure and perceived job insecurity from AI is not straightforward and requires further study.

Finally, perceptions of job insecurity are closely tied with employment protections (Probst et al., 2020) and the socioeconomic context more generally. So far, most research on AI exposure and employment effects are conducted in the US, where worker protection from dismissal is low. Labor market effects – and subsequent employability and job insecurity will be different in contexts where working conditions (e.g., wages, worker rights) are protected by layers of collective bargaining agreements. More knowledge is needed on the impact of AI on worker insecurity across different labor regimes.

In conclusion, emerging research on AI suggests that job insecurity will remain a stressor, but perhaps of a different shape: for career entrants it may be entry worries that dominate, whereas for more experienced workers, the job insecurity of others, qualitative job insecurity and occupational insecurity may follow from AI changes to jobs. This can have serious consequences for health, identity and the ability to adapt. The AI industry is optimistic that even in highly exposed fields (like science and research), there would be complementary downstream innovation thanks to the new technology (Eloundou et al., 2024). We would argue that such optimism warrants caution: These innovations are only likely if workers who are central to guiding AI to innovative outcomes feel secure in their jobs, secure in their valued job features and occupations, and secure about the future of others around them.

When Artificial Intelligence Fails: Disentangling its Influence on Working Professionals' Relationships via the Social Comparison Theory

Pok Man Tang & Joel Koopman

The 20th century saw a transformation of the workplace, as digital technology became inextricably linked with essentially all workplace functions (Hakken, 1993). Two decades into the 21st century, digital technology has transformed the workplace yet again in the form of artificial intelligence (AI). The frenzied pace to incorporate AI into business operations is largely predicated on the presumed value that will accrue from augmenting employee's jobs with AI. In this way, the conversation has tended to focus on (a) individual performance for (b) end-users of (c) AI that functions as intended (e.g., Malik et al., 2025). Yet as we will illustrate below, there are reasons to think that this perspective is unnecessarily restrictive and that the incorporation of AI into the workplace may also have effects on interpersonal relationships for third-party observers of AI that fails to function as intended (e.g., Tian et al., 2025).

To ground our entry into this conversation, consider the following: an employee becomes increasingly frustrated as an AI tool repeatedly fails to provide the expected output on a task. Anyone who has worked with modern AI tools can easily relate to this situation, and indeed such failures of technology have themselves been a focus of ongoing scholarly research (e.g., Honig & Oron-Gilad, 2018). Yet our focus is not on the employee dealing with AI failure, but rather on the coworker who, while not involved in the failure, observes it playing out in real time. This is a perspective that is easily overlooked in the current build-out of AI in the workplace. That is, while the experience of working with AI may be socially-isolating for the user (e.g., Tang et al., 2023), employees themselves may still conduct their work in the presence of others. For this reason, a third-party perspective is important, given that these processes are well-known to impact both observers and interpersonal relationships (Dhanani & LaPalme, 2019). Indeed, scholars have long recognized that work events do not occur in a social vacuum (e.g., James, 1890), and this has not changed with the introduction of AI to the workplace. However, AI scholars have been slow to consider such processes when assessing the consequences of incorporating AI into the workplace. We take up this charge as we identify the above situation as one that may cause what scholars term downward social comparison.

In this commentary, we draw from theory on social comparison to identify two affective mechanisms—schadenfreude and sympathy—that may be experienced by a third-party observer of AI failure. We extend this further by proposing downstream interpersonal consequences in the form of two behaviors that have significant occupational health implications (e.g., incivility and prosocial behavior). In so doing, we hope to draw attention to an underexamined phenomenon in the AI buildout that has significant, but less readily observable, consequences for worker health.

AI Failure and Social Comparison

Organizations are increasingly incorporating AI into business operations as a way of increasing efficiency, enhancing profits, and reducing risk (Benbya et al., 2020). As psychologists recently noted, one such critical challenge associated with AI is the not-infrequent phenomenon of these systems failing to operate as intended (e.g., Honig & Oron-Gilad, 2018). As human-AI pairings become increasingly commonplace (e.g., Tang et al., 2022), we submit that the effects of these failures may extend beyond the direct user to those who may observe their occurrence. On this point, scholars have noted that vicarious observations of others' experience—particularly when the observer finds themselves in a similar situation—may trigger social comparison processes (Festinger, 1954). We therefore explore the potential implications of such comparisons.

Contrastive Social Comparisons and Behavioral Outcomes

One type of social comparison that may occur following a failure such as that described above is a contrastive downward social comparison. Such comparisons reflect a focus on the simultaneous misfortune of another relative to their own good fortune (Kelly et al., 2003). Theory predicts that in this situation, people may feel

what are termed as "ill-will emotions" (Ortony et al., 2022, p. 92)—indeed, feeling pleasure during a situation in which a person's disadvantage makes salient an employee's relative advantage is natural (Smith, 2000). The result is that observers may feel a sense of distinctiveness compared to their coworker, which can lead to the emotion of schadenfreude ("pleasure at the misfortune of others"; Smith, 2000, p. 189).

This affective reaction may have particularly destructive consequences for the health and well-being of others in the workplace. For example, employees experiencing schadenfreude may be motivated to take actions that maintain (and, enhance) their distinctiveness by increasing the suffering of the focal employee (Xu et al., 2020). Specifically, we expect employees will enact a discrepancy-enlarging deviant behavior such as incivility (Andersson & Pearson, 1999; Koopman et al., 2020) as a means of maintaining their perceived superiority. Incivility is both a subtle, but also pernicious and destructive, behavior in the workplace. For example, Lim et al. (2008) showed that incivility has negative impacts for both mental and physical health and Nicholson and Griffin (2015) documented that experiencing incivility lingers with employees and interferes with their ability to recover after work (with effects lingering to the next day).

Assimilative Social Comparisons and Behavioral Outcomes

There is, however, an alternative type of social comparison that can result following a failure such as that described above—what scholars term an assimilative downward social comparison. Unlike contrastive comparisons, wherein observers may focus on enlarging the discrepancy, assimilative comparisons lead instead to discrepancy-reducing behavior. In this situation, instead of focusing on the misfortune of the employee experiencing AI failure, the employee may instead recognize that the situation could also happen to them. Thus, instead of focusing on distinctiveness, the employee may instead feel a sense of kinship (Smith, 2000). As such, instead of schadenfreude, employees may feel sympathy (Feather & Sherman, 2002).

The sense of sameness that accompanies sympathy should then result in very different behavioral outcomes than those previously described. That is, instead of creating distance, employees may instead feel a desire to emphasize their similarity with the affected coworker. For this reason, we would expect employees to enact prosocial behaviors towards the coworker in the form of citizenship (e.g., helping; Organ, 1997) as a way of enabling recovery from the failure. Here, the health consequences that accrue to employees are markedly different than those from above. That is, as pernicious and destructive as incivility is, helping behavior is beneficial and constructive. Helping is considered as a critical organizational resource (e.g., Demerouti et al., 2001) that can buffer employees from the stressful consequences of a multitude of job demands. When colleagues step in during a time of difficulty, such as an AI failing to work as intended, they may meaningfully reduce the strain that would have otherwise followed. More fundamentally, helping others is foundational to building community within the workplace, and should increase the level of positive affect for both parties involved (Fredrickson, 2001).

Implications

The Fourth Industrial Revolution has arrived, and human-AI interactions have become ubiquitous. The dominant conversation in this space has been focused on how AI that functions correctly enables the performance of end-users—a logical focus, as this forms the basis of the business case for incorporating this new technology. However, decision-makers would be remiss if they did not expand their view to consider how AI that fails may have broader, but less visible, consequences for the entire work unit. Our goal was to explicate this phenomenon and identify some of those consequences, and in so doing, we revealed that the situation is quite complex. There are good reasons to think third-party observers of AI failure may socially-compare with the target of that failure. Yet whether those social comparisons are contrastive or assimilative matters greatly, as they yield dramatically different behaviors with critical implications for occupational health. Thus, we call on scholars to not only investigate the propositions we have made herein, but to further delve into theory on social comparison to identify moderators that may explain when observers will tend to compare in a contrastive vs. assimilative manner. One potentially fruitful direction would be to consider the observer's technological competence. For those employees who perceive themselves as having greater ability or control over the matter (i.e., technology in this context), then the result should be tilted towards contrastive affective reactions and away from assimilative affective reactions. Overall, examining the relationships and processes discussed above is crucial for providing actionable guidance to practitioners that let us capitalize on the promise of this amazing technology.

Designing AI for Flourishing at Work: Integrating Performance and Well-Being

Louis Tay

For much of the past century, organizations and organizational researchers have prioritized improving worker and organizational performance, whereas the field of Occupational Health has emphasized protecting and promoting employee health and well-being, which traditionally has been understood as positive life evaluations, feelings, purposefulness, and good relationships (Diener et al., 2018; Ryff & Keyes, 1995). My colleagues and I have argued that these perspectives are not competing aims but jointly constitute the essential foundations of flourishing – or optimal functioning within and beyond the workplace (Tay et al., 2023). This broader view aligns with the vision of the U.S. National Institute for Occupational Safety and Health (NIOSH) Total Worker Health™ program, which advances a holistic approach to worker well-being that includes the preservation of decent and productive employment (Schill & Chosewood, 2013). Implicit within this vision is an acknowledgment that performing well at work can itself be ennobling and enabling. Yet, integrating these aims also introduces conceptual and practical complexity: understanding when and how "performance" and "well-being" (a shorthand that includes physical and psychological well-being) conflict - or when they mutually reinforce one another

- remains a central challenge. This challenge is further amplified in the age of AI, where technologies increasingly augment, reshape, or even replace human experiences and contributions to both performance and well-being.

What does the future of AI research related to this issue look like? A central proposition guiding future inquiry is that well-intended AI and technology use meant to enhance work and lives - both within and outside the workplace - can inadvertently heighten tensions between performance and well-being, sometimes undermining one or both. Yet it is possible that AI can also create powerful positive synergies when designed and implemented in ways that account for performance and well-being. Understanding when AI exacerbates these tensions and how it can be *designed* to enable flourishing represents a crucial frontier for occupational health research.

Tensions and the Undermining Aspects Of AI

Historically, each wave of productivity-enhancing technology has sparked concerns about diminishing meaning, engagement, and dignity in work. From a technocentric perspective, humans risk being viewed merely as "cogs" in an optimized workflow - an orientation that can erode autonomy, competence, skill utilization, and relational connection (see Jetha's commentary, this article). Emerging perspectives and evidence echo these fears. Algorithmic systems can reduce human decision-making (Parker & Grote, 2020); moreover, they can also lead to both deskilling and the inhibition of upskilling (Natali et al., 2025). At the organizational level, the substitution of AI for core human functions heightens perceived job insecurity and employment threats, which themselves undermine well-being and performance (McClure, 2017; see Selenko & van den Broek's commentary, this article).

Paradoxically, even AI designed to meet well-being goals, such as chatbots, virtual assistants, and socially assistive robots, may disrupt healthy patterns of human interaction (Dhimolea et al., 2022; see Tang & Koopman's commentary, this article). AI-mediated interactions can alter moral and social behavior: consumers interacting with AI agents, rather than humans, report weaker moral intentions, greater willingness to behave unethically, and reduced feelings of guilt (Giroux et al., 2022), and individuals acting through AI assistants show increased willingness to deceive others (Gratch & Fast, 2022). Moreover, the pursuit of feedback from AI-driven algorithms can even undermine productivity. Overreliance on AI for emotional or relational needs may also weaken authentic interpersonal relationships that are essential for well-being (Zimmerman et al., 2024). Even the pursuit of AI-generated feedback and conversations can create counterproductive dynamics, such as dependency, distraction, cognitive overload, or shifts away from deeper forms of learning and mastery (e.g., Adanyin, 2024). Part of the underlying problem is that AI technology may not be ready for such significant well-being applications: AI counselors may at times violate ethics in mental health counseling (Iftikhar et al., 2025) and can reinforce and amplify delusions in users (Hill & Freedman, 2025). These illustrate that AI, even for well-being purposes to meet a growing unmet need in mental health (Stade et al., 2024), can unintentionally undermine both well-being and positive performance.

Promoting Synergies by Design

By contrast, technology optimists have often cast advancements in a utopian light – emphasizing the promotive potential of technological innovation. From this perspective, AI is viewed as a catalyst for elevating human flourishing by creating greater well-being and performance. Indeed, AI can relieve workers of routine, repetitive, or cognitively burdensome tasks (Gandhi et al., 2023), potentially enabling more meaningful, creative, or relational work; or reducing workload and stress for people (Gihleb et al., 2025). While AI algorithmic management has often been criticized for overmonitoring of work, and thus reducing autonomy, relatedness, and competence (Gagné et al., 2022, see Behrend's commentary, this article), these very systems can also be intentionally designed to monitor, support, and optimize both performance and well-being if these dual goals are embedded from the outset, with a focus on well-being as a pathway to greater performance.

The central challenge is that AI technologies are evolving rapidly, and their effects ultimately depend on the assumptions and values governing their design. According to Parker and Grote (2020), work design and human-centered design principles need to be explicitly considered in technology design and implementation (see also Jetha's commentary, this article). I propose that current and future AI technologies in occupational health and organizational research will need to be architected with the key principles promoting performance and well-being. This connects directly to discussions around AI value alignment (Gabriel, 2020): instead of aligning AI solely with performance, its optimization criteria should explicitly incorporate well-being, and vice versa. This serves to provide an important counterbalance needed for human flourishing.

Further, the question of who architects AI systems is critical as their decisions underpin the principles and ethics of the AI product (Griffin, 2023; see also Bankins' commentary, this article). Current approaches to address this include regulatory mechanisms (e.g., EU AI Act), organizational ethics boards, and proactive design frameworks such as Value Sensitive Design (Friedman & Hendry, 2019). However, translating high-level principles into practical design requirements remains challenging (Umbrello & van de Poel, 2021). For AI applications in organizations, we need the explicit inclusion of industrial-organizational and occupational health psychologists in development teams, along with regulatory frameworks that mandate well-being impact assessments alongside performance metrics.

Beyond this, there is evidence to suggest that more transparent and explainable AI, as opposed to "black-box" AI, improves decision performance in human-AI collaborations (Senoner et al., 2024). This is likely because such collaborations help overcome human cognitive biases and improve trust in AI through understanding its logic. Transparent AI supports well-being by enabling worker autonomy because they can understand and evaluate AI recommendations rather than passively accept them (Shin et al., 2021). When employees lack understanding of how AI affects their work, they experience heightened anxiety and reduced sense of control (Zhang et al., 2022). At a broader systems level, designing AI for positive synergy for performance and well-being requires attending not only to the algorithmic architecture and greater explainability, but also to the organizational sociotechnical ecosystem in which AI

is embedded. This includes addressing data sources and biases, enhancing workflow integration, and cultivating supportive organizational attitudes toward AI through education, transparent communication, and participatory implementation.

Implications

First, future research must delineate the specific mechanisms and boundary conditions under which AI exacerbates tensions between performance and well-being versus when it generates positive complementarities. This requires moving beyond general claims of "AI harms" or "AI benefits" toward more granular examinations of how particular features affect different aspects of performance and well-being. Rigorous experimental, multilevel, and longitudinal methodologies will be essential for capturing the dynamic effects of AI on both performance trajectories and well-being outcomes. For example, researchers can employ experience sampling methods to examine how specific AI features (e.g., degree of algorithmic transparency, level of decision autonomy, explainability of AI recommendations) relate to momentary fluctuations in stress, engagement, and task performance across different organizational contexts and job types.

Second, research and practice must articulate design principles for AI systems that explicitly integrate performance and well-being as dual optimization criteria. Rather than assuming that well-being follows from performance or vice versa, AI should be architected to satisfy both sets of objectives concurrently. This includes embedding insights from work design, human-centered computing, and motivational theory into the AI development pipeline (e.g., experts in I-O and OHP on development teams, participatory research from employees); formalizing value alignment processes (e.g., stakeholder engagement in identifying requirements, ethical reviews); and specifying how transparency (e.g., disclosing data sources), explainability (e.g., providing interpretable rationale for AI behavior and recommendations), and human oversight can facilitate more accurate decision-making, trust, and positive forms of human-AI collaboration. Such principles must be empirically evaluated to determine their effects in real-world organizational settings.

Third, future work must examine AI within its full sociotechnical context, recognizing that the effects of AI are jointly shaped by technology, organizational structures, and social systems. Research is needed to understand how organizational policies, data infrastructures, workflow integrations, leadership communication, and cultural norms shape the impact of AI on workplace health, performance, and broader flourishing. This includes investigating how organizations can create policy and governance systems that mitigate risks (e.g., job insecurity, dependency, inequity) while amplifying potential benefits to human flourishing.

Readying OSH Professionals for AI and the Future of Work

Jay Vietas

As AI continues to be introduced to workplaces, these tools will significantly influence how work is accomplished. Additional skills may be required of OSH professionals to assess emerging risks as the types of tasks, numbers and expectations of workers change, and oversight of processes becomes more automated and, in some cases, dictated by computers. Traditional models for educating new OSH professionals, as defined by ABET and the Board of Certified Safety Professionals, focus primarily on developing skills to identify, evaluate, and control chemical, physical, and biological hazards (ABET, 2021, BSCP, 2019). While some of these risks are expected to endure, the work to be evaluated and tools needed to evaluate the work are in the process of change, with an increased need to better understand, evaluate and control psychosocial risks. Meanwhile, solutions to address potential worker exposures and risk assessment are adopting AI and other technology-driven tools to manage and address worker experiences. Concurrently, workers are employing or are subject to AI tools that in some cases remove the worker from "dull, dirty, or dangerous" jobs while demanding more human-computer interface and less human-to-human interaction. These changes necessitate adjustments to the training requirements and widening of the definition of OSH professionals of the future, with specific focus on developing the skills and experiences necessary to be successful in support, development, and use of AI systems in the workplace.

According to the Stanford Artificial Intelligence Index Report for 2025, "AI is rapidly moving from the lab to daily life," with "78% of organizations report[ing] using AI in 2024, up from 55% the year before" (Maslej et al., 2025). Despite the rapidly changing work environment, it is not clear if current OSH academic training programs meet the needs of tomorrow's work environment. The most recent, albeit somewhat outdated, comprehensive evaluation of this issue was conducted by Pishgar et al., which found a lack of papers addressing AI curriculum in academia and skills needs for OSH professionals (Pishgar et al., 2021). A related survey of 20 distance learning programs by Wilbanks et al. highlighted the mismatch between curriculum requirements and employer demands, particularly in the areas of project management, auditing, leadership and training (Wilbanks et al., 2023). Newman et al. (2020) emphasized that the role of technology, the intensification of work, and psychosocial stressors would have significant implications for OSH professionals, calling for "new levels of integration" and a need for systems thinking to address future OSH challenges.

New research should examine and evaluate OSH educational systems as they relate to employment needs and anticipated workforce health and safety risk to determine gaps and make recommendations on how to consider which competencies are necessary, which ones are nice to have, and which ones are no longer needed. Ideally, this should mimic the scope and depth of a report funded by the National Institute for Occupational Health to examine OSH professional competencies (e.g., McAdams et al., 2011) in order to develop both an upskilling roadmap and academic curriculum guidance. As a start, OSH professionals and OSH educational programs should

consider adding the following types of information to their respective programs: the language and types of artificial intelligence tools, an emphasis on systems thinking from an OSH perspective, and tools to anticipate the future.

Speak the Language of AI

OSH professionals should become familiar with the basics of how AI works, the various types of tools that have been created to enable autonomous and learning systems to work. Furthermore, OSH professionals should learn the language of technology and technology development to communicate risk from the C-suite to the IT department through to the frontline worker. This knowledge will help in the development of relationships with new multi-disciplinary partners: computer engineers, IT personnel, and data management individuals. Working collaboratively with traditional partners—such as management, operations, engineering, and human resources—the team can ensure these groups remain actively engaged, bringing a human-centered perspective to the design and implementation of new systems. This collaboration also helps anticipate and adapt to rapid technological change through proactive, forward-thinking approaches that shape the future work environment. In turn, the OSH community should extend the courtesy to IT personnel by teaching them the language and practices of occupational safety and health.

Emphasizing Systems Thinking

Meanwhile for OSH professionals, there is an ever-increasing need for systems thinking (Karanikas, 2022) which can assist in understanding complex problems to improve decision-making by considering interconnections and interdependencies. As workplaces continue to add technology and systems which employ artificial intelligence, systems thinking will enable more effective human-centered solutions and improve the ability to foresee negative outcomes before the system is employed. Finally, when unexpected or unplanned outcomes occur, systems thinking can be applied to use an understanding of relationships and patterns to find root causes and sustainable solutions instead of just fixing symptoms.

Anticipating the Future

The pace of change in workplaces continues to quicken, and artificial intelligence will likely hasten this process. Historically, OSH professionals react to address adverse health and safety outcomes sharing lessons learned and developing systems to minimize the likely of future incidents or events. While predicting the future is not possible, anticipating change can assist developing informed models of the future to improve decision-making, enhance preparedness and reduce risk. Tools such as strategic foresight have been demonstrated to assist organizations such as NIOSH to explore research and practice opportunities (Felknor et al., 2023). Maintaining awareness of the results of these efforts or producing them internally for organizational purposes can assist in maintaining a proactive stance towards change (see also Jetha's and Bankins' commentaries, this article).

Artificial intelligence is fundamentally transforming how work is accomplished. Transforming OSH education to address AI integration will empower the next generation of practitioners while motivating current professionals to develop the expertise needed for success in increasingly automated workplaces.

Concluding Thoughts

The advent of AI is prompting several pressing questions that can be summarized into three buckets: "can we?", "should we?", and "how should we?" Answers to the "can we?" question are largely being driven by technological advancements outside of the occupational health sciences and appear, in most cases, to be "yes". For example, Stanford's AI Index report (Maslej et al., 2025) indicates that AI already matches or surpasses human capabilities on the majority of performance benchmarks including image classification, reading and language comprehension, Ph.D. level science questions, and visual reasoning.

The "should we?" question was thoughtfully considered by many of the commentaries in this article as they weighed the emerging empirical evidence for the benefits and hazards that are posed by these technologies. Unfortunately, as Jetha notes, that empirical evidence greatly lags behind the rapid pace of adoption. Importantly, when examining those impacts, Tay calls for expanding beyond narrow efficiency goals to instead design systems that optimize both performance and well-being as foundations for human flourishing.

Where occupational health science can offer perhaps the greatest insight is in answering the "how should we" question. As many of our commentaries consistently make clear, the occupational health implications of AI are neither inherent nor inevitable. Rather, they will be a product of AI systems design choices (including alignment), organizational governance, and implementation practices. At the outset, Bankins argues that occupational health and safety must be treated as a core ethical criterion throughout the AI lifecycle and highlights the tradeoffs that can occur, for example, when weighing safety monitoring benefits against privacy risks and surveillance scope creep. Indeed, Behrend observes that the downstream effects of workplace monitoring depend less on the technology itself and more on how organizations adopt, implement, and use these systems in practice. Dragano notes that the current AI discussion can be situated within established technostress processes (e.g., techno-overload, techno-uncertainty, and techno-insecurity), while also raising the possibility of AI-specific stressors such as techno-unpredictability due to the opacity of AI systems.

Selenko and van den Broek delve further into the levels along which such insecurity may be triggered by AI ranging from the task- to job- to occupational-levels while arguing that these effects may have differential implications for early-, mid-, and late-career workers. Moreover, recognizing that our attitudes and behaviors are shaped by the experiences of those around us, Tang and Koopman explore how AI failures might prompt contrastive vs. assimilative downward social comparison processes with attendant implications for enactment of workplace incivility vs. prosocial support. Vietas aptly ends our set of commentaries by recognizing that just as AI is

impacting the world of work, it also requires us to consider how our field must change and what new competencies will be required of OSH professionals to ensure that we realize the beneficial effects of AI while minimizing its adverse consequences.

We offer a few final thoughts as the field moves forward to pursue the agenda set forth around AI and OHP. First, while laypeople, researchers (ourselves included), and practitioners frequently use the term "artificial intelligence" as though it denotes a singular construct, it is important to highlight that at its core, artificial intelligence represents a broad class of technologies capable of simulating human intelligence through perception, learning, reasoning, and problem-solving (National Aeronautics and Space Administration, 2024). Given that there are numerous applications of artificial intelligence (e.g., medical imaging analysis, generative AI, autonomous vehicles, recommendation engines, precision agriculture, algorithmic management platforms, etc.), it follows that there can be no singular or uniform "effects of AI" on occupational health, safety, and well-being.

Second, recognizing that AI is not a monolithic construct carries important implications for our field. Namely, research that treats it as such risks producing inconsistent findings and obscuring key underlying mechanisms. For example, many people now equate AI with large language models such as ChatGPT; yet these represent only one class of AI applications among many. Computer vision systems, predictive machine learning models, autonomous robotic systems, and algorithmic management tools pose qualitatively different demands, risks, and opportunities for workers. Greater specificity, therefore, is needed in how researchers operationalize AI as well as how these are situated within particular industry or organizational contexts. Barring this, any observed "effects of AI" may reflect heterogenous technologies rather than substantive causal processes.

Similarly, beyond specific technological applications, the functional deployment of AI also matters (Selenko et al., 2022). AI that is used to *replace* human tasks versus *support or augment* existing work versus *enable and generate* new forms of work is likely to have divergent impacts on OHP-related outcomes. For example, AI systems that substitute for human labor may raise concerns about job and occupational insecurity (Selenko and van den Broek), whereas those that ostensibly support workers may reduce cognitive load but may also adversely impact perceived decision authority and autonomy (Bankins; Jetha). Those that enable the creation of new tasks may reshape skill demands, performance expectations, and career trajectories (Bankins; Vietas). Therefore, it is incumbent upon us to identify the underlying mediating and moderating mechanisms that explain and determine when, why, and for whom varying forms of functional AI deployment enhance rather than undermine occupational safety, health, and well-being.

We end with this final reflection. Klaus Schwab, former chairman of the World Economic Forum and author of *The Fourth Industrial Revolution*, wrote:

> "Technology is not an exogenous force over which we have no control. We are not constrained by a binary choice between "accept and live with it" and "reject and live without it." Instead, take dramatic technological change as an invitation to reflect about who we are and how we see the world. The more we think about how to harness the technology revolution, the more we will examine

ourselves and the underlying social models that these technologies embody and enable, and the more we will have an opportunity to shape the revolution in a manner that improves the state of the world (Schwab, 2016, p. 9)."

This quote reminds us as OHP scientists and practitioners that we are not passive reactants to the massive technological changes that are occurring, nor is it useful to have a knee-jerk rejection of them. Rather, we have the opportunity to shape the very technologies being developed and deployed by bringing the critical voice and core values of OHP to improve worker health, safety, and well-being. The commentaries in this article collectively reveal how the field of OHP can take a leadership role in determining the course of the AI revolution. Drawing from their research and practice roadmap, we can better realize our goal of ensuring that AI systems are optimally aligned with the occupational safety, health and well-being interests of workers.

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