European Agency for Safety and Health at Work

ISSN: 1831-9343

Artificial intelligence for worker management: implications for occupational safety and health

Report

European Agency for Safety and Health at Work

Safety and health at work is everyone's concern. It's good for you. It's good for business.

Authors: Karin Reinhold, Marina Järvis (Tallin University of Technology), Aleksandr Christenko, Vaida Jankauskaitė, Agnė Paliokaitė (Visionary Analytics), Arnold Riedmann (Kantar)

Project management: Emmanuelle Brun, Maurizio Curtarelli (EU-OSHA)

Europe Direct is a service to help you find answers to your questions about the European Union

Freephone number (*):

00 800 6 7 8 9 10 11

(*) Certain mobile telephone operators do not allow access to 00 800 numbers, or these calls may be billed.

ISBN: 978-92-9479-679-0

Doi: 10.2802/76354

More information on the European Union is available on the Internet (http://europa.eu).

Table of contents

List of figures and tables 3
1 Introduction 5
1.1 Rationale and objectives 5
1.2 Scope 5
1.3 Research methods 6
Literature review 6
In-depth expert interviews 6
Statistical data analysis of ESENER-3 7
1.4 Structure of the report 7
2 AIWM and OSH 8
2.1 Risks of AIWM for workers' safety and health 8
2.2 Opportunities of AI-based management approaches for OSH 14
2.3 AIWM and OSH: evidence from ESENER-3 16
3 Prevention measures 21
4 Conclusions and recommendations 24
References 27
Annex I – Analysis of Third European Survey of Enterprises on New and Emerging Risks 2019 (ESENER-3) data 35
Annex II – Experts interview questionnaire 52

List of figures and tables

Figure 2-1: Establishments using digital technologies that discuss possible health and safety impacts of technologies, by type of technology (EU-27, %) 18
Figure 2-2: Establishments that discussed the impact of digital technologies by type of impacts discussed (EU-27, %) 19
Figure I-1: Workplaces reporting discussions on the possible health and safety impacts of digital technologies by size (EU-27, %) 45
Figure I-2: Workplaces reporting discussions on the possible health and safety impacts of digital technologies by main activity of the establishment (EU-27, %) 43

Table 2-1: Establishments by specific OSH risks (based on ESENER-3 Q200 and Q201) and the usage of digital technologies (based on ESENER-3 Q310) (EU-27, % - 2019) 17
Table I-1: Binomial logit regression models analysing factors correlated with the usage of robots that interact with workers (use of robots = 1) 36
Table I-2: Binomial logit regression models analysing factors correlated with the usage of machines, systems or computers determining the content or pace of work (machines determining the content or pace of work = 1) 38
Table I-3: Binomial logit regression models analysing factors correlated with the usage of monitoring technologies (monitoring = 1) 40

Table I-4: Binomial logit regression models analysing factors correlated with the usage of wearable devices, such as smart watches, data glasses or other (embedded) sensors (wearables = 1) 43

Table I-10: Workplaces by type of measures undertaken to prevent psychosocial risks in the last three years, by type of digital technology used (EU-27, %) 51

1 Introduction

1.1 Rationale and objectives

Based on research by the European Commission (2021), the European Parliamentary Research Service (2020, the High-Level Expert Group on Artificial Intelligence (2019a) and EU-OSHA (2019), **artificial intelligence (AI)-based worker management** (AIWM) is an umbrella term that refers to a **worker management system that gathers data, often in real time, on the workspace, workers, the work they do and the (digital) tools they use for their work, which is then fed into an AI-based model that makes automated or semi-automated decisions or provides information for decision-makers on worker management-related questions**. It is one of the recent developments in the workplace that presents opportunities but also risks and challenges for workers' safety and health.

Building on its foresight work, in 2020 the European Agency for Safety and Health at Work (EU-OSHA) initiated a four-year research programme on digitalisation and occupational safety and health (OSH). The aim of the programme is to support evidence-based policy-making by providing deeper insights into the consequences of digitalisation on workers' health, safety and wellbeing and how these are addressed at the research, policy and practice levels, as well as by describing examples of successful practices.

Complementing the findings presented in EU-OSHA (2022), this report presents OSH risks and opportunities of AIWM approaches, gives an overview of the current uses of AIWM systems and related OSH risks, identifies gaps, limitations, needs and priorities for OSH, and formulates recommendations for the prevention of OSH risks. It also highlights the need for further research.

According to the report, AIWM can provide potential avenues for opportunities in improving workers' OSH, for example, by providing tools for better monitoring of hazards and the mental health of workers, improving workers' engagement and job satisfaction, helping to design and conduct safety training, and more. However, the findings indicate that the use of AI to manage workers also poses numerous risks to OSH, including, but not limited to, workers losing control over their jobs, increased work intensity and performance pressure, decreased social support from managers, individualisation and dehumanisation of workers, creating an unhealthy competitive environment, a lack of transparency and a loss of power for workers and their representatives, mistrust, limited worker participation, blurring work–life balance, and more. These risks in turn might lead to numerous negative consequences for workers´ physical and psychosocial wellbeing, such as musculoskeletal disorders (MSDs), cardiovascular disorders, fatigue, stress, anxiety and burnout.

The report suggests that a strong 'prevention through design' approach that integrates a human-centred approach in the design and usage of AIWM is needed. AIWM should be designed, implemented and managed in a trustworthy, transparent, empowering and understandable way, guaranteeing workers' consultation, participation and equal access to information, as well as putting humans in control and therefore ensuring that AIWM is used not to replace workers but to support them. This can be achieved through different means, including open and effective dialogue, worker training and active participation in the development, implementation, use and evaluation of such systems, increasing awareness of relevant stakeholders (for example, developers, workers, employers) on how AIWM systems might negatively affect OSH, and creating a strong ethical framework describing how AIWM should be developed, implemented and used, as well as ensuring compliance with existing legal provisions applicable to AIWM. A set of recommendations for OSH risk prevention concludes the report.

1.2 Scope

The report builds on a recent EU-OSHA (2022) report that described what AIWM systems are, the possible reasons why organisations implement such systems, what challenges the implementation of such systems create, how the EU as a whole and the individual Member States regulate such systems, and more. Geographically, this report focuses on EU-27 (2020) countries with insights from the four European Free Trade Association countries (i.e. Iceland, Lichtenstein, Norway and Switzerland) discussed when relevant.

1.3 Research methods

The analysis presented in this report was carried out on information gathered through a literature review, in-depth expert interviews, and statistical data analysis of EU-OSHA's Third European Survey of Enterprises on New and Emerging Risks (ESENER-3).

Literature review

The literature review is one of the cornerstones of this research. The literature review was used to identify the risks, challenges and opportunities for OSH associated with the use of AIWM systems and was carried out on international scientific literature and grey literature on AIWM systems and OSH implications, complemented with searches for additional material on the Internet and researchers' network. The following databases were searched: Web of Science, ScienceDirect, Scopus, EBSCOhost, PubMed and Google Scholar. For the grey literature, publication databases of the main international organisations active in the areas of economics, statistics, labour (Organisation for Economic Co-operation and Development, International Labour Organisation, Eurofound, European Commission, European Trade Union Institute, Eurostat), and OSH (EU-OSHA, Health and Safety Executive, IRSST (*Institut de recherche Robert-Sauvé en santé et en sécurité du travail*), INRS (*Institut national de la recherche scientifique*), National Institute for Occupational Safety & Health) were reviewed.

The search strategy included predefined inclusion and exclusion criteria, subject indexing terms, and free-text terms for title, abstract and keyword searching. Keywords were used similarly in each database as follows: ("artificial intelligence" or "AI" or "algorithmic management") and ("occupational health" or "occupational health and safety" or "worker's health" or "worker's health and safety" or "OSH"). Keywords "AIWM" or "AI worker management system" were left out as they provided none or very few articles for review. Other keywords were used as well, for example, "health", "safety" or "worker monitoring", and "worker surveillance", but those gave too many hits.

All results were then screened based on the title, abstract and keywords; the full text for selected abstracts was obtained (if available through a university library engine or openly accessed via the Internet) and examined in more depth. In addition, reference sections were carefully reviewed to identify additional relevant articles. Altogether, 138 relevant papers were included in the analysis.

The following limitations were noted during the literature review:

- The terminology used by researchers to define AI and AIWM lacks uniformity.
- Scholars often fail to differentiate between AI and simple rule-based algorithms when describing new forms of worker management. For this reason, it is not always possible to determine the level of AI integration, or if AI is used at all in certain examples or cases described in the literature.
- AIWM is a new and emerging trend in the business world. As such, it has been primarily researched in the context of positive outcomes and opportunities for businesses. Research on AIWM implications on workers and/or OSH is still rare, but even so, it is important to make assumptions about risks or to provide empirical evidence.

In-depth expert interviews

In-depth expert interviews were carried out to gather more up-to-date and deeper insights into AIWM systems, the barriers and drivers of the implementation of these systems, their current uptake across European countries, and what OSH-related risks the implementation of such systems might bring. They were meant as well to gather insights on relevant policies, strategies, initiatives, programmes and codes of practice. In total, 22 interviews were carried out.

Individuals from the following sectors and areas were interviewed: academic experts in the field of AI, AIWM and OSH; representatives of relevant think tanks/advocacy groups; representatives from EU agencies and relevant international and national organisations; social community partners; and AIWM tool developers/consultants.

Statistical data analysis of ESENER-3

Statistical data analysis supplemented the research by providing insights on the impact of technologies that enable AIWM in a number of areas related to OSH, including internal discussions of such impacts. The analysis was carried out on ESENER-3[1] data employing bivariate and regression models. On the one hand, bivariate analyses provided general insights about the perceived health and safety consequences of technologies that enable AIWM. On the other hand, regression analyses allowed to validate and expand on the insights from the bivariate analysis. The full analysis is presented in Annex I, while an overview of the most interesting findings is included in section 2.3. The analyses of the uptake of the digital technologies enabling AIWM and the characteristics of the organisations that use them are not presented in this report, as they were presented in the related EU-OSHA (2022) report.

1.4 Structure of the report

In addition to this introductory section, the report is structured along the following chapters:

- **Chapter 2. AIWM and OSH** – a critical assessment of implications, both positive and negative, of AIWM systems on workers' safety and health.
- **Chapter 3. Prevention measures** – provides insights on how OSH risks and challenges stemming from the use of AIWM systems could be prevented.
- **Conclusions and recommendations** – summarises and concludes the report, and presents a number of recommendations.

A list of references, a statistical annex and the expert interview questionnaire complete the report.

[1] See: https://osha.europa.eu/en/facts-and-figures/esener

2 AIWM and OSH

AIWM refers to a worker management system that gathers data, often in real time, from the workspace, workers and the work they do, which is then fed into an AI-based system that makes automated or semi-automated decisions, or provides information for decision-makers (for example, human resources (HR) managers, employers and sometimes workers), on worker management-related questions (EU-OSHA, 2019; European Commission, 2021; European Parliamentary Research Service, 2020a; High-Level Expert Group on Artificial Intelligence, 2019a).

As extensively discussed in EU-OSHA (2022), AIWM systems are employed predominantly to improve productivity and efficiency of workers (Kellogg et al., 2020; Mateescu & Nguyen, 2019; PEGA, 2020). AIWM can help to achieve this through many different means, including, but not limited to: enhancing worker monitoring/surveillance through, for example, performance, safety, emotion monitoring (Ball, 2021; Eurofound, 2020); people analytics[2] that allows to identify, for example, if a worker left their assigned working route or to identify the workers who are planning to quit (Collins et al., 2019; Kellogg et al., 2020); automating scheduling and task allocation (Kellogg et al., 2020); providing directions and recommendations to workers in real time on how they can perform their tasks in a more efficient way (Fisher, 2019; Punnoose & Ajit, 2016), and much more. AIWM systems are able to perform these complicated tasks as they are able to evolve and 'learn' with minimal human supervision as they can 'figure out' the best course of actions based on data (for example, information on workers' performance) and how recommendations or decisions they provide (for example, how to perform a specific task) change the aforementioned data. Though currently such systems are relatively rarely used by organisations, their popularity is growing (EU-OSHA, 2022). Several interviewed experts consider that early adopters are the most innovative organisations across economic sectors and countries.

The growing popularity and fast development of AIWM systems leads to opportunities for the management of work and workers, but, at the same time, may pose some risks and challenges to ensure workers' safety, health and wellbeing. As noted by several scholars (Aloisi & Gramano, 2019; Jarota, 2021; Todoli-Signes, 2021; Wood, 2021), there is still scarce knowledge and little comprehensive scientific and empirical information regarding the various impacts of these powerful and intrusive innovations, particularly on OSH. Nevertheless, given that AI-based systems are expanding to many sectors, countries, professions and jobs (EU-OSHA, 2022), it is essential to consider the implications such systems may have for workers and their health and safety. Hence, the remainder of this chapter presents the risks, as well as the opportunities, that AIWM systems might create for OSH. The chapter concludes with an analysis of ESENER-3 data, which provides additional insights on how different technologies that can enable AIWM might affect OSH.

2.1 Risks of AIWM for workers' safety and health

Intensification of work

The **intensification of work** is one of the most frequently reported risks related to the use of AIWM systems. To increase productivity, organisations might implement AIWM systems that direct workers to **work without mini-breaks**, minimise the time for certain procedures and force them to **work at high speed**. A common example of the intensification of work due to AIWM can be found in warehouse operations: to speed up work, AIWM is used for tracking order completion time as well as workers' movements, mistakes and breaks, in order to eliminate 'unnecessary time lags. Such systems are also employed in white collar jobs. For example, Barclays, a bank based in the United Kingdom, uses tracking software in some of its offices to monitor the time workers spend at their desks or the length of their toilet breaks, informing the workers when their breaks are deemed by the algorithm to be too long, which results in increased work intensity (Eurofound, 2020; European Parliamentary Research Service, 2020). It is also important to mention that such direction systems, according to some authors, could be used to improve safety (Halawa et al., 2020). However, according to Mulholland and Stewart (2013), workers' safety and health is rarely a priority as it comes after lean logistics and the speed of work. More specifically, high speed in delivering goods has become so important that, for example, in some

[2] Systems that measure, report and understand employee performance (Collins et al., 2019) and other aspects of work (Kellogg et al., 2020).

warehouses workers are rewarded if they manage their tasks within half the time required and are thus able to complete more orders during their shifts.

Loss of job control and autonomy

Loss of job control and autonomy are also commonly reported risks related to the use of AIWM systems in the workplace: some AIWM systems can take over the control of work (e.g. content, pace, schedule) through, for example, worker direction, and little will be left to be decided by the worker (Curchod et al., 2020; Kellogg et al., 2020; Saithibvongsa & Yu, 2018). Also, most algorithmic and AI-based systems dictate how to perform work or tasks to the worker and this can result in a loss of control over their work (Curchod et al., 2020; Kellogg et al., 2020). The usage of AIWM systems that heavily control workers might also **take away the margin of manoeuvre** from workers. Margin of manoeuvre, according to Durand et al. (2016), refers to the possibility that a worker may develop different ways of working in order to meet production targets, without having adverse effects on their health. **The loss of job control and autonomy is frequently associated with high levels of stress, and also lead to lower productivity, poor performance and increased levels of sickness absence** (HSE, 2017). According to Karasek's (1979) job demands-control model, 'high-strain' jobs, where employees have high demands at work and at the same time very little control over what they do at work, have the highest negative impact on mental health. High demands and low control hinder a worker's capacity to choose the method and time frame to complete a job, yet require a high number of cognitive resources, which can lead to psychosocial ill health.

Dehumanisation of workers

Active use of AIWM systems, such as through excessive worker direction, evaluation or discipline, might also lead to **dehumanising workers** and, in the long run, force them to behave as machines (Carr, 2014; Danaher, 2018; EU-OSHA, 2018; Heaven, 2020), **which could then lead to decreased cognitive and intellectual capacities, decrease of creative thinking, a loss of autonomy, shortness of independence of thought and so on**. It is worth noting that while AIWM systems are expected to be able to inform workers and employers about risks (e.g. probability of fatigue and burnout), they might also lead to dehumanisation of workers as they might become dependent on the warning system created by AI and possibly **lose** their own **ability to recognise hazards** once something goes wrong. In turn, this might lead to ill health or work-related accidents.

'Datafication' of workers

It can also be argued that by introducing automation and AI-based technologies, organisations might start to see workers as mere objects or collections of 'objective' digital data that they produce while working (De Stefano, 2018), while at the same time removing margins of manoeuvre from workers, or even controlling their emotions. This dehumanisation can be referred to as the ***'datafication'*** of workers (Gal et al., 2020; Mai, 2016) – treating workers as collections of digital data. Although datafication is used for the digitisation of different aspects of work and tracking in real time, analysing and predicting workers' behaviour (Subedi & Pradhananga, 2021), the quantification of human life through data is controversial and may serve only economic purposes and can discriminate against individuals (Eubanks, 2017).

Worker discrimination and use of private and sensitive data

Discrimination is recognised as a main stress factor at work, and it is related to mental health issues. Usage of AIWM systems can also result in **worker discrimination**, as intrusive monitoring can involve **collecting private and sensitive data** (Ravid et al., 2020),[3] which can in turn be used to make automated or semi-automated decisions about the worker. This can result in favouring certain workers and discriminating against others, for example, at the stages of hiring or appraising/promoting workers. Even though AIWM systems may offer accuracy when looking at the desired profile of candidates in a selection process, they may make assumptions on candidates based on their characteristics (for example, gender, ethnicity, nationality, age, sexual orientation, gender identity) and then make decisions resulting in some form of worker discrimination (EU-OSHA, 2018; Fernández-Martínez &

[3] AI can also be employed to collect data to infer about workers' beliefs, choices or life style. For example, Wang and Kosinski (2018) demonstrated that, with the help of deep neural networks, a facial detection software able to identify a person's sexual orientation can be developed, while Yaden et al. (2018) proved that with the help of computational linguistics, it is possible to predict an individual's religious affiliation.

Fernández, 2020), especially when AIWM systems are designed incorporating a bias. Also, AIWM may be misused when rewarding and disciplining workers. For example, according to Kellogg et al. (2020), 'workers who exhibit desired behaviour are rewarded with promotions, higher pay …' (p. 380), which might include rewarding workers who overwork, or who belong to a specific age or ethnic group.

However, it bears mentioning that in the EU, the collection of private or highly sensitive data is restricted by existing regulations, such as the General Data Protection Regulation (GDPR).[4] Nevertheless, according to interviewed experts and some academic literature, the GDPR, Council of Europe's Data Protection Convention 108+ (COE),[5] the newly proposed regulation on AI,[6] and others have many limitations preventing them from truly safeguarding workers from excessive monitoring and subsequent discrimination. According to Oostveen (2016), the regulations adopt an old-fashioned understanding of the three-phase process of data processing: acquisition, analysis and application. This is an issue as regulations do not prevent from using personal and non-sensitive data to infer, derive or predict highly intimate sensitive information, such as emotional wellbeing (Privacy International, 2017). In addition, though GDPR provisions allow individuals to prevent organisations from collecting their private data, it is not enough for workers: the GDPR makes little reference to workers and workers are sometimes forced by employers to give their consent to collect their data due to fear of losing their jobs in case they refuse. This prevents many workers from exercising their data protection rights.[7] Privacy of workers and ethical implementation of AIWM are the most striking issues highlighted in the reviewed literature (Gal et al., 2020), which, if ignored, can lead to stress, anxiety, performance pressure and other OSH-related issues.

Performance monitoring and impact on workers

AIWM can also force workers to work faster through **constant monitoring, including monitoring the actions they perform and their productivity**. When workers are aware that they are constantly monitored and their performance is evaluated, they may refuse to take breaks when needed and they might also neglect social interactions with other peers (EU-OSHA, 2018) in order to catch up with the schedule or follow the directions provided by the AIWM system. For example, when Disney Resorts introduced an electronic leader board with a traffic light theme that tracked the performance of laundry staff, workers were struggling to keep up and started skipping bathroom breaks. The workers referred to the leader board as 'the electronic whip' (Lewis, 2019). Such systems that create a complete overview of one's performance that is visible to peers may also result in an unhealthy **competitive environment between colleagues**. In turn, this kind of pressure can lead to anxiety and low self-esteem in workers (EU-OSHA, 2018). Similarly, according to de Oliveira (2021), gamification[8] is also often associated with work intensification.

Research (EU-OSHA, 2019; Jarota, 2021; Neagu & Vieriu, 2019) reveals that the **constant monitoring and assessment of workers** facilitated by AIWM is also found to **increase workers' exhaustion, stress, anxiety and fear of losing their jobs** and, therefore, might increase the probability of mental health disorders. In addition, according to Palmer (2021) and Cater and Heikkilä (2021) who studied drivers who had AI-powered cameras integrated in their cars, it was found that these workers often feel extra pressure as they are constantly monitored, leading to anxiety or fear of losing their jobs. Similarly, according to Berger et al. (2019), some United Kingdom Uber drivers might experience elevated levels of anxiety caused by constant monitoring by AIWM systems. Data gathering and constant monitoring through AIWM systems can also lead to **techno-stress**, and, more specifically, **to techno-anxiety** and **techno-fatigue** (Eurofound, 2020; Todoli-Signes, 2021). Techno-stress is defined as any negative impact on thoughts, behaviour, attitudes and psychological states that are associated with the use of new technologies and can lead not only to mental fatigue, anxiety and a sense of ineffectiveness but also to human error and possible accidents. Expanding on this, Brivio et al. (2018) point out the different dimensions of techno-stress. One of these dimensions is defined as techno-anxiety, referring to technology use that creates fear and apprehension when the individual feels unsure about technology. Another type of techno-anxiety can be described as 'time panic' when an employee feels that they lack

[4] For more, see: https://gdpr.eu/

[5] See: https://www.coe.int/en/web/data-protection/convention108-and-protocol and https://rm.coe.int/1680078b37

[6] See: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021PC0206

[7] For more insights on existing EU and national-level regulations that might apply to AIWM and the gaps they contain, see the EU-OSHA (2022) report.

[8] Gamification refers to bringing ideas and concepts from games, such as rewards for milestones, into the work environment to improve efficiency and productivity (Savignac, 2019).

time to understand and remember everything in connection with technology and finishing tasks on time (Wang et al., 2008). Techno-fatigue, on the other hand, is characterised ‘by feelings of exhaustion and mental and cognitive exhaustion due to the use of technology, which is also accompanied by sceptical attitudes and inefficiency beliefs regarding the use of information technology’ (Estrada-Muñoz et al., 2020, p. 8).

Worker rating systems

Performance pressure might also be exacerbated by, according to Wood and Lehdonvirta (2021), customer satisfaction rating systems that lead to customer algorithmic empowering. More specifically**, AIWM can use customers’ rankings to penalise workers, ignoring possible biases in the opinions of customers, and leading to insecurity among workers** (Frey & Osborne, 2013; Lee et al., 2015). According to interviewed experts, these issues might be further exacerbated if there is no transparency from the managers on how workers are rated, as well as if workers are unable to contest these ratings and evaluations.

Risky and unsafe worker behaviours

If the performance pressure is created by AIWM, for example, through algorithmic direction that increases the speed of work, or through evaluation algorithms that rate workers and force them to work more, this creates a tendency for **risky or unsafe behaviours** as workers may need to choose between following directions and being productive or staying safe and healthy. For example, workers may decide to remove the safety guard of a machine in order to complete the work procedure in a shorter amount of time or take a faster or more dangerous route to deliver goods to the consumer. Excessive control can also lead **to a low safety culture** as workers start to favour productivity over safety, as well as have less time to communicate with their peers and thereby transfer their OSH knowledge (EU-OSHA, 2018).

Repetitive movements, awkward postures and ergonomic issues

The push to work faster can also lead to a **higher number of repetitive movements, awkward postures due to rushing, and less attention paid to a worker’s body and limb position and ergonomics**. The repetitive movements that involve the same muscle groups, a fast pace and high quantity of work are especially hazardous, as the worker has no time to recover in the short periods of time between the motions. In the long run, the body needs more effort to perform the task and recovery time becomes even more important. Hence, the faster the pace, the less time is available for recovery, and the higher the risk for MSDs (Descatha et al., 2020; Finneran & O’Sullivan, 2010). In addition, intense work can result in high levels of work-related stress, fatigue, exhaustion and burnout (EU-OSHA, 2018).

AIWM systems might also help to boost productivity through **customisation**. That is, workstations can be personalised for each individual worker, tailored to their specific characteristics, including using movement data from workplaces and calculating the probability of each worker’s ergonomic risks. However, this positive aspect can also lead to risks. For example, if another worker who is using the workstation temporarily or for another reason does not know how to re-customise, it **can lead to ergonomic-related problems and MSDs if such a workstation is used for a prolonged period of time**. The habit to customise can also further cause problems with working stations and equipment used for purposes other than for which they were designed (EU-OSHA, 2018). In addition, working with personalised AIWM allows to provide personalised support to an ageing workforce or extending working life for a longer period of time – they can work flexible personalised working times, or with the most suitable equipment adapted to their individual needs, or complete tasks that do not need quick movements and so on. This positive aspect may turn into a negative aspect when extending working life to an older age means that the individual is exposed to OSH risks specific to their workplace for more years and, thus, develop ill health, which may not have happened if the worker had retired earlier (EU-OSHA, 2018).

Worker reskilling and deskilling

In addition, according to EU-OSHA (2018), some tasks taken over by new technology may lead to situations where workers’ initiative, concentration and skills are not required and jobs may lose meaning, and thus result in decreased job satisfaction. Interviewed experts also stressed the issues of **reskilling and deskilling of the workforce** because of AIWM, which may lead to a high level of work-related stress, increased levels of boredom and lower job satisfaction (CWA, 2017; Mishra et al., 2019). The study of an Italian Amazon warehouse reveals that algorithmic direction dispossesses workers of essential and required knowledge for performing their work tasks (Delfanti, 2019). In addition, fast technological change may require workers to learn new skills (Ra et al., 2019) and, even, may lead to skills-displacing technological change, which can be defined as 'technological change that may render workers' skills obsolete' (McGuinness et al., 2019, p. 3). Related to AIWM, this implies that some systems, such as those that direct workers, might lead to workers losing some of their skills.

Worker loneliness and social isolation

In addition, extensive usage of AIWM by an organisation can also make workers **feel lonely and isolated**. This is because such systems often force workers to communicate less with their peers by forcing them to work more and focus on productivity. In turn, due to the lack of communication between workers, and a lack of social support, the environment is not encouraging for camaraderie and no close work community is formed (Bérastégui, 2021). This, in turn, may lead to **fierce competition** among employees and thus endanger cooperation and team spirit and the working climate more generally. These problems can increase work-related stress and, initially, may also cause workplace bullying and mobbing (O'Moore & Lynch, 2007). In turn, feelings of loneliness and isolation can lead to depression (Cacioppo et al., 2006), anxiety (EU-OSHA, 2019), and can even decrease people's capacity for reasoning and decision-making (Murthy, 2017). Working in isolation can also decrease one's professional identity – employees lack role models or mentors and therefore cannot establish a consistent and strong professional identity (Bérastégui, 2021). In addition, Hawkley et al. (2010) showed that if the effect of loneliness accumulates, it can increase systolic blood pressure. The same study also indicated that the effect of loneliness on systolic blood pressure did not depend on age, ethnicity, gender, medications or health conditions. Finally, **loss of support from managers/supervisors** in cases where AIWM systems replace them might lead to increased stress, anxiety and, in some cases, burnout in workers (Bérastégui, 2021). This is because supervisors play a key role in providing support to workers, as well as rewards and resource allocation (Jabagi et al., 2020), which often serves to mitigate the negative effects of high-strain jobs (Bérastégui, 2021).

Resisting algorithmic management

Usage of AIWM might also lead to workers **resisting algorithmic management**, which might lead to **animosity and lack of trust between workers and employers, in turn leading to negative psychosocial effects**. For example, Lee et al. (2015) studied Uber and Lyft platform drivers and their motivation to follow algorithmic directions and algorithmically assigned work and found that they did not always obey the rules. Workers found several reasons to manipulate the system, for example, briefly turning it off to avoid long trips or dangerous neighbourhoods, or staying tuned in when needing a break, and parking in-between other ride sharing cars in order to get the hourly payment promotion, while not getting a ride request at the same time. This, in turn, might lead to stress and anxiety in workers if an algorithm would interpret such actions as negative and punish workers as a consequence. Though the example refers to platform work, similar issues can apply in all organisations where AIWM tracks and dictates how workers should perform their work.

Lack of transparency and trust

The **lack of transparency about how AIWM systems operate** is a frequently reported issue. Namely, many scholars and interviewed experts argue that worker monitoring, or usage of AIWM systems, is not usually implemented in a transparent way in organisations. Most managers and workers do not know how AIWM systems work, while some workers may not even be aware of being controlled or monitored by AI-based systems. Therefore, employees must be trained and clearly informed about the functioning of the AIWM systems and what data is collected and why, as well as be able to trust their employers to implement AIWM systems for good reasons, and this requires transparency within the organisation and proper worker consultation and participation. However, according to interviewed experts, many organisations are not truly transparent about what kind of data they collect and how it is used. This lack of transparency is reportedly related to informational asymmetries (Gregory, 2021; Rosenblat & Stark, 2016; Shapiro, 2018; Veen et al., 2020), which provide an advantage only to those who hold full information.

This is also an issue at the AIWM system development level. Hutson (2018), citing Odd Erik Gundersen, reported that according to a survey of '400 algorithms presented in papers at two top AI conferences in the past few years where he found that only 6% of the presenters shared the algorithm's code … [o]nly a third shared the data they tested their algorithms on, and just half shared the "pseudocode" – a limited summary of an algorithm' (Hutson, 2018, p. 725), to point out that developers often hide crucial information about their systems.

The lack of transparency in the deployment of AIWM systems in the workplace, according to several interviewed experts, might in turn **endanger good relations between employers and workers**, **reduce workers' trust in the manager**, and consequently **discourage the acceptance and proper use of AIWM systems**. For example, Garzia (2013, as cited in Eurofound, 2020) reports that workers feel discomfort, frustration and vulnerability when working in an organisation that uses monitoring systems, which are associated with a lack of trust in management. Here the main issue seems to be the lack of communication about why and how the monitoring systems were used. Therefore, many interviewed experts stressed that it is important to ensure transparency in the organisations. More specifically, according to them, if in an organisation workers are managed through control and command approaches, the usage of AIWM systems will predominantly be based on monitoring and controlling workers. However, if an organisation promotes the participation and the involvement of workers' trust, the same tools will be used to support workers in their work.

Power asymmetry

AIWM systems are also reported to **deeply alter the industrial relations** within an organisation (Aloisi & Gramano, 2019). For instance, the heavily competitive culture that AIWM systems might create through, for example, gamification can prevent workers from teaming up and can lead to the deterioration of organising and negotiating power (Eurofound, 2020). Similarly, heavy worker monitoring that allows employers to collect sensitive data on workers further shifts some power from workers to employers. The **power asymmetry can trigger feelings of anxiety and vulnerability in workers** (Curchod et al., 2020). A recent study by Tomprou and Lee (2022), focusing on how algorithmic management may affect the relationship between employer and employees with a focus on psychological contracts and employees' perceptions of their own and their employers' obligations, sheds some light on this. For example, the study demonstrates that the way in which employees form and evaluate their psychological contracts with an algorithmic (versus human) agent depends on inducements (e.g. relational or transactional). According to Tomprou and Lee (2022), employees perceived greater employer commitments when the human agent communicated and explained the relational inducements in recruiting (e.g. during a video-based recruiting process). In addition, regardless of the inducement type, people reported greater turnover intention when the human agents under-delivered as compared to the algorithmic agents. Finally, according to some (e.g. Sarbadhikari & Pradhan, 2020), as well as several interviewed experts, the COVID-19 pandemic led to further shifts of power from workers to employers. This is because as many people started to work from home many organisations started to employ intrusive worker monitoring systems, often called 'tattleware, that are installed on workers' computers and that monitor their activities all the time (Kelly, 2021; Sarbadhikari & Pradhan, 2020). In turn, this leads to information asymmetry where employers have insights on what workers are doing all the time (for more, see EU-OSHA, 2022). These are some initial findings as to why, according to several researchers (Duggan et al., 2019; Meijerink & Bondarouk, 2021; Tomprou & Lee, 2022, Wood, 2021), more research is necessary on how algorithmic management affects employee–employer relationships.

Malfunctioning and consequences for workers

The aforementioned risks can be further exacerbated if **AIWM malfunctions** through data input or analysis problems, inaccuracies with systems and other software problems (Brione, 2020; EU-OSHA, 2019). For example, if an AIWM tool directs workers towards a hazardous situation, it can **lead to severe physical harm and, in some cases, even death**. This issue is especially prevalent in the manufacturing sectors and warehouse-centric work where accidents between vehicles and humans can occur. Malfunctioning AIWM systems can also have a negative psychological effect as workers might feel frustrated and/or confused when they do not get clear and sufficient responses to their questions and relevant information, for instance, on how to perform tasks, or when communication and the distribution of tasks within an organisation is organised and managed by using automatic response systems and AI-based systems (Todoli-Signes, 2021). Issues of AIWM malfunction can also further increase as AIWM systems often employ black box approaches that might lead to **difficulties to understand models that, if they make a mistake, are often not immediately apparent**. Therefore, when AIWM, and an AI-based system in general, is implemented, it is essential that employers and workers are involved in the risk assessment process in order to identify and assess important risks, which, in the long run, may result in the ill health of workers. In other words, it is crucial to keep 'the human in the loop' during the development, deployment, usage and evaluation stages of such systems.

Other risks related to AIWM

A heavy use of AIWM systems might also negatively affect workers indirectly by, for example, increasing the need for stronger Wi-Fi networks, such as those that utilise 5G technology, in turn **increasing levels of electromagnetic fields** to which workers are exposed (Karaboytcheva, 2020). For example, according to Kerravala (2021) and Karaboytcheva (2020), 5G allows one to create and use low latency, mass connectivity, high reliability, and high bandwidth AI, and presumably AIWM, systems. One example of this related to AIWM is the monitoring of vehicle assembly by thousands of cameras where visual inspection software with deep learning algorithms can be used to detect defects in vehicles, as well as to instruct workers and allocate tasks following the inspection. However, caution has to be taken with systems that increase the intensity of electromagnetic fields at the workplace as, according to some (IARC, 2011; Russell, 2018), this might lead to issues such as headaches, anxiety, nausea and fatigue all the way to sperm damage, immune dysfunction and possible carcinogenic effects. However, it must be mentioned that the effects of 5G technology on health are still relatively poorly explored where some researchers support possible health-related risks while others do not (Karaboytcheva, 2020).

On a final note, it is worth mentioning that many organisations **do not sufficiently consider how AIWM, and AI-based systems in general, might affect OSH**. For example, one expert stated that risk assessment of AIWM is usually done only at the development stage by developers, and that validation tests lack OSH considerations. In addition, organisations may not conduct adequate risk assessments before starting to use these AIWM systems because of the complexity of the systems themselves.

2.2 Opportunities of AI-based management approaches for OSH

Opportunities for OSH

In addition to the risks described in section 2.1, AIWM systems might also bring opportunities for OSH, as highlighted by interviewed experts and the scientific literature (e.g. Brione, 2020; EU-OSHA, 2018; Maroney, 2018; Mullen, 2021; Tursunbayeva, 2019). As mentioned earlier in this report, such systems can collect and analyse large amounts of data, often in real time. Therefore, they are able, for example, to:

- provide early alerts and warnings of OSH risks to workers;
- analyse the efficiency of different OSH-related solutions; and
- propose possible interventions on how to improve OSH.

However, according to interviewed experts, though the potential of AIWM systems to support and contribute to OSH improvement is high, currently a majority of organisations employ these systems to increase productivity of workers and raise profits, rather than enhance OSH. Nevertheless, if organisations are required, by law or through other means, to ensure that AIWM systems also support OSH, they might bring a lot of value to workers. Hence, the remainder of this section discusses in more detail what kind of opportunities AIWM might bring to OSH. For more information on how it can be ensured through regulations that AIWM takes OSH into account, see EU-OSHA (2022).

Risks monitoring

One way in which AIWM might improve OSH is through improving monitoring of the workplace, the workers and the work they do by analysing, in real time, human behaviour and work patterns. This can be used to improve **OSH risks monitoring** (Min et al., 2019). For example, AIWM tools that direct workers on how to perform their tasks might also monitor their posture to identify if it is inappropriate and if it poses MSD risks (Katwala, 2017). This can be done by, for example, using a framework developed by Alwasel et al. (2017) that allows to identify whether workers are working in a productive way without jeopardising their health through unsafe poses. One expert also mentioned that such systems can be used to identify **whether or not a worker who is working with dangerous equipment is concentrated** on the work tasks being carried out, as mistakes due to distractions or lack of concentration could lead to injuries. Other scholars (Aliabadi et al., 2014; Ciullo et al., 2019 Iida et al., 2021) have also acknowledged the advantages of AIWM systems as a supportive tool for OSH experts and occupational health doctors, for example, by providing data and analyses for the diagnoses of work-related, or even occupational, diseases. **AI can also be used to detect if a worker is wearing the right protective gear**, thus reducing the risk of accidents and health disorders. For example, AIWM can detect if a worker is working at a designated height without taking adequate safety precautions (e.g. harness equipment) and warn them about this, as well as send an alarm to the control centre (Palazon et al., 2013).

Mental health monitoring

Enhanced monitoring through AIWM systems can also allow for workers' **mental health monitoring**, for example, by assessing workers' psychological distress levels as revealed in a Japanese study (Doki et al., 2021) and in an Italian–Mexican study (Hernandez-Leal et al., 2015), or estimating the probabilities for different psychosocial issues (e.g. burnout) (Oracle and Workplace Intelligence, 2020; Zel & Kongar, 2020). The idea behind mental health monitoring using technology is not new, as the first attempts were conducted already in 1968 to utilise voice analysis to predict cognitive stress and detect emotions (Hecker et al., 1968). AI allows to bring this forward by creating tools that are able to more accurately, and in real time, identify stress in workers through their writing and speech patterns (Lu et al., 2012; Rachuri et al., 2010). Nevertheless, researchers note that in order to predict a worker's stress level through voice or emotion analysis, a large amount of data is needed for the development of a user-specific model, and classification accuracy can be problematic (Hernandez-Leal et al., 2015), as different individuals respond to different stressful situations differently (i.e. coping abilities, coping styles and personalities can vary to a great extent). AIWM can also be employed to **detect burnout and exhaustion** in workers and would therefore allow for prevention measures. For example, Estevez-Mujica and Quintane (2018) propose a model that, according to them, explains about 34% and 37% of the variance of burnout and exhaustion, respectively, and successfully distinguishes between workers with higher and lower risks for burnout. Additionally, AIWM systems that can listen in on workers talking and that are able to analyse this information can identify and detect cases of **bullying or sexual harassment**. The same can apply to AIWM that can **perform speech or text (e.g. content of emails) analysis**. For example, Sanchez-Medina et al. (2020) described an AI-based tool that can explore and analyse relationships between certain personality traits (e.g. psychopathy) and potential sexual cyberbullying behaviours.

Digital counselling

Another way to use AIWM for improving workers' mental health is through **digital counselling**. Given that the good mental health of workers, which leads to higher productivity, recently became an important goal for many organisations, some of them started to experiment with AI-based mental health chatbots (Cameron et al., 2017; Oracle and Workplace Intelligence, 2020). Such chatbots may serve as a cost-effective and efficient way to help workers overcome anxiety and stressful situations at the workplace. Experts predict that by 2025, such personalised tools tailored to an individual's psychological situation, will be readily available for usage (Brassey et al., 2021). In addition, according to the 2020 Oracle and Workplace Intelligence survey conducted among 12,000 employees across 11 countries, 83% of employees are in favour of their company providing digital solutions to support their mental health. Approximately 35% of respondents would be ready to use proactive health monitoring tools, 35% of respondents would like to have access to wellness or meditation apps, and 28% of respondents would use a chatbot to answer health-related questions (Oracle and Workplace Intelligence, 2020).

Worker engagement and satisfaction

An AIWM system might also be used to promote employee **engagement and satisfaction** (Hughes et al., 2019). For example, AIWM systems that are less focused on heavy worker control but more on supporting workers (e.g. AI-powered worker collaboration systems that improve communication between workers and help to identify people with relevant skills who can help on a job) may facilitate engagement, as it might give more freedom to workers (Hughes et al., 2019). Gamification technologies that reward workers for their job performance might also improve engagement (Hughes et al., 2019). Similarly, AI-powered chatbots and virtual assistants that workers can use to get relevant HR or work-related information can also help with improving worker satisfaction (Galin & Meshcheryakov, 2020; Zel & Kongar, 2020).

Personalising workstations and work routines

In addition, AI-based systems can also be used to **personalise workstations and work routines based on workers' needs** to create a better match between the worker and the task. As was mentioned in section 2.1, this might lead to several OSH risks, but personalisation can also improve OSH by improving a workplace's ergonomics, for instance, tailoring it for disabled or ageing workers (Segkouli et al., 2021; Soter Analytics, 2020). For example, a Japanese study showed a significant improvement in physical activity when an AI-based system that monitors workers was introduced together with height-adjustable desks in a renovated activity-based office where workers could choose their workstation according to their tasks or mood (Jindo et al., 2020). The study observed a significant change in time that workers spent moving before and after the office renovation, from 312.5±42.9min/day to 347.3±43.5min/day, respectively. Similarly, Herzog and Harih (2020) also proposed an AI-based decision support system that identifies/categorises workers with disabilities and then selects the most suitable work routines or physical workplaces according to the requirements for disabled workers. Finally, personalised work planning and scheduling could also take into account workers' health (e.g. fatigue levels) in order to assign easier work to those who are overworked (Brione, 2020; Tursunbayeva, 2019).

Designing healthy and safe jobs and workplaces

By collecting data from the workplace, AIWM systems can also be of support in designing and implementing safety training programmes for workers or can be used to inform the development of the most appropriate health and safety strategies, as stated by the interviewed experts. In addition, AIWM systems can be used to better plan and design activities, tasks and workers' schedules in order to minimise risks. This can allow employers to monitor, minimise and control workers' exposure to psychosocial risks and to hazards such as chemicals, noise, vibration and others. Additionally, AIWM systems can provide individual risk-related profiles for workers based on their health surveillance on possible health risks, their current risk level, and the likelihood of future health risk by, for instance, analysing and identifying which workers are more sensitive and susceptible to specific hazards, such as noise, high/low temperatures and similar (Chamorro-Premuzic, 2020; EU-OSHA, 2018). However, it is important to note that – along the lines of what is reported in section 2.1 – some organisations might also misuse such systems by, for example, firing workers with higher risk profiles instead of adapting the work and the working environment to them. Finally, AI-based systems have been developed as a response to the COVID-19 pandemic to help workers to prevent contracting the virus by making sure that they maintain an adequate distance from each other at any time (Shamim Kaiser et al., 2021; Zaroushani, 2021), as in the case of the Distance Assistant, a tool that checks if employees are maintaining social distancing, warning them if they are not, created by Amazon during the pandemic (Porter, 2020).

To summarise, AIWM systems may bring certain benefits to employers and OSH. However, even with good intentions, they still might negatively impact workers' health, safety and wellbeing. Because of this, it is crucial for organisations to design and introduce prevention measures ensuring that AIWM systems are developed, implemented, used and evaluated in a safe, healthy, ethical and transparent manner. Section 3 of this report discusses relevant prevention measures, while a discussion on how the OSH risks in relation to AIWM could be prevented through regulations at the EU and national levels is provided in EU-OSHA (2022).

2.3 AIWM and OSH: evidence from ESENER-3

To complement the discussion on risks and opportunities that AIWM might bring to OSH, this section provides a brief overview of the analysis of ESENER-3 data with the aim to explore the relationship between digital technologies enabling AIWM and the health and safety of workers. More in-depth analyses can be found in Annex I of this report.

Impacts of AIWM technologies on health and safety

ESENER-3 survey data contain information on OSH risks and also on the presence of digital technologies that enable AIWM systems in workplaces, and therefore the relationship between them can be investigated. The AIWM-enabling digital technologies surveyed by ESENER-3 include: (i) robots that interact with workers; (ii) machines, systems or computers determining the content or pace of work;

(iii) machines, systems or computers monitoring workers' performance; and (iv) wearable devices, such as smart watches, data glasses or other (embedded) sensors.

Table 2-1 below displays that the proportion of workplaces reporting the existence of physical or psychosocial risks is in most cases higher in workplaces that use digital technologies enabling AIWM compared to workplaces where such technologies are not used.

Table 2-1: Establishments by specific OSH risks (based on ESENER-3 Q200 and Q201) and the usage of digital technologies (based on ESENER-3 Q310) (EU-27, % - 2019)

		Digital technologies				No digital technologies
		Robots that interact with workers	Machines, systems or computers determining the content or pace of work	Machines, systems or computers monitoring workers' performance	Wearable devices, such as smart watches, data glasses or other (embedded) sensors	
Physical risks	Lifting or moving people or heavy loads	71.3%	67.9%	64.6%	64.2%	52.1%
	Repetitive hand or arm movements	79.1%	76.8%	76.4%	72.8%	62.7%
	Prolonged sitting	72.1%	67.6%	69.0%	70.1%	60.7%
	Tiring or painful positions	43.9%	42.4%	41.0%	43.4%	30.8%
	Loud noise	50.8%	45.3%	39.4%	39.9%	28.8%
	Heat, cold or draught	52.2%	49.3%	47.5%	46.4%	35.9%
	Risk of accidents with machines or hand tools	71.0%	66.6%	59.7%	58.7%	45.7%
	Risk of accidents with vehicles in the course of work but not on the way to and from work	63.5%	58.9%	59.5%	56.3%	43.5%
	Chemical or biological substances in the form of liquids, fumes or dust	61.4%	54.6%	50.7%	48.9%	35.9%
	Increased risk of slips, trips and falls	51.3%	48.6%	47.1%	45.9%	35.5%
Psychosocial risks	Time pressure	61.1%	59.1%	60.2%	59.2%	47.3%
	Poor communication or cooperation within the organisation	32.0%	29.0%	29.9%	27.2%	19.7%
	Fear of job loss	21.0%	19.7%	21.7%	18.5%	12.7%
	Having to deal with difficult customers, patients, pupils, etc.	59.6%	60.5%	65.6%	66.4%	61.5%
	Long or irregular working hours	34.4%	32.0%	33.7%	34.8%	23.7%

Source: Authors' elaboration on ESENER-3 data.

Note: establishment proportional weighting factor *estprop* applied that corrects for the disproportionalities of the sample with regard to size and country and adjusts for unequal response by size, sector and country.

A number of factors could be at play in the relationship between the digital technologies enabling AIWM and the OSH risks. Workplace size, sector of activity and existence of mitigating policies are among them. In order to explore the complexity of this relationship, a number of regression models for each of the four digital technologies were estimated. While the full models are presented and discussed in detail in Annex I, in the remainder of this subsection the main findings are presented.

The usage of **robots that interact with workers** is statistically significant and positively correlated with traditional risks such as repetitive hand or arm movements and risk of accidents with machines or hand tools. Given that the regression model controls for different organisational and other factors (see Annex I for details), the results imply that the usage of these technologies fosters more repetitive work, which in turn might increase the risk for MSDs. The results also imply that the usage of robots is related to an intensification of work as the only two psychosocial risks that statistically significantly correlate with the usage of robots are time pressure and long or irregular working hours.

The usage of **machines, systems or computers determining the content or pace of work** is statistically significant and positively correlated with tiring or painful positions and risk of accidents with vehicles in the course of work, but not on the way to and from work. This might imply that such technologies foster a fast and uncomfortable working environment that might lead to, for example, MSD problems due to tiring and painful positions, or increased risk of accidents. In addition, these digital technologies are also strongly correlated with the risks of time pressure, implying that they might increase work intensity, which might lead to OSH risks, such as an increase in the probability of accidents. It is worth mentioning that these results can also be explained by the fact that these technologies are more frequently used in manufacturing settings.

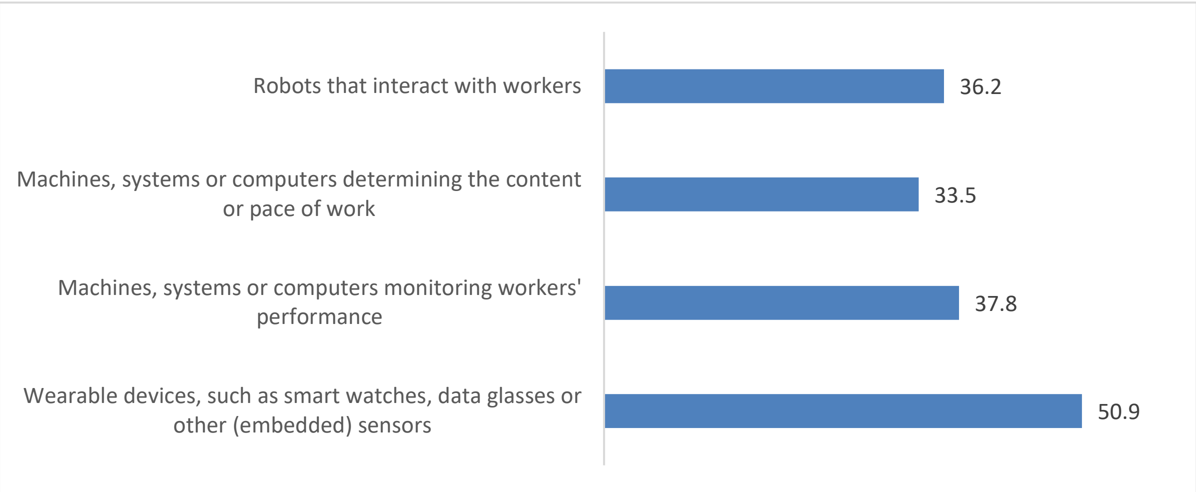
The usage of **machines, systems or computers monitoring workers' performance** is more common in manufacturing and as a consequence correlates with the risk of repetitive hand or arm movements and the risk of accidents with machines or hand tools. In addition, the usage of machines, systems or computers monitoring workers' performance is strongly and positively correlated with the risks of poor communication or cooperation within the organisation. This might also involve a lack of communication regarding the usage of such technologies to workers, meaning that workers might often be unaware if they are watched and for what reason. This conclusion is also supported by several interviewed experts who expressed similar concerns.

Finally, the usage of **wearable devices, such as smart watches, data glasses or other (embedded) sensors** correlates positively with a risk of tiring or painful positions. This implies that such tools might be more frequently used in workplaces where workers perform work tasks in tiring positions. In addition, the usage of this technology also correlates with long or irregular working hours, which also implies that this technology might be connected to some extent to an intensification of work.

Discussing the impact of digital technologies in the workplace

ESENER-3 data also include information regarding the consultation of workers about the implications for OSH of using digital technologies enabling AIWM. According to ESENER-3 data, not all the establishments that use any of the four digital technologies have internally discussed with employees the effects of such technologies on OSH (Figure 2-1). Such discussions are most frequently reported in workplaces that use wearable devices, such as smart watches and glasses (51%) and in organisations using machine, systems or computers monitoring worker performance (38%). To a large extent, these results are also supported by the regression analysis (see Annex I). Nevertheless, it is worth mentioning that – depending on the type of technology – discussions are carried out relatively rarely, implying that either most organisations do not consider the risks that new technologies might bring or in any case consider the consultation or the participation of workers in this area not important. This, in turn, implies a need for more awareness raising on how new technologies might negatively affect OSH and the importance of informing and consulting staff on this matter.

Figure 2-1: Establishments using digital technologies that discuss possible health and safety impacts of technologies, by type of technology (EU-27, %)



Source: Authors' elaboration on ESENER-3 data.
Note: establishment proportional weighting factor *estprop* applied that corrects for the disproportionalities of the sample with regard to size and country and adjusts for unequal response by size, sector and country.

Overall, the topic most often discussed in establishments that use digital technologies is the need for continuous training to keep skills updated – 77% of establishments that use any of the aforementioned technologies discussed this issue. Discussions on prolonged sitting (66%) and increased flexibility for employees (63%) are reported by around two thirds of the establishments. Fear of job loss is the issue that is least discussed by far with only 21% of organisations doing so. This is followed by blurring boundaries between work and private life (47%) and information overload (52%). These results imply that those organisations that discuss potential OSH impacts do in fact discuss different risks that might stem from the usage of digital technologies. These results imply that these organisations see serious OSH risks as less likely to be caused by the introduction of new technologies, as discussions focus more on risks that are less directly connected to OSH directly (e.g. need for upskilling), as well as several positive aspects that AIWM might bring to organisations (i.e. increased flexibility). This further implies a need for awareness raising on how the usage of such digital technologies might affect OSH.

Figure 2-2: Establishments that discussed the impact of digital technologies by type of impacts discussed (EU-27, %)

Source: Authors' elaboration on ESENER-3 data.
Note: establishment proportional weighting factor *estprop* applied that corrects for the disproportionalities of the sample with regard to size and country and adjusts for unequal response by size, sector and country.

There is also some variability regarding these discussions across economic sectors. Sectors of activity that seem least likely to have such discussions are the accommodation and food services, art, entertainment and recreation, and manufacturing sectors, with around 17%, 20% and 20% of enterprises in these sectors having such discussions, respectively (see Figure I-2 in Annex I). On the other hand, sectors in which organisations have such discussions the most are obviously those where digital technologies have more frequently been adopted, that is information and communication (31% of enterprises surveyed in ESENER-3), education (30%), administrative and support service activities (30%), and finance and real estate (29%).

Several additional insights on the discussions of different risks that technologies might create can also be derived from the regression analysis results.

Firstly, as expected, enterprises that have specific risks also often discuss these risks. For example, there is a very strong positive correlation between workplaces discussing risks related to prolonged sitting, fear of job loss, time pressure and the presence of these risks in enterprises.

Secondly, regression results also support that organisations that use newer, more advanced or controversial technologies also more often discuss the risks associated with them.

Thirdly, discussions on risks related to increased worker intensity or time pressure are more frequent in organisations that employ systems for monitoring worker performance and determining the pace and content of work while organisations that use personal computers and laptops, as well as machines, systems or computers determining the content or pace of work, discussed information overload more frequently. Additionally, discussions on the issue of repetitive movements are most frequently reported in organisations that use machines, systems or computers determining the content or pace of work, while the risk of repetitive movements is negatively correlated with the use of laptops.

The discussion on the need for continuous training is strongly positively correlated with the use of laptops, robots that interact with workers, and systems that determine the content and pace of work. Given quite a large number of technologies correlating with the need for continued training implies that in organisations that use such technologies, workers might lack some relevant knowledge regarding them. Regarding the discussion on flexibility, it correlated with the use of laptops, machine systems or computers that determine the pace of work, and wearable devices.

The discussion on blurring boundaries between work and private life is raised in enterprises that use any of the technologies previously mentioned, except robots that interact with workers. This implies that the large number of technologies might blur these lines, and, hence, it is crucial to ensure that new technologies only collect the bare minimum data on workers necessary for operation.

Finally, the possibility of job loss is most often discussed in enterprises that use robots that interact with workers and machines that determine the content or pace of work. In working environments where robots are used, the discussions about the possibility of job loss most likely reflect the workers' fear of their jobs being automated.

3 Prevention measures

This section explores possible prevention measures at the enterprise level. More specifically, based on expert interviews and the literature review, several strategies that organisations might employ to prevent AIWM risks to OSH in a number of areas are presented and discussed here. It is important to note that this section does not discuss regulations, except for the need for an ethical framework, as an extensive overview of regulations that can mitigate OSH risks brought by AIWM, including preventive actions, is discussed in EU-OSHA (2022).

When introducing AIWM systems in the workplace, a **precautionary principle** is advised. Often, given the newness of the technology, it is impossible to predict all risks that might arise due to the use of an AIWM system. Hence, a **human-centred approach** should be adopted to carefully inform all the stages in designing, developing, integrating, using and assessing AIWM systems.

Effective workers/employer dialogue and workers' participation

According to many interviewed experts, human-centred AIWM systems should be pursued by organisations fostering **effective dialogue** between workers, employers and AIWM systems developers (where relevant), and – most importantly – ensuring **workers' involvement and participation** in all stages of the design, development, implementation and assessment of AIWM systems in the workplace. Workers' participation is considered by most of the consulted experts the cornerstone of preventing the negative impacts of AIWM on OSH and identifying the possible opportunities that come with them. That implies that workers should be at the table when deciding on safeguarding workers' privacy and data protection, addressing surveillance, tracking and monitoring, making the purpose of AI algorithms transparent, ensuring the exercise of their right to explanations regarding decisions made by algorithms or machine learning models, and ensuring that workers' safety and health is at the forefront of the discussion. This will allow to improve transparency, fairness, data privacy, trust, accountability and OSH within an organisation when using AIWM. For example, Lee et al. (2021) described participatory algorithmic management for worker wellbeing and proposed elicitation methods for building wellbeing models by workers. Interviewed experts also gave the example of Germany, where employers are required to have at least a dialogue with workers when integrating new technologies, including AIWM, due to co-determination rules. Another good case example, according to one interviewed expert, is an agreement between employees and employer in one organisation that states that Google smart glasses can be used by workers for only six hours at a time in order to minimise eye fatigue. However, it is important to mention that these examples of transparent communication and keeping workers involved are outliers rather than the norm. More specifically, based on interviewed experts, organisations (i.e. managers) rarely consult employees or their representatives before deploying AI-based systems. In the majority of cases, at best, managers simply inform workers when such systems become integrated into their workspace and work. Hence, given that employers rarely integrate such participatory approaches of their own volition, according to interviewed experts, worker participation should be guaranteed through regulations. It is important to note that this is already ensured by some existing regulations, such as the OSH Framework Directive, but gaps remain, as discussed in the EU-OSHA (2022a) report.

Considering the implications of AIWM for OSH at the early stages

It is also important to highlight that, in general, considerations on how AIWM can affect OSH should already be taken into account at **the research and design phase** of such systems. The key aspect here is that it is important to understand the original purpose for which AIWM systems are being introduced in workplaces (e.g. improving productivity, efficiency, cooperation between workers) and if this can pose risks to OSH. Hence, to ensure that AIWM systems do not lead to negative OSH effects, such systems should predominantly support and protect humans, ensuring their safety, sustainability and reliability (i.e. making sure that such systems do not make mistakes that might harm workers). In other words, newly designed AI-based systems need to be integrated into work environments in such a way that all their configurations focus on the health, safety and wellbeing of workers (EU-OSHA, 2018).

Risk assessment of AIWM in all stages

According to interviewed experts, an advanced **risk assessment of AIWM** needs to be conducted not only when the AIWM systems are deployed in the workplace (e.g. as part of the workplace risk assessment) but also at the earlier design and development stage by developers. The assessment should focus on the full range of possible impacts in terms of OSH challenges and risks, as identified and described in this report and in EU-OSHA (2022), but also cover the opportunities and advantages offered by AIWM. In addition, given that AIWM systems are able to evolve and self-learn, a systematic approach of analysing AIWM and its effect on OSH is crucial. That is, the assessment of such systems should be carried out periodically, with the involvement of workers, to ensure that previously safe systems have not become harmful over time.

Skills and training for workers to understand and safely use AIWM systems

It is important to note that some workers might lack the necessary skills and knowledge to fully understand AIWM systems and its potential risks, which limits how much they can contribute to ensuring ethical and transparent development, implementation and assessment of such systems. Because of this, experts recommend **providing relevant training for workers**, as well as providing them with relevant **support systems**. Support to workers can be provided through a system where work councils or other worker representations could make use of external experts to ask questions about data usage and the workings of algorithmic and AI systems. Regarding training, education efforts, according to several interviews experts, should focus on providing workers with sound awareness, knowledge and understanding of how AI works and how to work alongside it, and foreseeing how AI can change employees' tasks and roles at work, as well as the impact of AI on their health and career, are also crucial (Ponce del Castillo, 2020). These educational efforts should also provide workers with the know-how on how to challenge the decisions/recommendations made/proposed by an AI, or AIWM, system. This is also highlighted by Ponce del Castillo (2020) who emphasised that purely obtaining technical skills is insufficient. In addition, **upskilling and reskilling efforts**, according to several interviewed experts, should not solely be focused on workers but also on trade unions, employers' confederations and developers of AI-based systems. Education efforts should also focus on helping the older generation understand these new systems, as they might go against them due to the fact that they might be generally averse to new technologies and, due to this lack of knowledge, they might also feel anxiety, low self-esteem and/or insecurity (Alcover et al., 2021). Keeping this in mind, some interviewed experts recommended that special training with a focus on OSH should be compulsory for all workers and employers (companies) who deploy and use AI-based systems. To some extent this already exists, as, for example, experts mentioned that some AI-based system developers provide training for organisations on how to use these systems and talk with organisations that will use them about risks. In addition, developers also sometimes provide special training sessions for workers in the field of OSH, however, undergoing such training is rarely compulsory.

Developing an EU-level ethical framework

Ensuring that AIWM does not lead to negative OSH effects can be fostered, as highlighted by several interviewed experts, through the **development of an EU-level ethical framework** for digitalisation that would dictate how AIWM, and AI-based systems in general, can be used in the workplace. More specifically, interviewed experts considered that there are ethical ways to adopt and implement AIWM systems to promote safety and health at the workplace. This is supported by several publications (e.g. Abdullah, 2019), some of which even provide proposals on what such an ethical framework could look like (e.g. High-Level Expert Group on Artificial Intelligence, 2019b).

For example, according to one interviewed expert, **transparency** can be ensured by: (i) giving workers the means to negotiate how their data is collected, analysed, stored and off-boarded/sold (for more, see Colclough, 2020); (ii) ensuring worker representation in the co-governance of AI-based systems (for more, see Colclough, 2020); (iii) building a clear line of responsibility of what should happen if an AI system leads to harm to humans; (iv) ensuring that AI system developers are transparent on how they operate; and (v) ensuring that such systems are developed, used and evaluated following a human-centric approach. Similarly, the High-Level Expert Group on Artificial Intelligence (2019b) recommended focusing on the following aspects to ensure a trustworthy AI: transparency of the collected data, implemented AI-based systems and AI business models; and technical robustness and safety of AI-based systems need to be ensured, resilient and secure. In addition, diversity, non-discrimination and fairness need to be acknowledged in order to avoid any negative implications of AI-based systems.

There is also a need to develop certain mechanisms in order to ensure responsibility and accountability for AI systems and their outcomes (High-Level Expert Group on Artificial Intelligence, 2019b). This aspect should also be reflected in the ethical framework.

4 Conclusions and recommendations

AIWM systems in the workplace can provide potential opportunities to improve OSH, as they can be used to improve workplaces' hazards monitoring or workers' mental health monitoring, representing an important chance to improve the health, safety and wellbeing of workers. For example, an AIWM system that directs workers might at the same time monitor their posture, alerting them of poor postures and of the increased risk of developing an MSD. Similarly, such systems might also monitor workers' stress or risk of burnout or bullying by analysing their body language, speech patterns or writing patterns. AIWM systems can also be used to promote engagement and satisfaction in workers by, for example, fostering workers' easy communication and cooperation on tasks. In addition, AIWM may allow workers to personalise their workstation and/or their work based on their needs: an AIWM system can be used to identify if workers have ailments or impairments and to assign them work tasks or a schedule that is more appropriate and therefore meet the needs of the affected workers. Finally, AIWM systems might also help with designing and conducting OSH training and can support the design of OSH strategies, as they can be based on the data on the working environment, workers and the way they work, which these systems normally collect.

The findings discussed in this report highlight nonetheless that the use of AI to manage workers also poses numerous risks to OSH, especially in terms of psychosocial risks. AIWM systems can increase work intensity and the speed of work, as when they are used to direct workers, they might force workers to not take breaks or to work at high speed. AIWM systems can also significantly reduce the autonomy and the control workers have over their work, leading to high levels of stress, and sometimes lower productivity, poor performance and increased levels of sickness absences. Furthermore, those AIWM systems that monitor and evaluate worker performance might create performance pressure. In turn, this might lead to health issues in workers, such as an increased risk of MSDs, or an increase in workers' exhaustion, accidents, stress, anxiety and fear of losing their jobs. Some AIWM systems, such as those that exercise a strict control on workers, are thought to dehumanise workers: such systems might 'datafy' workers, who become an object of data collection, and force them to work like machines, leading to decreased cognitive and intellectual capacities and creative thinking, a loss of autonomy, and a lack of independent and critical thought. This can result in work-related stress, fatigue, exhaustion, burnout, anxiety or fear of losing their job, techno-stress, techno-anxiety and techno-fatigue. Finally, intrusive AIWM systems that are based on intensive monitoring of workers can lead to collecting private and sensitive data and blurring lines between work and private life. Such systems might also lead to discriminating against some workers, if the system is based on biased data that gives preferential treatment to, for example, workers of a specific age, ethnicity or gender.

The report suggests that a strong 'prevention through design' approach that integrates a human-centred approach in the design and usage of AIWM is needed. AIWM should be designed, implemented and managed in a trustworthy, transparent, empowering and understandable way, guaranteeing workers' consultation, participation and equal access to information, as well as putting humans in control, and thereforeensuring that AIWM is used not to replace workers but to support them. This can be achieved through different means, including open and effective dialogue, worker training and active participation in the development, implementation, use and evaluation of such systems, increasing awareness of relevant stakeholders (for example, developers, workers, employers) on how AIWM systems might negatively affect OSH, and creating a strong ethical framework describing how AIWM should be developed, implemented and used, as well as ensuring compliance with existing legal provisions applicable to AIWM.

In order to address the risks related to the implementation of AIWM systems in the workplace, a number of recommendations for better prevention measures and to make the most of AIWM systems in terms of OSH improvements can be formulated.

Recommendation 1: AIWM systems need to be based on a human-centred approach

AIWM systems must be designed, implemented and managed to be safe and transparent, guaranteeing workers' consultation, participation and equal access to information at all stages, and making sure that humans are in command at any time. To ensure this, close and effective dialogue between workers and employers and collaboration between researchers, developers, industry, social partners and governments on research and innovation in designing AIWM are needed and should be actively pursued.

Recommendation 2: Risk assessment must be tailored to AIWM systems

Given the novelty of AIWM, risk assessment must cover all of the work-related factors, and it should be carried out together with specialists in the programming of algorithms in order to address and consider the existence of uncertainties and ascertained risks. In this regard, it seems necessary to develop standardised technical procedures for the risk assessment of AI-based systems based on sufficient scientific endorsement. The analysis should also follow a holistic approach, in order to address the possible risks of AIWM on OSH at different levels, such as at the specific job, organisation, sector, region or country. In addition, given that AIWM systems are able to evolve and self-learn, the assessments of such systems should be carried out periodically.

Recommendation 3: Raising awareness and sharing knowledge on AIWM systems

Raising awareness and sharing knowledge on AIWM systems usage and the related implications for OSH among employers, HR departments, workers and their representatives, OSH actors including labour inspectorates and AIWM systems developers is of utmost importance. There is a clear need to provide training for managers and workers about AIWM systems, focusing on how these can affect OSH and how to prevent related risks. Upskilling and reskilling efforts should go beyond simply giving technical knowledge to workers and they should focus on providing workers with sound awareness, knowledge and understanding of how AI works and how to safely work alongside it, and foreseeing how AI can change employees' tasks and roles at work, as well as the impact of AI on their health and career. Education efforts should also not solely focus on workers, but also on trade unions, employers and their confederations, and developers of AI-based systems. Regarding support systems, workers should have the means to request and get support on different issues related to AIWM and its possible effects on OSH.

Recommendation 4: Developing an EU-level ethical framework

Interviewed experts also emphasised the need for the development of an EU-level ethical framework that would dictate how AIWM, and AI-based systems in general, can be used in the workplace. At the same time, many experts agree that ethical frameworks alone will not be sufficient, and compliance with existing legal provisions applicable to AIWM (such as OSH legislation, GDPR, forthcoming Artificial Intelligence Act and anti-discrimination law) should be ensured.

A number of additional recommendations relate more directly to the research and knowledge gaps that were identified. Overall, it is worth highlighting that in order to reduce and manage risks and make the most of the opportunities for OSH stemming from the AIWM systems, it is crucial to rely on robust and evidence-based research, which will allow to design and implement informed interventions at workplace level and also policy and regulations at national or even EU levels. Research specifically focusing on the effects of AIWM on OSH, especially that based on empirical evidence, is rather limited, and a number of gaps and research needs exist, as pointed out by interviewed experts but also in relevant academic literature (e.g. European Commission, 2013; Kagermann et al., 2013).

Recommendation 5: Conducting interdisciplinary and holistic research on AIWM and OSH

More interdisciplinary and holistic research on how AIWM might affect OSH should be undertaken. The holistic approach should include, but should not be limited to, analysing how AIWM might affect OSH in general terms, how negative effects of OSH can be mitigated through a transparent and ethical design, development, implementation and analysis of AIWM systems, how to ensure that AIWM systems do not collect data on workers beyond what is needed for their functioning, how to help workers to exercise their legal rights to prevent such systems from collecting unnecessary private information and how to help them to challenge the recommendations and decisions made by such systems, how to mitigate the negative effects of AIWM on OSH at the development stage, and more.

Recommendation 6: Include the human-in-command approach in the research on AIWM

Research should focus on identifying to what extent humans are kept in command and AIWM systems are used to support workers rather than replace them and that their deployment does not lead to OSH risks. More focused research would allow to improve existing regulations, which have many drawbacks, including not being based on social dialogue, seldom covering workers, not including a strong accountability clause of who is to blame when AIWM systems lead to harm, and more, by ensuring that workers are always kept at the centre of them, as stated by several interviewed experts and the literature (e.g. De Stefano, 2021; Ponce del Castillo, 2021).

Recommendation 7: Consider how business management models and AIWM interact

More research is needed to understand whether existing business management models are sufficient to prevent and manage the OSH risks that AIWM might bring. As the adoption of an AIWM system often requires changes to the business management model, it is not 'a given' that the interaction between the AIWM system and the existing business management model will not lead to OSH risks. Because of this, research should focus on evaluating if currently used business models are compatible with AIWM systems and if they will not lead to negative OSH effects. If research shows lack of compatibility, it is then important to develop new models that will ensure workers' health, safety and wellbeing when AIWM systems are introduced.

Recommendation 8: Pursuing knowledge sharing between researchers and AIWM developers

More knowledge sharing between researchers and developers of AIWM systems is needed. Given that AI-based systems rely heavily on programming and also often rely on big data, in order to ensure transparency, replicability and that such systems do not lead to harm, it is crucial that the developers of AIWM systems share all relevant information with the research community at large (including also the policy and OSH communities, and other relevant stakeholders). This will allow researchers to design and carry out more accurate and informed research about how such systems might affect OSH, which could be of help in designing risk assessment tools, prevention measures, policies and regulatory initiatives.

Recommendation 9: Research on AIWM systems and OSH should be carried out on a continuous basis

Analysis to determine whether AIWM systems continue to be safe should be carried out periodically. Given that AI-based systems are able to learn from the environment and evolve, it is incorrect to assume that they are stable and not changing (Dahlin, 2021). The is means that research efforts on how AIWM affects OSH should not only be carried out once at the development or integration stage of AIWM systems. An evaluation/analysis should be carried out periodically to ensure that AIWM systems that were previously deemed safe are still harmless to workers.

References

Abdullah, S. M. (2019). Artificial intelligence (AI) and its associated ethical issues. *ICR Journal, 10*(1), 124–126. https://doi.org/10.52282/icr.v10i1.78

Alcover, C.-M., Guglielmi, D., Depolo, M., & Mazzetti, G. (2021). "Aging-and-tech job vulnerability": A proposed framework on the dual impact of aging and AI, robotics, and automation among older workers. *Organizational Psychology Review, 11*(2), 175–201. https://doi.org/10.1177%2F2041386621992105

Aliabadi, M., Farhadian, M., & Darvishi, E. (2014). Prediction of hearing loss among the noise-exposed workers in a steel factory using an artificial intelligence approach. *International Archives of Occupational and Environmental Health, 88*, 779–787. https://doi.org/10.1007/s00420-014-1004-z

Aloisi, A., & Gramano, E. (2019). Artificial intelligence is watching you at work. Digital surveillance, employee monitoring, and regulatory issues in the EU context. *Comparative Labor Law & Policy Journal, 41*(1), 95–121. https://cllpj.law.illinois.edu/archive/vol_41/

Alwasel, A., Sabet, A., Nahangi, M., Haas, C. T., & Abdel-Rahman, E. (2017). Identifying poses of safe and productive masons using machine learning. *Automation in Construction, 84*, 345–355. https://doi.org/10.1016/j.autcon.2017.09.022

Badri, A., Boudreau-Trudel, B., & Ahmed Saâdeddine Souissi, A. S. (2018). Occupational health and safety in the industry 4.0 era: A cause for major concern? *Safety Science, 109*, 403–411. https://doi.org/10.1016/j.ssci.2018.06.012

Ball, K. (2021). *Electronic monitoring and surveillance in the workplace: Literature review and policy recommendations*. Publications Office of the European Union. https://data.europa.eu/doi/10.2760/5137

Bérastégui, P. (2021). *Exposure to psychosocial risk factors in the gig economy: A systematic review*. ETUI. https://www.etui.org/publications/exposure-psychosocial-risk-factors-gig-economy

Berger T., Frey, C. B., Levin, G., & Danda S. R. (2019). Uber happy? Work and wellbeing in the 'Gig Economy'. *Economic Policy, 34*(99), 429–477. https://doi.org/10.1093/epolic/eiz007

Brassey, J., Güntner, A., Isaak, K., & Silberzahn, T. (2021, July 8). *Using digital tech to support employees' mental health and resilience.* McKinsey & Company. https://www.mckinsey.com/industries/pharmaceuticals-and-medical-products/our-insights/using-digital-tech-to-support-employees-mental-health-and-resilience#.

Brione, P. (2020). *My boss the algorithm: An ethical look at algorithms in the workplace.* ACAS. https://www.acas.org.uk/my-boss-the-algorithm-an-ethical-look-at-algorithms-in-the-workplace

Brivio, E., Gaudioso, F., Vergine, I., Mirizzi, C. R., Reina, C., Stellari, A., & Galimberti, C. (2018). Preventing technostress through positive technology. *Frontiers in Psychology, 9*, Article 2569. https://doi.org/10.3389/fpsyg.2018.02569

Cacioppo, J. T., Hughes, M. E. Waite, L. J., Hawkley, L. C., & Thisted, R. A. (2006). Loneliness as a specific risk factor for depressive symptoms: Cross-sectional and longitudinal analyses. *Psychology and Aging, 21*(1), 140–151. https://doi.apa.org/doi/10.1037/0882-7974.21.1.140

Cameron, G., Cameron, D., Megaw, G., Bond, R., Mulvenna, M., O'Neill, S., Armour, C., & McTear, M. (2017). Towards a chatbot for digital counselling. In *Proceedings of the 31st International BCS Human Computer Interaction Conference (HCI 2017)* (pp. 1–7). BCS Learning and Development Ltd. https://doi.org/10.14236/ewic/HCI2017.24

Carr, N. (2014). *The glass cage: Where automation is taking us.* The Bodley Head.

Cater, L., & Heikkilä, M. (2021, May 27).*Your boss is watching: How AI-powered surveillance rules the workplace.* Politico. https://www.politico.eu/article/ai-workplace-surveillance-facial-recognition-software-gdpr-privacy/

Chamorro-Premuzic, T. (2020, August 4). *Can surveillance AI make the workplace safe?* MIT Sloan Management Review. https://sloanreview.mit.edu/article/can-surveillance-ai-make-the-workplace-safe/

Ciullo, A. S., Catalano, M. G., Bicchi, A., & Ajoudani, A. (2019). A supernumerary soft robotic hand-arm system for improving worker ergonomics. In M. C. Carrozza, S. Micera, & J. L. Pons (Eds), *Wearable robotics: Challenges and trends* (pp. 520–524). Springer International Publishing.

Colclough, C. (2020, September 3). *Workers' rights: Negotiating and co-governing digital systems at work.* Social Europe. https://www.socialeurope.eu/workers-rights-negotiating-and-co-governing-digital-systems-at-work

Collins, L., Fineman, D. R., & Tshuchica, A. (2017, February 28). *People analytics: Recalculating the route.* Deloitte Insights. https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2017/people-analytics-in-hr.html

Curchod, C., Patriotta, G., Cohen, L., & Neysen, N. (2020). Working for an algorithm: Power asymmetries and agency in online work settings. *Administrative Science Quarterly*, 65(3), 644–676. https://doi.org/10.1177%2F0001839219867024

CWA. (2017). *Occupational Safety and Health Fact Sheet #21. Occupational Stress & the Workplace*. Communications Workers of America (CWA). https://cwa-union.org/sites/default/files/osh-fact-sheet-21-occupational_stress_and_the_workplace.pdf

Dahlin, E. (2021). Mind the gap! On the future of AI research. *Humanities and Social Sciences Communications, 8*(1), Article 71. https://doi.org/10.1057/s41599-021-00750-9

Danaher, J. (2018). Toward an ethics of AI assistants: An initial framework. *Philosophy & Technology, 31*, 629–653. https://doi.org/10.1007/s13347-018-0317-3

De Stefano, V. (2018). *"Negotiating the algorithm": Automation, artificial intelligence and labour protection*. EMPLOYMENT Working Paper No. 246, International Labour Organization. https://www.ilo.org/employment/Whatwedo/Publications/working-papers/WCMS_634157/lang--en/index.htm

De Stefano, V. (2021, April 16). *The EU Proposed Regulation on AI: A threat to labour protection? Global Workplace Law & Policy.* http://regulatingforglobalization.com/2021/04/16/the-eu-proposed-regulation-on-ai-a-threat-to-labour-protection/

Delfanti, A. (2019). Machinic dispossession and augmented despotism: Digital Work in an Amazon warehouse. *New Media & Society, 23*(1), 39–55. https://doi.org/10.1177/1461444819891613

Descatha, A., Evanoff, B. A., Leclerc, A., & Roquelaure, Y. (2020). Occupational determinants of musculoskeletal disorders. In U. Bültmann, & J. Siegrist (Eds), *Handbook of disability, work and health. Handbook series in occupational health sciences* (Vol. 1) (pp. 169–188). Springer. https://doi.org/10.1007/978-3-030-24334-0_8

Doki, S., Sasahara, S., Hori, D., Oi, Y., Takahashi, T., Shiraki, N., Ikeda, Y., Ikeda, T., Arai, Y., Muroi, K., & Matsuzaki, I. (2021). Comparison of predicted psychological distress among workers between artificial intelligence and psychiatrists: A cross-sectional study in Tsukuba Science City, Japan. *BMJ Open, 11*, Article e046265. http://dx.doi.org/10.1136/bmjopen-2020-046265

Duggan, J., Sherman, U., Carbery, R., & McDonnell, A. (2019). Algorithmic management and app-work in the gigeconomy: A research agenda for employment relations and HRM. *Human Resource Management Journal, 30*(1), 114–132. https://doi.org/10.1111/1748-8583.12258

Durand, M.-J., Vézina, N., & Richard, M.-C. (2016). *Concept of margin of manoeuvre in return to work*. In I. Schultz, & R. Gatchel (Eds), *Handbook of return to work. Handbooks in health, work, and disability* (Vol. 1) (pp. 53–65). Springer. https://doi.org/10.1007/978-1-4899-7627-7_3

Estevez-Mujica, C. P., & Quintane, E. (2018). Email communication patterns and job burnout. *PLoS ONE, 13*(3), Article e0193966. https://doi.org/10.1371/journal.pone.0193966

Estrada-Muñoz, C., Castillo, D., Vega-Muñoz, A., & Boada-Grau, J. (2020). Teacher technostress in the Chilean school system. *International Journal of Environmental Research and Public Health, 17*(15), Article 5280. https://doi.org/10.3390/ijerph17155280

Eubanks, V. (2017). *Automating inequality*. St Martin's Press.

EU-OSHA – European Agency for Safety and Health at Work, *Foresight on new and emerging occupational safety and health risks associated with digitalisation by 2025*, 2018. Available at: https://osha.europa.eu/en/publications/foresight-new-and-emerging-occupational-safety-and-health-risks-associated/view

EU-OSHA – European Agency for Safety and Health at Work, *OSH and the Future of Work: benefits and risks of artificial intelligence tools in workplaces*, 2019. Available at: https://osha.europa.eu/en/publications/osh-and-future-work-benefits-and-risks-artificial-intelligence-tools-workplaces

EU-OSHA – European Agency for Safety and Health at Work, *Artificial intelligence for worker management: an overview*, 2022. Preprint.

Eurofound. (2020). *Employee monitoring and surveillance: The challenges of digitalisation.* Publications Office of the European Union. https://www.eurofound.europa.eu/sites/default/files/ef_publication/field_ef_document/ef20008en.pdf

European Commission. (2013). Factories of the future. Multi-annual roadmap for the contractual PPP under Horizon 2020. Prepared by European Factories of the Future Research Association (EFFRA). https://www.effra.eu/sites/default/files/factories_of_the_future_2020_roadmap.pdf

European Commission. (2021). *Proposal for a Regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial intelligence Act) and amending certain Union legislative acts*. COM/2021/206 final. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021PC0206

European Parliamentary Research Service. (2020). *Data subjects, digital surveillance, AI and the future of work.* https://www.europarl.europa.eu/RegData/etudes/STUD/2020/656305/EPRS_STU(2020)656305_EN.pdf

Fernández-Martínez, C., & Fernández, A. (2020). AI and recruiting software: Ethical and legal implications. *Paladyn, Journal of Behavioral Robotics, 11*(1), 199–216. https://doi.org/10.1515/pjbr-2020-0030

Finneran, A., & O'Sullivan, L. (2010). Force, posture and repetition induced discomfort as a mediator in self-paced cycle time. *International Journal of Industrial Ergonomics, 40*(3), 257–266. https://doi.org/10.1016/j.ergon.2010.01.004

Fisher, A. (2019, August 1). *HR managers, with a little help from AI, can decide your next pay hike.* The Print. https://theprint.in/features/hr-managers-with-a-little-help-from-ai-can-decide-your-next-pay-hike/270927/

Frey, C., & Osborne, M. A. (2013). *The future of employment: How susceptible are jobs to computerisation?* Oxford Martin School, University of Oxford. https://www.oxfordmartin.ox.ac.uk/downloads/academic/The_Future_of_Employment.pdf

Gal, U., Blegind Jensen, T., & Stein, M. K. (2020). Breaking the vicious cycle of algorithmic management: A virtue ethics approach to people analytics. *Information and Organization, 30*(2), Article 100301. https://doi.org/10.1016/j.infoandorg.2020.100301

Galin, R., & Meshcheryakov, R. (2020). Collaborative robots: Development of robotic perception system, safety issues, and integration of AI to imitate human behavior. In A. Ronzhin, & V. Shishlakov (Eds), *Proceedings of 15th International Conference on Electromechanics and Robotics "Zavalishin's Readings"* (pp. 175–185). Springer. https://doi.org/10.1007/978-981-15-5580-0_14

Gregory, K. (2021). 'My life is more valuable than this': Understanding risk among on-demand food couriers in Edinburgh. *Work, Employment and Society, 35*(2), 316–331. https://doi.org/10.1177%2F0950017020969593

Halawa, F., Dauod, H., Lee, I. G., Li, Y., Yoon, S. W., & Chung, S. H. (2020). Introduction of a real time location system to enhance the warehouse safety and operational efficiency. *International Journal of Production Economics, 224*, Article 107541. https://doi.org/10.1016/j.ijpe.2019.107541

Hawkley, L. C, Thisted, R. A., Masi, C. M., & Cacioppo, J. T. (2010). Loneliness predicts increased blood pressure: 5- year cross-lagged analyses in middle-aged and older adults. *Psychology and Aging, 25*(1), 132–141. https://doi.apa.org/doi/10.1037/a0017805

Heaven, W. D. (2020, June 4). This startup is using AI to give workers a “productivity score”. *MIT Technology Review*. https://www.technologyreview.com/2020/06/04/1002671/startup-ai-workers-productivity-score-bias-machine-learning-business-covid/

Hecker, M. H. L., Stevens, K. N., von Bismarck, G., & Williams C. E. (1968). Manifestations of task-induced stress in the acoustic speech signal. *The Journal of the Acoustical Society of America, 44*(4), 993–1001. https://doi.org/10.1121/1.1911241

Hernandez-Leal, P., Maxhuni, A., Sucar, L. E, Osmani, V., Morales, E. F., & Mayora, O. (2015). Stress modelling using transfer learning in presence of scarce data. In J. Bravo, R. Hervás, & V. Villarreal (Eds), *Ambient intelligence for health. AmIHEALTH 2015. Lecture Notes in Computer Science* (Vol. 9456) (pp. 224–236). Springer. https://doi.org/10.1007/978-3-319-26508-7_22

Herzog, N. V., & Harih, G. (2020). Decision support system for designing and assigning ergonomic workplaces to workers with disabilities. *Ergonomics, 63*(2), 225–236. https://doi.org/10.1080/00140139.2019.1686658

High-Level Expert Group on Artificial Intelligence. (2019a). *A definition of artificial intelligence: Main capabilities and scientific disciplines.* European Commission. https://digital-strategy.ec.europa.eu/en/library/definition-artificial-intelligence-main-capabilities-and-scientific-disciplines

High-Level Expert Group on Artificial Intelligence. (2019b). *Ethics guidelines for trustworthy AI*. European Commission. https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

HSE. (2017). *Tackling work-related stress using the Management Standards approach. A step-by-step workbook.* Health and Safety Executive. https://www.hse.gov.uk/pubns/wbk01.pdf

Hughes, C., Robert, L., Frady, K., & Arroyos, A. (2019). *Managing technology and middle- and low-skilled employees: Advances for economic regeneration* (The changing context of managing people). Emerald Publishing Limited.

Hutson, M. (2018). Artificial intelligence faces reproducibility crisis. Science, 359(6377), 725–726. https://doi.org/10.1126/science.359.6377.725

IARC. (2011). *IARC classifies radiofrequency electromagnetic fields as possibly carcinogenic to humans.* Press Release No 208, International Agency for Research on Cancer (IARC). https://www.iarc.who.int/wp-content/uploads/2018/07/pr208_E.pdf

Iida, Y., Watanabe, K., Ominami, Y., Toyoguchi, T., Murayama, T., & Honda, M. (2021). Development of rapid and highly accurate method to measure concentration of fibers in atmosphere using artificial intelligence and scanning electron microscopy. *Journal of Occupational Health, 63*(1), Article e12238. https://doi.org/10.1002%2F1348-9585.12238

Jabagi, N., Croteau, A. M., & Audebrand, L. (2020). Perceived organizational support in the face of algorithmic management: A conceptual model. In *Proceedings of the 53rd Hawaii International Conference on System Sciences* (pp. 4001–4010). University of Hawaiʻi at Mānoa. http://hdl.handle.net/10125/64231

Jarota, M. (2021) Artificial intelligence and robotisation in the EU - Should we change OSH law? *Journal of Occupational Medicine and Toxicology, 16*(18), 1-9. https://doi.org/10.1186/s12995-021-00301-7

Jindo, T., Kai, Y., Kitano, N., Wakaba, K., Makishima, M.,Takeda, K., Iida, M., Igarashi, K., & Arao, T. (2020). Impact of activity-based working and height-adjustable desks on physical activity, sedentary behavior, and space utilization among office workers: A natural experiment. *International Journal of Environmental Research and Public Health, 17*(1), Article 236. https://doi.org/10.3390/ijerph17010236

Kagermann, H., Wahlster, W., & Helbig, J. (2013). *Securing the future of German manufacturing industry. Recommendations for implementing the strategic initiative Industrie 4.0. Final report of the Industrie 4.0 Working Group*. acatech – National Academy of Science and Engineering. https://en.acatech.de/publication/recommendations-for-implementing-the-strategic-initiative-industrie-4-0-final-report-of-the-industrie-4-0-working-group/

Karaboytcheva, M. (2020). *Effects of 5G wireless communication on human health*. European Parliamentary Research Service. https://europarl.europa.eu/RegData/etudes/BRIE/2020/646172/EPRS_BRI(2020)646172_EN.pdf

Karasek, R. A. (1979). Job demands, job decision latitude, and mental strain: Implications for job redesign. *Administrative Science Quarterly, 24*(2), 285–308. https://doi.org/10.2307/2392498

Katwala, A. (2017, July 18). *Making factories safer with VR, smart clothes and robots.* Institution of Mechanical Engineers. http://www.imeche.org/news/news-article/making-factories-safer-with-vr-smart-clothes-and-robots

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Kelly, J. (2021, September 26). *The future of hybrid and remote work will increase Orwellian Big-Brother 'tattleware' spyware for surveilling workers.* Forbes. https://www.forbes.com/sites/jackkelly/2021/09/26/the-future-of-hybrid-and-remote-work-will-increase-orwellian-big-brother-tattleware-spyware-for-surveilling-workers/

Kerravala, Z. (2021, September 10). *How AI and 5G will power the next wave of innovation*. ZDNet. https://www.zdnet.com/article/how-ai-and-5g-will-power-the-next-wave-of-innovation/

Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). *Working with machines: The impact of algorithmic and data-driven management on human workers.* In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (pp. 1603–1612). Association for Computing Machinery. https://doi.org/10.1145/2702123.2702548

Lee, M. K., Nigam, I., Zhang, A., Afriyie, J., Qin, Z., & Gao, S. (2021). *Participatory algorithmic management: Elicitation methods for worker well-being models*. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society* (pp. 715–726). Association for Computing Machinery. https://doi.org/10.1145/3461702.3462628

Lewis, N. (2019). *Be careful: Gamification at work can go very wrong.* SHRM. https://www.shrm.org/resourcesandtools/hr-topics/technology/pages/gamification-at-work-can-go-very-wrong.aspx

Lu, H., Frauendorfer, D., Rabbi, M., Mast, M. S., Chittaranjan, G. T., Campbell, A. T., Gatica-Perez, D., & Choudhury, T. (2012). StressSense: Detecting stress in unconstrained acoustic environments using smartphones. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing* (pp. 351–360). Association for Computing Machinery. https://doi.org/10.1145/2370216.2370270

Mai, J.-E. (2016). Big data privacy: The datafication of personal information. *The Information Society, 32*(3), 192–199. https://doi.org/10.1080/01972243.2016.1153010

Maroney, J. (2018, January 2). *2018 Global workplace trends*. Workforce Institute. https://workforceinstitute.org/2018-global-workplace-trends/

Mateescu, A., & Nguyen, A. (2019, February 6). *Explainer: Algorithmic management in the workplace.* Data & Society. https://datasociety.net/library/explainer-algorithmic-management-in-the-workplace/

McGuinness, S., Pouliakas, K., & Redmond, P. (2019). *Skills-displacing technological change and its impact on jobs: Challenging technological alarmism?* IZA Discussion Paper No. 12541, IZA Institute of Labor Economics. http://ftp.iza.org/dp12541.pdf

Meijerink, J., & Bondarouk, T. (2021). The duality of algorithmic management: Toward a research agenda on HRM algorithms, autonomy and value creation. *Human Resource Management Review*, Article 100876. Advance online publication. https://doi.org/10.1016/j.hrmr.2021.100876

Min, J., Kim, Y. M., Lee, S., Jang, T. W., Kim, I., & Song, J. (2019). The Fourth Industrial Revolution and its impact on occupational health and safety, worker's compensation and labor conditions. *Safety and Health at Work, 10*(4), 400–408. https://doi.org/10.1016/j.shaw.2019.09.005

Mishra, A. N., Cao, C., & George, J. (2019). IT-induced employment irregularities and deskilling: Impacts on temporary worker welfare. In H. Krcmar, J. Fedorowicz, W. Fong Boh, J. M. Leimeister, & S. Wattal (Eds), *Proceedings of the 40th International Conference on Information Systems*. Association for Information Systems. https://aisel.aisnet.org/icis2019/general_topics/general_topics/26

Mulholland, K., & Stewart, P. (2013). Workers in food distribution: Global commodity chains and lean logistics. *New Political Economy, 19*(4), 534–558. https://doi.org/10.1080/13563467.2013.829431

Mullen, C. (2021, December 21). *Our 2021 annual workplace predictions.* Workforce Institute. https://workforceinstitute.org/our-2021-annual-workplace-predictions/

Murthy, V. (2017, September 26). *Work and the loneliness epidemic*. Harvard Business Review. https://hbr.org/2017/09/work-and-the-loneliness-epidemic

Neagu, S. N., & Vieriu, A.-M. (2019). *The impact of technological progress on young people.* In *Proceedings of the 15th International Scientific Conference eLearning and Software for Education* (Vol. 2) (pp. 351–358). Carol I National Defence University Publishing House. https://doi.org/10.12753/2066-026X-19-119

O'Moore, M., & Lynch, J. (2007). Leadership, working environment and workplace bullying. *International Journal of Organizational Theory & Behavior, 10*(1), 95–117. https://doi.org/10.1108/IJOTB-10-01-2007-B005

de Oliveira, R. C. (2021). Gamification and Uberized work in application companies. *Revista de Administração de Empresas, 61*(4), 1–10. http://dx.doi.org/10.1590/S0034-759020210407

Oostveen, M. (2016). Identifiability and the applicability of data protection to big data. *International Data Privacy Law, 6*(4), 299–309. https://doi.org/10.1093/idpl/ipw012

Oracle and Workplace Intelligence. (2020). *As uncertainty remains, anxiety and stress reach a tipping point at work: Artificial intelligence fills the gaps in workplace mental health support.* Oracle. https://www.oracle.com/a/ocom/docs/oracle-hcm-ai-at-work.pdf

Palazon, J. A., Gozalvez, J., Maestre, J. L., & Gisbert, J. R. (2013) Wireless solutions for improving health and safety working conditions in industrial environments. In *IEEE 15th International Conference on e-Health Networking, Applications and Services (Healthcom 2013)* (pp. 544–548). IEEE Xplore. https://doi.org/10.1109/HealthCom.2013.6720736

Palmer, A. (2021, February 3). *Amazon is using AI-equipped cameras in delivery vans and some drivers are concerned about privacy.* CNBC. https://www.cnbc.com/2021/02/03/amazon-using-ai-equipped-cameras-in-delivery-vans.html

PEGA. (2020). *The future of work. New perspectives on disruption & transformation*. https://www.pega.com/system/files/resources/2021-04/pega-future-of-work-report.pdf

Ponce del Castillo, A. (2020). *Labour in the age of AI: Why regulation is needed to protect workers*. Foresight Brief #08, ETUI. https://www.etui.org/sites/default/files/ForesightBriefs2020.pdf

Ponce del Castillo, A. (2021). *The AI Regulation: Entering an AI regulatory winter? Why an ad hoc directive on AI in employment is required*. ETUI Research Paper - Policy Brief 2021.07. https://dx.doi.org/10.2139/ssrn.3873786

Porter, B. (2020, June 24). *Amazon introduces 'Distance Assistant'.* Amazon. https://www.aboutamazon.com/news/operations/amazon-introduces-distance-assistant

Privacy International. (2017). *Data is power: Profiling and automated decision-making in GDPR.* https://privacyinternational.org/sites/default/files/2018-04/Data%20Is%20Power-Profiling%20and%20Automated%20Decision-Making%20in%20GDPR.pdf

Punnoose, R., & Ajit, P. (2016). Prediction of employee turnover in organizations using machine learning algorithms. *International Journal of Advanced Research in Artificial Intelligence, 5*(9), 22–26. https://dx.doi.org/10.14569/IJARAI.2016.050904

Ra, S., Shresthaa, U., Khatiwada, S., Yoon, S-W., & Kwon, K. (2019). The rise of technology and impact on skills. *International Journal of Training Research, 17*(1), 26–40. https://doi.org/10.1080/14480220.2019.1629727

Rachuri, K. K., Musolesi, M., Mascolo, C., Rentfrow, P. J., Longworth, C., & Aucinas, A. (2010). *EmotionSense: A mobile phones based adaptive platform for experimental social psychology research.* In *Proceedings of the 12th ACM International Conference on Ubiquitous Computing* (pp. 281–290). Association for Computing Machinery. https://doi.org/10.1145/1864349.1864393

Ravid, D. M., Tomczak, D. L., White, J. C., & Behrend, T. S. (2020). EPM 20/20: A review, framework, and research agenda for electronic performance monitoring. *Journal of Management, 46*(1), 100–126. https://doi.org/10.1177%2F0149206319869435

Rosenblat, A., & Stark, L. (2016). Algorithmic labor and information asymmetries: A case study of Uber's drivers. *International Journal of Communication, 10*, 3758–3784. https://ijoc.org/index.php/ijoc/article/view/4892/1739

Russell, C. L. (2018). 5 G wireless telecommunications expansion: Public health and environmental implications. *Environmental Research, 165*, 484–495 https://doi.org/10.1016/j.envres.2018.01.016

Saithibvongsa, P., & Yu, J. E. (2018). Artificial intelligence in the computer-age threatens human beings and working conditions at workplaces. *Electronics Science Technology and Application, 5*(3). http://dx.doi.org/10.18686/esta.v5i3.76

Sanchez-Medina, A. J., Galvan-Sanchez, I., & Fernandez-Monroy, M. (2020). Applying artificial intelligence to explore sexual cyberbullying behaviour. *Heliyon, 6*(1), Article e03218. https://doi.org/10.1016%2Fj.heliyon.2020.e03218

Sarbadhikari, S. N., & Pradhan, K. B. (2020). The need for developing technology-enabled, safe, and ethical workforce for healthcare delivery. *Safety and Health at Work, 11*(4), 533–536. https://doi.org/10.1016/j.shaw.2020.08.003

Savignac, E. (2019). *La gamification du travail: L'ordre du jeu*. ISTE Group.

Segkouli, S., Giakoumis, D., Votis, K., Triantafyllidis, A., Paliokas, I., & Tzovaras, D. (2021). Smart workplaces for older adults: Coping 'ethically' with technology pervasiveness. *Universal Access in the Information Society*. Advance Online Publication. https://doi.org/10.1007/s10209-021-00829-9

Shamim Kaiser, M., Mahmud, M., Noor, M. B. T., Zenia, N. Z., Mamun, S. A., Abir Mahmud, K. M., Azad, S., Manjunath Aradhya, V. N., Stephan, P., Stephan, T., Kannan, R., & Hanif, M. (2021). *IWorksafe: Towards healthy workplaces during COVID-19 with an intelligent pHealth app for industrial settings. IEEE Access, 9*, 13814–13828. https://doi.org/10.1109/ACCESS.2021.3050193

Shapiro, A. (2018). Between autonomy and control: Strategies of arbitrage in the "on demand" economy. *New Media & Society, 20*(8), 2954–2971. https://doi.org/10.1177%2F1461444817738236

Soter Analytics. (2020, November 4). *How AI-driven algorithms improve an individual's ergonomic safety.* https://soteranalytics.com/soter-blog/how-ai-driven-algorithms-improve-an-individuals-ergonomic-safety/

Subedi, S., & Pradhananga, N. (2021). Mapping datafication in construction-worker safety research to minimize injury-related disputes. *Journal of Legal Affairs and Dispute Resolution in Engineering and Construction, 13*(2),1–29. https://doi.org/10.1061/%28ASCE%29LA.1943-4170.0000464

Todoli-Signes, A. (2021). Making algorithms safe for workers: Occupational risks associated with work managed by artificial intelligence. *Transfer: European Review of Labour and Research, 27*(4), 433–452. https://doi.org/10.1177%2F10242589211035040

Tomprou, M., & Lee, M. K. (2022). Employment relationships in algorithmic management: A psychological contract perspective. *Computers in Human Behavior, 126*, Article 106997. https://doi.org/10.1016/j.chb.2021.106997

Tursunbayeva, A. (2019). Human resource technology disruptions and their implications for human resources management in healthcare organizations. *BMC Health Services Research, 19*, Article 268. https://doi.org/10.1186/s12913-019-4068-3

Veen, A., Barratt, T., & Goods, C. (2020). Platform-Capital's 'App-etite' for control: A labour process analysis of food-delivery work in Australia. *Work, Employment and Society, 34*(3), 388–406. https://doi.org/10.1177%2F0950017019836911

Wang, K., Shu, Q., & Tu, Q. (2008). Technostress under different organizational environments: An empirical investigation. *Computers in Human Behavior, 24*(6), 3002–3013. https://doi.org/10.1016/j.chb.2008.05.007

Wang, Y., & Kosinski, M. (2018). Deep neural networks are more accurate than humans at detecting sexual orientation from facial images. *Journal of Personality and Social Psychology, 114*(2), 246–257. https://psycnet.apa.org/doi/10.1037/pspa0000098

Wood, A. J. (2021). *Algorithmic management: Consequences for work organisation and working conditions*. JRC124874, European Commission. https://ec.europa.eu/jrc/sites/default/files/jrc124874.pdf

Wood, A. J., & Lehdonvirta, V. (2021). Antagonism beyond employment: How the 'subordinated agency' of labour platforms generates conflict in the remote gig economy. *Socio-Economic Review*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3820645

Yaden, D. B., Eichstaedt, J. C., Kern, M. L., Smith, L. K., Buffone, A., Stillwell, D. J., Kosinski, M., Ungar, L. H., Seligman, M. E. P., & Schwartz, H. A. (2018). The language of religious affiliation: Social, emotional, and cognitive differences. *Social Psychological and Personality Science, 9*(4), 444–452. https://doi.org/10.1177%2F1948550617711228

Zaroushani, V. (2021). Occupational safety and health and response to COVID-19 using the Fourth Industrial Revolution technologies. *Journal of Health and Safety at Work, 10*(4), 329–348. https://jhsw.tums.ac.ir/article-1-6411-en.html

Zel, S., & Kongar, E. (2020). Transforming digital employee experience with artificial intelligence. In *2020 IEEE/ITU International Conference on Artificial Intelligence for Good (AI4G)* (pp. 176–179). IEEE Xplore. https://doi.org/10.1109/AI4G50087.2020.9311088

Annex I – Analysis of Third European Survey of Enterprises on New and Emerging Risks 2019 (ESENER-3) data

Digital technologies enabling AIWM and implications for OSH

An analysis of the implication of the use of digital technologies enabling AIWM systems for OSH is carried out by analysing ESENER-3 data.[9] An analysis of the use of digital technologies in European establishments was already presented in EU-OSHA (2022), while the focus here is to explore the relationship between the use of digital technologies enabling AIWM and selected OSH variables.

To do so, a number of regressions models were estimated. More specifically, individual digital technologies as identified by question Q310 (Q310_3 to Q310_6) were used as individual dependent variables (0 = no technology, 1 = technology) in several logit regression models, while a variety of variables indicating insights related to OSH were used as independent variables. In total, four types of digital technologies enabling AIWM were considered and four different models for each technology were estimated following a stepwise approach. The four regression models are as follows:

- **Model 1** – base model that includes only a number of different establishment characteristics, such as the size, sector and type of organisation.
- **Model 2** – is an expansion of the base model that, in addition to the establishment characteristics, contains OSH risks as identified in ESENER-3 question Q200 on physical risks and question Q201 on psychosocial risks.
- **Model 3** – expands on the second model by including different mitigation factors that can help to prevent negative OSH effects**.** These include, but are not limited to, variables that indicate if an enterprise provides a workplace risk assessment, trains team leads and employees on OSH management, has an action plan in place to prevent psychosocial risks, and similar. However, it bears mentioning that not all variables that are included in ESENER-3 and that cover mitigation factors were included in this model to improve its reliability and robustness. For example, question Q308 that described the main obstacles of dealing with psychosocial risks was excluded from the model; it was not included as respondents relatively rarely answered this question, and its inclusion would have immensely decreased the sample size of the model.
- **Model 4** – is the final regression model that contains only statistically significant variables, which were identified using a stepwise sequential elimination of variables that had a p-value lower than 0.1. That is, the sequential elimination was carried out until only statistically significant results remained.

Usage of robots that interact with workers

The first group of regression models presented in Table I-1 provides the regression results exploring the correlation between an establishment's use of robots that interact with workers' technology and a number of other variables. The following insights can be derived from the results:

- Regarding establishment factors, first, as the establishment size increased, the odds that an organisation employing robots that interact with workers also increased. Second, there is no statistically significant correlation between whether an organisation is a single site or a multi-site establishment, or between public and private organisations in terms of the usage of robots that interact with workers. Third, regarding employee representation, according to three out of four models, there is a statistically significant positive relationship between organisations having employee representation through a trade union and the usage of robots that interact with

[9] Relevant technologies in ESENER-3 that can serve as proxies of AIWM include: (i) robots that interact with workers; (ii) machines, systems or computers determining the content or pace of work; (iii) machines, systems or computers monitoring workers' performance; and (iv) wearable devices, such as smart watches, data glasses or other (embedded) sensors.

workers. Similarly, health and safety representation also positively correlates with the use of such robots.

- Regarding the correlation between physical risk factors and the usage of robots that interact with workers, there are no risks that are consistently significant throughout all models. However, the risk of repetitive hand and arm movement injury, risk of accidents with machines or hand tools, and risks related to chemical or biological substances are significant in the second and third models. It bears mentioning that it is unclear if AI tools create these risks, as their significance might also indicate that jobs that demand repetitive hand movements, use machines or hand tools, and use chemicals more often employ such robots.
- Regarding the correlation with psychosocial risks, time pressure is the only risk that is statistically significant, even though, in the majority of cases, it was at a low significance level (i.e. 0.1), in all three models. However, this does not necessarily imply any specific insights about how the technology affects risks, and more likely simply shows that workplaces with high time pressures tend to employ such robots more frequently.
- Regarding mitigation factors, only promoting sports activities outside of working hours is consistently significant. Regular discussions of health and safety issues at the top levels of management and confidential counselling for employees are significant in the fourth model. In addition, there is also a strong and positive correlation with discussions on the effects of technologies on OSH and robot technologies. This implies that, though some worker management technologies might bring negative consequences, in organisations where they are used there is also an ongoing discussion about them.

Table I-1: Binomial logit regression models analysing factors correlated with the usage of robots that interact with workers (use of robots = 1)

Variables	Item	Model 1	Model 2	Model 3	Model 4
Constant		0.0532***	0.0207***	0.0214***	0.0258***
Establishment size (reference: 5-9 employees)	**10-49 employees**	1.2161	1.0779	-	-
	50-249 employees	1.6912***	1.3029**	1.0607	-
	250+ employees	3.1579***	2.2305***	1.8342**	1.9547***
NACE Rev. 2 sections (main activity) (reference: NACE A)	**B**	0.4995	0.5359	0.4549	0.4723**
	C	1.0858	1.1	0.9136	
	D	0.2744**	0.3432*	>0.0001***	0.2013***
	E	0.5636*	0.5998	0.3332	0.3727***
	F	0.2572***	0.2383***	0.1249***	0.2648***
	G	0.3802***	0.5265***	0.4748	0.4017***
	H	0.2085***	0.2266***	0.2039***	0.2361***
	I	0.2392***	0.3258***	0.3065*	0.2059***
	J	0.3391***	0.6766	0.5279	0.5721***
	K	0.2779***	0.6071	>0.0001***	0.6319**
	L	0.2574***	0.3973*	0.2999	0.3544***
	M	0.5318**	0.7637	0.7287	
	N	0.2676***	0.3964***	0.0986***	0.2447***
	O	0.198***	0.3057***	0.0563***	0.1277***
	P	0.4372***	0.7692	0.5486	0.3043***
	Q	0.3222***	0.4254***	0.1439***	0.3018***
	R	0.2821***	0.4094*	0.3967	0.2472***
	S	0.2927***	0.4028**	0.3631	0.2608***
Is a single-site company		0.9705	1.0093	1.4013*	-
Is a public company		0.9852	0.9115	0.8158	-
Employee representation (reference: no representation)	**Work council**	1.1492	1.2024*	1.1579	-
	Trade union representation	1.2173**	1.1189	1.5792**	1.3566***
	Health and safety committee	1.1588	1.1917	0.8552	-
	Health and safety representative	1.3986***	1.3288***	1.0783	-
Physical risks (reference: no risks)	**Lifting or moving people or heavy loads**	-	1.1841	1.4605	1.2885***
	Repetitive hand or arm movements	-	1.1687	1.6297**	1.5899***
	Prolonged sitting	-	1.0933	1.0063	-
	Tiring or painful positions	-	0.8916	0.7908	-

Variables	Item	Model 1	Model 2	Model 3	Model 4
	Loud noise	-	1.2917**	1.0742	-
	Heat, cold or draught	-	0.9415	1.0207	-
	Risk of accidents with machines or hand tools	-	1.4915***	1.276	1.3499***
	Risk of accidents with vehicles in the course of work, but not on the way to and from work	-	1.0779	1.1383	-
	Chemical or biological substances in the form of liquids, fumes or dust	-	1.3625***	1.4582	1.2917***
	Increased risk of slips, trips and falls	-	1.1939*	0.9238	-
Psychosocial risks (reference: no)	Time pressure	-	1.1766*	1.3401*	1.1662**
	Poor communication or cooperation within the organisation	-	1.0772	1.0967	-
	Fear of job loss		0.9232	0.8186	-
	Having to deal with difficult customers, patients, pupils, etc.	-	0.9255	1.0269	-
	Long or irregular working hours	-	1.1409	1.3389*	1.1404*
Establishment promotes sports activities outside of working hours		-	-	1.3455*	1.2547***
Establishment promotes back exercises, stretching or other physical exercise at work		-	-	1.1184	-
Health and safety issues are discussed at the top levels of management (reference: occasionally)	Regularly	-	-	1.3902	1.3009***
	Practically never	-		0.3743	-
Team leaders received training on how to manage health and safety in their team		-	-	1.7166*	-
Employees personally received training on how to manage health and safety		-	-	0.8944	-
Establishment regularly carries out workplace risk assessment		-	-	0.6025	-
Establishment has an action plan to prevent work-related stress		-	-	1.1271	-
An employee survey including questions on work-related stress was conducted in the last 3 years		-	-	1.086	-
Workplace used one of the following measures in the last 3 years to prevent psychosocial risks (reference: no measures)	Reorganisation of work in order to reduce job demands and work pressure	-	-	0.9919	-
	Confidential counselling for employees	-	-	0.897	1.1664**
	Training on conflict resolution	-	-	1.2706	-
	Intervention, if excessively long or irregular hours are worked	-	-	0.8896	-
	Allowing employees to make more decisions on how to do their job	-	-	0.7884	-
Are psychosocial risks easier or more difficult to address than other risks? (reference: no big difference)	Easier	-	-	1.1195	-
	More difficult	-		0.8371	-
Workplace provides training on how to prevent psychosocial risks, such as stress or bullying		-	-	1.0892	-
OSH issues discussed in staff or team meetings (ref: occasionally)	Regularly	-	-	0.6708	-
	Practically never	-	-	0.5608*	-
Possible effect of using technologies on OSH has been discussed in the establishment		-	-	1.7062***	1.8017***
	N	13,562	12,711	2,797	14,634

Source: Authors' elaboration on ESENER-3 data.
Note 1: * indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.
Note 2: Robust quasi-maximum likelihood robust standard error was applied to ensure robustness.
Note 3: Majority of models do not have collinearity issues as estimated by the Variance Inflation Factor (VIF) and, when it was present, it only affected the control variables in the model.
Note 4: Establishment size variable has different references for different models, as in the models with more variables, which are much smaller in size, no information was available for organisations with 5-9 employees.
Note 5: NACE Rev. 2 sectors: A – Agriculture, Forestry and Fishing; B – Mining and Quarrying; C – Manufacturing; D – Electricity, Gas, Steam, and Air Conditioning Supply; E – Water Supply; Sewerage, Waste Management, and Remediation Activities; F – Construction; G – Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles; H – Transportation and Storage; I – Accommodation and Food Service Activities; J – Information and Communication; K – Financial and Insurance Activities; L – Real Estate Activities; M – Professional, Scientific, and Technical Activities; N – Administrative and Support Service Activities; O – Public Administration and Defence, Compulsory Social Security; P – Education; Q – Human Health and Social Work Activities; R – Arts, Entertainment, and Recreation; S – Other Service Activities.

Usage of machines, systems or computers determining the content or pace of work

The second group of regression models, presented in Table I-2, which covers the usage of machines, systems or computers determining the content or pace of work, in general, provides similar results to the first group of models previously discussed, but some differences are worth noting:

- In the majority of models, single-site and public companies have a negative relationship with the dependent variable, as the odds ratio presented in the models are below 1. This implies that larger organisations use such technologies more frequently. Besides that, the results connected to establishment factors are consistent with Table I-1.
- Regarding traditional risks – tiring or painful positions and loud noise are strongly and positively associated with the usage of machines, systems or computers that determine the content or pace of work in almost all models. The mention of tiring positions might imply that such technologies are pushing workers to perform their work faster than they are comfortable with, while the significance of loud noises might imply that such technologies are predominantly used around large machinery.
- The highlighted insights about tiring positions are also supported by the psychosocial risks' results, where the only consistently significant risk is time pressure. More specifically, according to the three models that included time pressure among the risks as the independent variable, it is positively and statistically significant in all of them.
- Regarding mitigation measures, first of all, the results are consistent with the previous group of models. Beyond that, the models in which technologies were related to the use of technologies determining the content and the pace of work also strongly and positively correlated with more difficulties in addressing and assessing psychosocial risks.

Table I-2: Binomial logit regression models analysing factors correlated with the usage of machines, systems or computers determining the content or pace of work (machines determining the content or pace of work = 1)

Variables	Item	Model 1	Model 2	Model 3	Model 4
Constant		0.1931***	0.0952***	0.0934***	0.1232***
Establishment size (reference: 5-9 employees)	**10-49 employees**	1.4291***	1.3011***	-	-
	50-249 employees	1.6978***	1.4376***	1.0676	-
	250+ employees	2.5219***	1.906***	1.2532	1.4852***
NACE Rev. 2 sections (main activity) (reference: NACE A)	**B**	1.1277	1.285	3.1705*	-
	C	1.7209***	1.7399***	2.5509***	2.3753***
	D	0.967	1.0356	0.5206	-
	E	0.9331	0.9847	1.2638	-
	F	0.4689***	0.4415***	0.6498	0.6872**
	G	0.6896***	0.8351	1.3725	-
	H	0.8752	0.9774	1.1245	-
	I	0.6774**	0.8559	1.6259	-
	J	0.7181*	1.0051	1.4184	-
	K	0.338***	0.5316**	0.6049	-
	L	0.6694*	0.8773	1.6599	-
	M	0.5351***	0.739	0.87	-

Variables	Item	Model 1	Model 2	Model 3	Model 4
	N	0.4851***	0.609**	0.9114	-
	O	0.4285***	0.5519***	0.5012*	0.7192*
	P	0.3344***	0.4977***	0.5161*	0.54***
	Q	0.4953***	0.6338**	1.014	-
	R	0.4988***	0.6927	0.873	-
	S	0.5731***	0.6765*	0.5713	-
Is a single-site company		0.8018***	0.8414**	0.8542	0.8031***
Is a public company		0.7221***	0.7015***	0.6949**	0.7041***
Employee representation (reference: no representation)	Work council	1.1223**	1.1264*	0.927	-
	Trade union representation	1.2592***	1.1704**	1.2786**	1.2758***
	Health and safety committee	1.1161*	1.0816	0.9892	-
	Health and safety representative	1.0901	1.0919	0.99	-
Traditional OSH risks (reference: no risks)	Lifting or moving people or heavy loads	-	1.0333	0.9146	-
	Repetitive hand or arm movements	-	1.2947***	1.1857	-
	Prolonged sitting	-	1.0245	0.942	-
	Tiring or painful positions	-	1.2537***	1.2113*	1.246***
	Loud noise	-	1.2257***	1.5376***	1.3626***
	Heat, cold or draught	-	1.0161	1.1784	-
	Risk of accidents with machines or hand tools	-	1.3529***	1.3176*	-
	Risk of accidents with vehicles in the course of work, but not on the way to and from work	-	1.1033	1.183	1.5405***
	Chemical or biological substances in the form of liquids, fumes or dust	-	1.1275*	1.0602	-
	Increased risk of slips, trips and falls	-	0.8671**	0.6852***	-
Psychosocial risks (reference: no risks)	Time pressure	-	1.1951***	1.2436*	1.2634***
	Poor communication or cooperation within the organisation	-	0.9284	1.0032	-
	Fear of job loss	-	1.009	1.0958	-
	Having to deal with difficult customers, patients, pupils, etc.	-	0.9512	0.7978*	0.811***
	Long or irregular working hours	-	1.1325**	1.2496**	-
Establishment promotes sports activities outside of working hours		-	-	0.7783**	0.7496***
Establishment promotes back exercises, stretching or other physical exercise at work		-	-	1.0565	0.8078**
Health and safety issues are discussed at the top levels of management (reference: occasionally)	Regularly	-	-	0.9495	-
	Practically never	-	-	0.9558	-
Team leaders received training on how to manage health and safety in their team		-	-	1.0643	-
Employees personally received training on how to manage health and safety		-	-	0.7689	-
Establishment regularly carries out workplace risk assessment		-	-	0.8016	0.814**
Establishment has an action plan to prevent work-related stress		-	-	1.1589	-
An employee survey including questions on work-related stress was conducted in the last 3 years		-	-	1.0149	-
Workplace used one of the following measures in the last 3 years to prevent psychosocial risks (reference: no)	Reorganisation of work in order to reduce job demands and work pressure	-	-	1.1091	-
	Confidential counselling for employees	-	-	1.2561*	1.275***

Variables	Item	Model 1	Model 2	Model 3	Model 4
	Training on conflict resolution	-	-	1.0655	-
	Intervention, if excessively long or irregular hours are worked	-	-	0.8942	-
	Allowing employees to make more decisions on how to do their job	-	-	0.9935	-
Are psychosocial risks easier or more difficult to address than other risks? (reference: no big difference)	**Easier**	-	-	1.2268	1.1684*
	More difficult	-	-	1.2849**	1.2499***
Workplace provides training on how to prevent psychosocial risks, such as stress or bullying		-	-	0.9696	-
OSH issues discussed in staff or team meetings (reference: occasionally)	**Regularly**	-	-	1.5368*	1.3588**
	Practically never	-	-	1.4574*	1.3464***
The possible effects of using technologies on OSH has been discussed in the establishment		-	-	1.8329***	1.7328***
	N	**13,512**	**12,673**	**2,794**	**6,369**

Source: Authors' elaboration on ESENER-3 data.
Note 1: * indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.
Note 2: Robust quasi-maximum likelihood robust standard error was applied to ensure robustness.
Note 3: Majority of models do not have collinearity issues as estimated by the Variance Inflation Factor (VIF) and, when it was present, it only affected the control variables in the model.
Note 4: Establishment size variable has different references for different models as in the models with more variables, which are much smaller in size, no information was available for organisations with 5-9 employees.
Note 5: NACE Rev. 2 sectors: A – Agriculture, Forestry, and Fishing; B – Mining and Quarrying; C – Manufacturing; D – Electricity, Gas, Steam, and Air Conditioning Supply; E – Water Supply; Sewerage, Waste Management, and Remediation Activities; F – Construction; G – Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles; H – Transportation and Storage; I – Accommodation and Food Service Activities; J – Information and Communication; K – Financial and Insurance Activities; L – Real Estate Activities; M – Professional, Scientific, and Technical Activities; N – Administrative and Support Service Activities; O – Public Administration and Defence, Compulsory Social Security; P – Education; Q – Human Health and Social Work Activities; R – Arts, Entertainment, and Recreation; S – Other Service Activities.

Usage of machines, systems or computers monitoring workers' performance

The third group of regression models, presented in Table I-3, explores the usage of monitoring technologies and provides similar results to the previous two model groups. The first of only two noteworthy differences is that in this group of models the presence of trade unions in the workplace does not have a statistically significant correlation with the dependent variable, unlike in the previous two model groups and, instead, employee representation through a health and safety committee is statistically significant. Second, risks from repetitive hand movements are positively and strongly significant, which might simply indicate that monitoring solutions are more frequently used in organisations with many repetitive, or routine, tasks.

Table I-3: Binomial logit regression models analysing factors correlated with the usage of monitoring technologies (monitoring = 1)

Variables	Item	Model 1	Model 2	Model 3	Model 4
Constant		0.1162***	0.0688***	0.0754***	0.0672***
Establishment size (reference: no information is available on 5-9 employees and hence the reference is 10-49 employees)	**10-49 empl.**	1.5096***	1.3792***	-	-
	50-249 empl.	1.9332***	1.6997***	1.0156	-
	250+ empl.	3.2851***	2.702***	1.4506**	1.8106***
NACE Rev. 2 sections (main activity) (reference: NACE A)	**B**	0.8684	0.8721	1.4462	
	C	0.8948	0.8236	1.4627	1.1925**
	D	0.5185	0.5382	0.5537	-

Variables	Item	Model 1	Model 2	Model 3	Model 4
	E	0.7802	0.7496	1.205	-
	F	0.3483***	0.3102***	0.6999	0.443***
	G	0.7326**	0.7278*	1.356	-
	H	1.3411*	1.1536	1.3279	-
	I	0.5831***	0.6326***	0.6997	-
	J	0.7816	0.7936	1.2074	-
	K	0.7277	0.8219	1.8772	-
	L	0.2723***	0.3075***	0.4509	0.3465***
	M	0.4259***	0.4551***	0.6603	0.5787***
	N	0.6653**	0.6659**	1.0766	
	O	0.4933***	0.4314***	0.5029*	
	P	0.3003***	0.3211***	0.3102***	0.4824***
	Q	0.409***	0.4221***	0.5735	0.3442***
	R	0.4686***	0.5441**	0.7777	0.5352***
	S	0.5859**	0.5853**	0.7065	-
Is a single-site company		0.8479**	0.8548**	0.8171	0.8552**
Is a public company		0.6824***	0.7081***	1.0021	-
Employee representation (reference: no representation)	**Work council**	1.1318	1.1273*	1.1555	-
	Trade union representation	1.1485*	1.0551	0.9507	-
	Health and safety committee	1.3635***	1.366***	1.2841**	1.4854***
	Health and safety representative	1.4688***	1.4376***	1.1128	-
Traditional OSH risks (reference: no)	**Lifting or moving people or heavy loads**	-	0.9861	0.8035	-
	Repetitive hand or arm movements	-	1.4904***	1.481***	1.429***
	Prolonged sitting	-	1.0558	1.0874	-
	Tiring or painful positions	-	1.0281	0.9605	-
	Loud noise	-	1.2196***	1.4811***	1.275***
	Heat, cold or draught	-	0.9852	1.1276	-
	Risk of accidents with machines or hand tools	-	0.9662	0.9864	1.2695***
	Risk of accidents with vehicles in the course of work, but not on the way to and from work	-	1.2677***	1.1599	-
	Chemical or biological substances in the form of liquids, fumes or dust	-	1.0761	1.2593*	-
	Increased risk of slips, trips and falls	-	0.9195	0.9904	-
Psychosocial risks (reference: no)	**Time pressure**	-	1.1336	1.029	-
	Poor communication or cooperation within the organisation	-	1.1411*	1.1023	1.2028**
	Fear of job loss	-	1.1171	1.1399	-
	Having to deal with difficult customers, patients, pupils, etc.	-	1.1057	0.9285	-
	Long or irregular working hours	-	1.0901	1.1306	-
Establishment promotes sports activities outside of working hours		-	-	1.4394***	1.2437***
Establishment promotes back exercises, stretching or other physical exercise at work		-	-	0.9029	-
Health and safety issues are discussed at the top levels of management (reference: occasionally)	**Regularly**	-	-	0.8537	-
	Practically never	-	-	1.013	-
Team leaders received training on how to manage health and safety in their team		-	-	1.1105	-
Employees personally received training on how to manage health and safety		-	-	0.8963	-
Establishment regularly carries out workplace risk assessment		-	-	1.2069	-

Variables	Item	Model 1	Model 2	Model 3	Model 4
Establishment has an action plan to prevent work-related stress		-	-	0.9737	-
An employee survey including questions on work-related stress was conducted in the last 3 years		-	-	0.9373	-
Workplace used one of the following measures in the last 3 years to prevent psychosocial risks (reference: no measures)	**Reorganisation of work in order to reduce job demands and work pressure**	-	-	1.0052	-
	Confidential counselling for employees	-	-	1.1096	1.2874***
	Training on conflict resolution	-	-	1.2282*	-
	Intervention if excessively long or irregular hours are worked	-	-	1.198	1.2571***
	Allowing employees to make more decisions on how to do their job	-	-	0.9462	-
Are psychosocial risks easier or more difficult to address than other risks? (reference: no big difference)	**Easier**	-	-	0.8996	-
	More difficult	-	-	0.8571	-
Workplace provides training on how to prevent psychosocial risks, such as stress or bullying		-	-	0.9965	-
OSH issues discussed in staff or team meetings (reference: occasionally)	**Regularly**	-	-	0.8034	-
	Practically never	-	-	0.7872	-
The possible effect of using technologies on OSH has been discussed in the establishment		-	-	1.5004***	1.5583***
	N	**13,542**	**12,695**	**2,791**	**12,876**

Source: Authors' elaboration on ESENER-3 data.
Note 1: * indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.
Note 2: Robust quasi-maximum likelihood robust standard error was applied to ensure robustness.
Note 3: Majority of models do not have collinearity issues as estimated by the Variance Inflation Factor (VIF) and, when it was present, it only affected the control variables in the model.
Note 4: Establishment size variable has different references for different models as in the models with more variables, which are much smaller in size, no information was available for organisations with 5-9 employees.
Note 5: NACE Rev. 2 sectors: A – Agriculture, Forestry and Fishing; B – Mining and Quarrying; C – Manufacturing; D – Electricity, Gas, Steam and Air Conditioning Supply; E – Water Supply; Sewerage, Waste Management and Remediation Activities; F – Construction; G – Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles; H – Transportation and Storage; I – Accommodation and Food Service Activities; J – Information and Communication; K – Financial and Insurance Activities; L – Real Estate Activities; M – Professional, Scientific and Technical Activities; N – Administrative and Support Service Activities; O – Public Administration and Defence, Compulsory Social Security; P – Education; Q – Human Health and Social Work Activities; R – Arts, Entertainment and Recreation; S – Other Service Activities.

Usage of wearable devices, such as smart watches, data glasses or other (embedded) sensors

The final group of models, presented in Table I-4, explores how different factors correlated with the usage of wearable devices, such as smart watches, data glasses or other (embedded) sensors. The results are consistent with other groups of models, with several noteworthy differences. First, employee representation in the form of a health and safety representative is strongly correlated to the dependent variable. Second, the risk of long or irregular working hours has a strong and positive connection with the dependent variable. This might imply that such technologies foster unhealthy working time patterns, though no concrete conclusions can be made regarding this.

Table I-4: Binomial logit regression models analysing factors correlated with the usage of wearable devices, such as smart watches, data glasses or other (embedded) sensors (wearables = 1)

Variables	Item	Model 1	Model 2	Model 3	Model 4
Constant		0.05***	0.0294***	0.0216***	0.021***
Establishment size (reference: no information is available on 5-9 employees and hence the reference is 10-49 employees)	**10-49 employees**	1.06	1.0445	-	-
	50-249 employees	1.2113	1.2094	1.4451*	-
	250+ employees	1.8287***	1.7589***	1.9948***	1.4749***
NACE Rev. 2 sections (main activity) (reference: NACE A)	**B**	0.9092	1.0612	0.7044	-
	C	0.9806	0.9402	0.6612	0.7598***
	D	1.1608	1.1352	0.4418	-
	E	1.4042	1.3256	0.8407	-
	F	1.0545	0.9692	0.7831	-
	G	0.9106	0.9535	1.2622	-
	H	1.8349**	1.7365**	1.1194	-
	I	0.5627**	0.5448**	0.6276	0.6832**
	J	1.8784**	1.9769**	1.2328	-
	K	0.6725	0.7603	0.8585	0.4649***
	L	1.0393	1.0498	>0.0001***	-
	M	1.1044	1.2086	1.1238	-
	N	0.9959	1.0562	1.2447	-
	O	0.8739	0.9358	0.9607	-
	P	0.8806	0.9364	0.9997	-
	Q	0.925	0.8674	0.6741	0.5968***
	R	0.7272	0.8361	1.3674	-
	S	0.9572	0.9391	1.5131	0.607*
Is a single-site company		0.8532	0.8784	0.8982	-
Is a public company		0.7157***	0.6762***	0.8294	0.7619***
Employee representation (reference: no representation)	**A work council**	1.0514	1.0191	0.874	-
	A trade union representation	0.9937	0.911	0.6875**	-
	A health and safety committee	1.2205***	1.2007*	0.8152	-
	A health and safety representative	1.4843***	1.4817***	1.5221**	1.2826**
Traditional OSH risks (reference: no)	**Lifting or moving people or heavy loads**	-	1.1827*	1.1964	-
	Repetitive hand or arm movements	-	1.2462**	1.5885**	-
	Prolonged sitting	-	1.038	0.96	-
	Tiring or painful positions	-	1.1551*	1.4185**	1.3567***
	Loud noise	-	1.1082	1.0836	-
	Heat, cold or draught	-	0.9685	1.0477	-
	Risk of accidents with machines or hand tools	-	1.0464	0.9355	-
	Risk of accidents with vehicles in the course of work, but not on the way to and from work	-	0.9411	0.9171	-
	Chemical or biological substances in the form of liquids, fumes or dust	-	1.0461	1.0669	-
	Increased risk of slips, trips and falls	-	0.9288	0.7097**	-
Psychosocial risks (reference: no)	**Time pressure**	-	1.0157	1.0076	-
	Poor communication or cooperation within the organisation	-	0.828*	1.03	-
	Fear of job loss	-	1.1766	1.2151	-
	Having to deal with difficult customers, patients, pupils, etc.	-	1.2727***	1.1254	-
	Long or irregular working hours	-	1.3566***	1.4158**	1.3225***
Establishment promotes sports activities outside of working hours		-	-	0.7951	-

Variables	Item	Model 1	Model 2	Model 3	Model 4
Establishment promotes back exercises, stretching or other physical exercise at work		-	-	1.0262	1.2058**
Health and safety issues are discussed at the top levels of management (reference: occasionally)	**Regularly**	-	-	1.3324	1.1781*
	Practically never	-	-	1.1154	-
Team leaders received training on how to manage health and safety in their team		-	-	0.808	1.2765**
Employees personally received training on how to manage health and safety		-	-	0.7104	0.7684**
Establishment regularly carries out workplace risk assessment		-	-	1.2098	-
Establishment has an action plan to prevent work-related stress		-	-	1.3428*	-
An employee survey including questions on work-related stress was conducted in the last 3 years		-	-	1.1551	-
Workplace used one of the following measures in the last 3 years to prevent psychosocial risks (reference: no)	**Reorganisation of work in order to reduce job demands and work pressure**	-	-	0.9438	-
	Confidential counselling for employees	-	-	1.1421	1.3411***
	Training on conflict resolution	-	-	1.2046	1.1617*
	Intervention if excessively long or irregular hours are worked	-	-	1.0892	1.1973**
	Allowing employees to make more decisions on how to do their job	-	-	1.3029	-
Are psychosocial risks easier or more difficult to address than other risks? (reference: no big difference)	**Easier**	-	-	0.7771	-
	More difficult	-	-	0.8635	-
Workplace provides training on how to prevent psychosocial risks, such as stress or bullying		-	-	1.035	-
OSH issues discussed in staff or team meetings (reference: occasionally)	**Regularly**	-	-	0.9044	-
	Practically never	-	-	0.61*	-
The possible effect of using technologies on OSH has been discussed in the establishment		-	-	2.8537***	2.7423***
	N	**13,557**	**12,708**	**2,797**	**12,597**

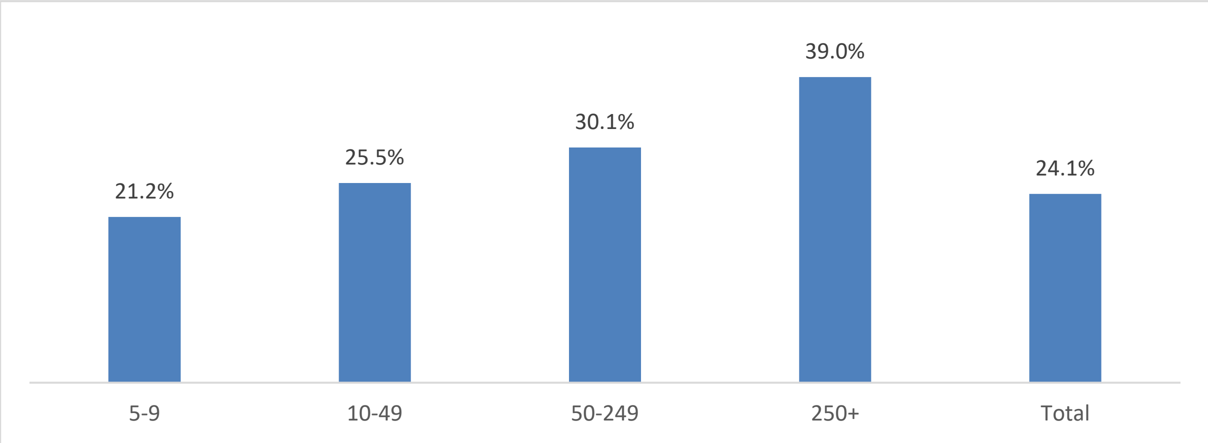
Source: Authors' elaboration on ESENER-3 data.
Note 1: * indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.
Note 2: Robust quasi-maximum likelihood robust standard error was applied to ensure robustness.
Note 3: Majority of models do not have collinearity issues as estimated by the Variance Inflation Factor (VIF) and, when it was present, it only affected the control variables in the model.
Note 4: Establishment size variable has different references for different models as in the models with more variables, which are much smaller in size, no information was available for organisations with 5-9 employees.
Note 5: NACE Rev. 2 sectors: A – Agriculture, Forestry and Fishing; B – Mining and Quarrying; C – Manufacturing; D – Electricity, Gas, Steam and Air Conditioning Supply; E – Water Supply; Sewerage, Waste Management and Remediation Activities; F – Construction; G – Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles; H – Transportation and Storage; I – Accommodation and Food Service Activities; J – Information and Communication; K – Financial and Insurance Activities; L – Real Estate Activities; M – Professional, Scientific and Technical Activities; N – Administrative and Support Service Activities; O – Public Administration and Defence, Compulsory Social Security; P – Education; Q – Human Health and Social Work Activities; R – Arts, Entertainment and Recreation; S – Other Service Activities.

Discussions of the impact of digital technologies in the workplace

Expanding on the impact analysis, variable Q311 of the ESENER-3 dataset is used for measuring the awareness of persons responsible for safety and health at work about the potential risks of digital technologies. However, for reasons of the questionnaire's economy, the question was asked in only a general way, and was not related to each applied technology separately, but to any of the technologies asked about in Q310_1 to Q310_6. This needs to be kept in mind when interpreting the answers to this question, that is, if an establishment uses different technologies and answered the question with a ‘yes’, a discussion of possible OSH consequences has not necessarily taken place for each of the technologies used, but possibly just for one or some of them.

In spite of this, on average, only less than a quarter of the establishments using any of the digital technologies mapped in ESENER-3 (Q310_1 to Q310_6) indicated that they have discussed in their establishment the possible health and safety impacts of the use of these technologies. Larger establishments have more often indicated such discussions than smaller ones, which can be explained, to an extent, by the fact that large establishments more frequently use such technologies and have internal representations of workers.

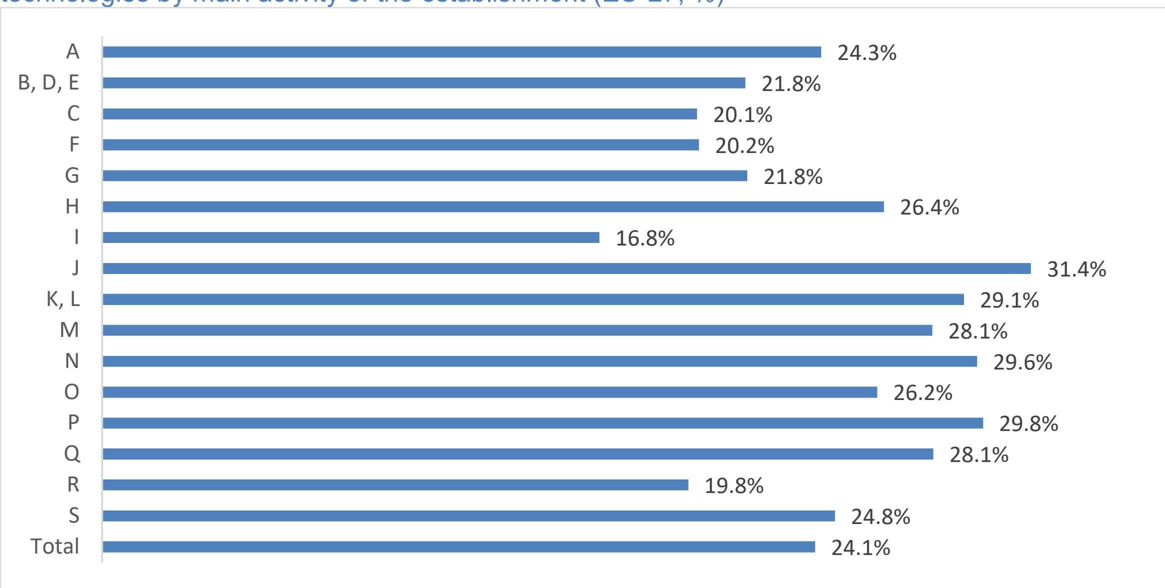
Figure I-1: Workplaces reporting discussions on the possible health and safety impacts of digital technologies by size (EU-27, %)



Source: Authors’ elaboration on ESENER-3 data.
N=34,351
Note: establishment proportional weighting factor *estprop* applied that corrects for the disproportionalities of the sample with regard to size and country, and adjusts for unequal response by size, sector, and country.

Figure I-2 provides insights on the discussion on the impacts related to the use of digital technologies by sector of activity.

Figure I-2: Workplaces reporting discussions on the possible health and safety impacts of digital technologies by main activity of the establishment (EU-27, %)



Source: Authors’ elaboration on ESENER-3 data; N=34,351
Note 1: sectors highlighted with an * were summarised due to the small sample size.
Note 2: establishment proportional weighting factor *estprop* applied that corrects for the disproportionalities of the sample with regard to size and country and adjusts for unequal response by size, sector and country.

Note 3: NACE Rev. 2 sectors: A – Agriculture, Forestry and Fishing; B – Mining and Quarrying; C – Manufacturing; D – Electricity, Gas, Steam and Air Conditioning Supply; E – Water Supply; Sewerage, Waste Management and Remediation Activities; F – Construction; G – Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles; H – Transportation and Storage; I – Accommodation and Food Service Activities; J – Information and Communication; K – Financial and Insurance Activities; L – Real Estate Activities; M – Professional, Scientific and Technical Activities; N – Administrative and Support Service Activities; O – Public Administration and Defence, Compulsory Social Security; P – Education; Q – Human Health and Social Work Activities; R – Arts, Entertainment and Recreation; S – Other Service Activities.

In addition to the bivariate analysis, a binomial logit regression analysis was carried out (see Table I-5). This analysis was aimed at identifying key variables that independently of each other correlate with the discussion on health and safety. This includes variables related to the usage of different digital technologies that may enable AIWM. It also bears mentioning that the models do not include variables related to prevention as any correlation between prevention and discussion would not add much value to the research, as it would simply indicate whether organisations that actively try to prevent OSH risks also discuss them. The models generally confirm most of the bivariate findings. Also, it is interesting to note that any kind of worker representation in an organisation has a positive effect on discussions, which implies that effective social dialogue in the workplace is fostered by the presence of employees' representations, and, in turn, this might lead to fewer OSH-related risks.

Table I-5. Binomial logit regression analysing factors correlated with the take-up of discussions on health and safety implications of digital technologies used at the establishment (=dependent variable Q311 = 'yes')

Variables	Item	Model 1	Model 2	Model 3
Constant		0.3063***	0.1094***	0.0919***
Establishment size (reference: 5-9 employees)	**10-49 employees**	1.0653	0.965	-
	50-249 employees	1.111	0.9112	-
	250+ employees	1.6128***	1.216**	1.2046***
NACE Rev. 2 sections (main activity) (reference: NACE A)	**B**	0.7613	0.7284	-
	C	0.9828	0.9139	0.8695***
	D	0.7315	0.7688	-
	E	0.8975	0.8905	-
	F	0.776*	0.8197	0.9032*
	G	0.9804	0.9944	-
	H	1.0981	0.8919	-
	I	0.6693***	0.8351	-
	J	1.5326***	1.4785**	1.4351***
	K	0.8442	0.9013	1.1778*
	L	1.2899	1.4044*	1.4286***
	M	1.195	1.2395	1.245***
	N	1.0759	1.1361	1.3***
	O	1.0154	1.0484	1.2153***
	P	1.2194	1.3393*	1.4302***
	Q	1.0507	1.1365	1.368***
	R	0.9987	1.0911	-
	S	0.9228	0.9335	-
Is a single-site company		0.9368	1.0133	-
Is a public company		0.8384**	0.8711*	0.9318*
Employee representation (reference: no representation)	**A work council**	1.2221***	1.2593***	1.2151***
	A trade union representation	1.0301	0.9491	0.941*
	A health and safety committee	1.2242***	1.185***	1.2383***
	A health and safety representative	1.3833***	1.3329***	1.3091***
Traditional OSH risks (reference: no)	**Lifting or moving people or heavy loads**	-	1.013	-
	Repetitive hand or arm movements	-	0.9533	-
	Prolonged sitting	-	1.4961***	1.3797***
	Tiring or painful positions	-	0.8825**	0.9278**
	Loud noise	-	1.0143	-
	Heat, cold or draught	-	0.9746	0.887***
	Risk of accidents with machines or hand tools	-	1.0607	-
	Risk of accidents with vehicles in the course of work, but not on the way to and from work	-	1.1301**	-
	Chemical or biological substances in the form of liquids, fumes or dust	-	1.0985*	1.1247***

Variables	Item	Model 1	Model 2	Model 3
	Increased risk of slips, trips and falls	-	1.0525	1.1305***
Psychosocial risks (reference: no)	Time pressure	-	1.1282***	-
	Poor communication or cooperation within the organisation	-	0.9288	0.8904***
	Fear of job loss	-	0.8949*	0.9226**
	Having to deal with difficult customers, patients, pupils, etc.	-	1.1431***	1.1801***
	Long or irregular working hours	-	1.028	
Technologies used (reference: no)	Personal computers at fixed workplaces	-	1.2455***	1.2833***
	Laptops, tablets, smartphones or other mobile computer devices	-	1.2909***	1.4701***
	Robots that interact with workers	-	1.3034***	1.4433***
	Machines, systems or computers determining the content or pace of work	-	1.5575***	1.5365***
	Machines, systems or computers monitoring workers' performance	-	1.3256***	1.4826***
	Wearable devices, such as smart watches, data glasses or other (embedded) sensors	-	2.861***	2.7756***
	N	**12,829**	**12,030**	**11,925**

Source: Authors' elaboration on ESENER-3 data.
Note 1: * indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.
Note 2: Robust quasi-maximum likelihood robust standard error was applied to ensure robustness.
Note 3: Majority of models do not have collinearity issues as estimated by the Variance Inflation Factor (VIF) and, when it was present, it only affected the control variables in the model.
Note 4: Establishment size variable has different references for different models in the models with more variables, which are much smaller in size, no information was available for organisations with 5-9 employees.
Note 5: NACE Rev. 2 sectors: A – Agriculture, Forestry and Fishing; B – Mining and Quarrying; C – Manufacturing; D – Electricity, Gas, Steam and Air Conditioning Supply; E – Water Supply; Sewerage, Waste Management and Remediation Activities; F – Construction; G – Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles; H – Transportation and Storage; I – Accommodation and Food Service Activities; J – Information and Communication; K – Financial and Insurance Activities; L – Real Estate Activities; M – Professional, Scientific and Technical Activities; N – Administrative and Support Service Activities; O – Public Administration and Defence, Compulsory Social Security; P – Education; Q – Human Health and Social Work Activities; R – Arts, Entertainment and Recreation; S – Other Service Activities.

All establishments that discussed health and safety implications of at least some of the digital technologies that can be used to enable AIWM are analysed here below. As displayed in Table I-6, larger establishments are more likely to discuss all or some of these possible OSH impacts of the digital technologies that they use, with a difference of up to 14 percentage points between the smallest and the largest size class. But while some issues such as increased work intensity, information overload, prolonged sitting and a need for continuous training are quite clearly correlated with the size of the establishment in the bivariate analysis, differences are much smaller for some other potential impacts, particularly the increase of flexibility, the blurring boundaries between work and private life, and repetitive movements.

Table I-6: Workplaces by type of health and safety impacts of digital technologies discussed, by size (EU-27, %)

Size-class (number of employees on the payroll)	Increased work intensity or time pressure	Information overload	Prolonged sitting	Repetitive movements	Need for continuous training to keep skills updated	More flexibility for employees in terms of place of work and working time	Blurring boundaries between work and private life	Fear of job loss
5 to 9 employees	57.2%	52.1%	62.1%	58.1%	74.2%	64.4%	47.8%	20.2%
10 to 49 employees	57.3%	51.3%	66.3%	55.7%	77.3%	62.2%	46.3%	21.3%
50 to 249 employees	60.1%	54.7%	72.3%	62.4%	81.0%	63.9%	47.6%	21.9%
250 or more employees	71.1%	64.8%	74.4%	62.8%	84.4%	67.8%	52.2%	26.1%

Source: Authors' elaboration on ESENER-3 data.
Note: establishment proportional weighting factor *estprop* applied that corrects for the disproportionalities of the sample with regard to size and country and adjusts for unequal responses by size, sector and country.

Looking at the types of possible OSH impacts discussed by sector of activity, the bivariate analysis in Table I-7 shows that the need for continued training is the most discussed topic all around, with the exception of some economic sectors, such as B, D, E (which includes manufacturing and similar occupations), O (public administration), and M (professional, scientific and technical activities), where a discussion on prolonged sitting is dominant. The issue that is most rarely discussed in all sectors is the fear of job loss.

Table I-7: Workplaces by type of health and safety impacts of digital technologies discussed, by sector of activity (EU-27, %)

Sector of activity (NACE Rev. 2)	Increased work intensity or time pressure	Information overload	Prolonged sitting	Repetitive movements	Need for continuous training to keep skills updated	More flexibility for employees in terms of place of work and working time	Blurring boundaries between work and private life	Fear of job loss
A	56.7%	52.2%	62.8%	60.6%	73.3%	61.5%	41.9%	20.6%
B, D, E*	36.4%	37.0%	83.8%	72.7%	75.8%	57.0%	44.0%	18.0%
C	58.1%	46.5%	61.7%	63.4%	73.8%	61.5%	40.1%	22.7%
F	61.0%	48.5%	60.4%	59.7%	77.1%	62.2%	41.7%	20.5%
G	51.3%	49.1%	57.7%	56.2%	76.6%	62.7%	43.9%	22.4%
H	60.2%	50.3%	70.0%	60.1%	73.2%	64.4%	43.3%	17.3%
I	55.4%	47.4%	47.8%	67.3%	72.5%	66.6%	57.9%	26.1%
J	65.1%	53.1%	80.3%	58.3%	81.7%	79.6%	55.6%	18.4%
K, L*	60.2%	60.5%	76.6%	60.9%	77.0%	67.6%	57.3%	22.3%
M	65.9%	60.0%	84.6%	55.2%	77.5%	72.6%	51.4%	19.9%
N	60.8%	51.0%	67.5%	58.0%	79.1%	67.6%	45.9%	19.9%
O	63.0%	56.2%	83.4%	63.0%	81.2%	56.5%	45.8%	21.8%
P	54.7%	59.0%	60.8%	45.9%	79.0%	50.7%	47.1%	20.0%
Q	57.3%	52.2%	58.9%	49.9%	77.7%	61.6%	53.4%	19.4%
R	56.3%	55.4%	68.8%	56.6%	69.6%	63.7%	40.2%	12.4%
S	66.7%	58.6%	71.9%	63.8%	73.1%	66.7%	47.9%	26.4%

Source: Authors' elaboration on ESENER-3 data.
Note 1: sectors highlighted with an * were summarised due to their small sample size.
Note 2: establishment proportional weighting factor *estprop* applied that corrects for the disproportionalities of the sample with regard to size and country, and adjusts for unequal responses by size, sector and country.

Table I-8 shows the prevalence of possible impacts discussed with differentiation by country. In 19 of the 27 countries, the need for continuous training to keep skills updated was the issue most often raised, followed by prolonged sitting that was discussed in six countries. In two countries – Malta and Romania – more flexibility for employees in terms of place of work and working time was the most frequently named issue. Regarding discussions on the impact of technologies on fear of job loss, although this is generally only a rarely mentioned aspect, it was raised rather frequently in Romania and Lithuania.

Table I-8: Workplaces by type of health and safety impacts of digital technologies discussed, by country (EU-27, %)

Country	Increased work intensity or time pressure	Information overload	Prolonged sitting	Repetitive movements	Need for continuous training to keep skills updated	More flexibility for employees in terms of place of work and working time	Blurring boundaries between work and private life	Fear of job loss
AT	58%	51%	67%	53%	83%	64%	42%	19%
BE	56%	41%	58%	44%	67%	61%	47%	18%
BG	57%	51%	77%	68%	40%	63%	32%	19%
CY	57%	40%	53%	53%	73%	60%	36%	21%
CZ	44%	44%	66%	39%	86%	56%	37%	11%
DE	60%	62%	63%	50%	82%	63%	51%	17%
DK	71%	49%	45%	54%	82%	71%	64%	35%
EE	59%	50%	77%	71%	81%	64%	39%	18%
EL	68%	61%	61%	63%	85%	67%	48%	30%
ES	46%	49%	80%	75%	74%	65%	35%	19%
FI	73%	75%	68%	61%	76%	73%	66%	27%
FR	58%	39%	53%	52%	73%	49%	55%	19%
HR	61%	65%	74%	54%	78%	73%	44%	27%
HU	74%	54%	66%	53%	82%	74%	50%	26%
IE	64%	48%	50%	55%	90%	71%	58%	28%
IT	49%	48%	72%	56%	79%	59%	36%	19%
LT	52%	50%	74%	73%	70%	73%	58%	41%

Country	Increased work intensity or time pressure	Information overload	Prolonged sitting	Repetitive movements	Need for continuous training to keep skills updated	More flexibility for employees in terms of place of work and working time	Blurring boundaries between work and private life	Fear of job loss
LU	54%	46%	57%	57%	77%	71%	57%	15%
LV	61%	53%	82%	67%	60%	61%	48%	19%
MT	73%	56%	50%	50%	75%	81%	56%	25%
NL	51%	42%	58%	55%	53%	57%	45%	16%
PL	52%	51%	76%	74%	76%	62%	39%	24%
PT	52%	44%	60%	61%	85%	68%	57%	14%
RO	78%	58%	75%	70%	78%	81%	63%	48%
SE	67%	61%	45%	39%	76%	66%	52%	13%
SI	54%	52%	73%	62%	62%	69%	33%	15%
SK	51%	44%	64%	51%	74%	65%	45%	25%

Source: Authors' elaboration on ESENER-3 data.
Note: establishment proportional weighting factor *estprop* applied that corrects for the disproportionalities of the sample with regard to size and country and adjusts for unequal response by size, sector, and country.

As previously discussed, the usage of any of the technologies covered in ESENER-3 does not reveal to what degree they are actually used to implement AIWM systems in the workplace. However, some of these technologies are more closely fit for this purpose than others. Therefore, separate analyses of the impact of each technology were performed. The following insights can be highlighted from the analyses:

- Increased work intensity or time pressure, as well as repetitive movements, are the most frequently discussed in workplaces that use systems for monitoring workers' performance or for determining the content or pace of work.
- The need for continuous training to keep skills updated is particularly often discussed in establishments using robots and those establishments that have systems for monitoring workers' performance or determining the content or pace of work.
- Blurring boundaries between work and private life is often raised as an issue in workplaces using systems to monitor workers' performance and in workplaces using wearable devices. Particularly for the latter, this is a surprising result, as these wearable devices are rather unlikely to be used at home.
- Finally, the fear of job loss as a potential impact of the use of digital technologies is most frequently discussed in workplaces using robots or systems monitoring workers' performance. This indicates the fear of individuals of losing their jobs to robots, as well as that computerised control of worker performance may spread fears among workers that those not complying with standards will be dismissed.

Table I-9: Workplaces by type of health and safety impacts of digital technologies discussed, by type of technology (EU-27, %)

Q310 answers		Increased work intensity or time pressure	Information overload	Prolonged sitting	Repetitive movements	Need for continuous training to keep skills updated	More flexibility for employees in terms of place of work and working time	Blurring boundaries between work and private life	Fear of job loss
Use of personal computers at fixed workplaces	**Yes**	58.1%	52.8%	66.8%	57.6%	77.1%	63.3%	46.8%	21.1%
	No	55.4%	45.4%	47.1%	56.9%	69.2%	64.3%	52.1%	20.8%
Use of laptops, tablets, smartphones or other mobile devices	**Yes**	58.2%	53.0%	66.3%	57.7%	77.5%	64.7%	48.2%	21.2%
	No	55.5%	46.9%	59.4%	56.6%	70.1%	53.0%	39.2%	19.8%
Use of robots interacting with workers	**Yes**	64.4%	54.1%	61.9%	61.1%	85.0%	72.6%	50.7%	28.4%
	No	57.5%	52.2%	65.7%	57.3%	76.1%	62.8%	47.0%	20.5%

Q310 answers		Increased work intensity or time pressure	Information overload	Prolonged sitting	Repetitive movements	Need for continuous training to keep skills updated	More flexibility for employees in terms of place of work and working time	Blurring boundaries between work and private life	Fear of job loss
Use of machines, systems or computers determining the content or pace of work	**Yes**	67.4%	54.0%	62.8%	66.8%	82.3%	73.2%	51.4%	24.6%
	No	55.8%	51.9%	66.1%	55.5%	75.4%	61.3%	46.3%	20.2%
Use of machines, systems or computers monitoring workers' performance	**Yes**	71.6%	57.8%	63.1%	67.1%	81.5%	69.5%	54.3%	27.4%
	No	55.6%	51.5%	62.1%	56.1%	75.8%	62.3%	46.1%	20.0%
Use of wearable devices, such as smart watches, data glasses or other (embedded) sensors	**Yes**	61.1%	51.6%	61.5%	58.0%	76.8%	74.2%	53.7%	22.2%
	No	57.5%	52.4%	65.9%	57.5%	76.6%	62.1%	46.4%	20.9%
All (regardless of whether or not any of the digital technologies are used)	**Yes**	61.3%	52.8%	66.9%	59.5%	78.1%	66.7%	48.9%	23.3%
	No	36.1%	45.2%	32.2%	39.4%	20.9%	31.8%	49.0%	75.1%

Source: Authors' elaboration on ESENER-3 data.
Base: All cases where any of the new technologies are used and where their OSH implications are discussed (Q311 = yes).
Establishment proportional weighting factor *estprop* applied that corrects for the disproportionalities of the sample with regard to size and country and adjusts for unequal responses by size, sector and country.

Prevention measures

In an effort to see whether the use of digital technologies correlates not only with the discussion of potential risks but also with concrete measures to prevent risks, digital technologies were cross-tabulated with the question on measures taken in the last three years to prevent psychosocial risks (Table I-10). All five types of measures asked in ESENER-3 were reported more often from establishments using digital technologies, with only one exception (allowing employees more decision-making power on how to do their jobs in establishments using personal computers at workplaces). The use of technology is, however, not necessarily the (main) cause of these results. Namely, these results might be due to the fact that larger enterprises more often employ such technologies, more often lead to different OSH challenges, more often discuss issues that might stem from digital technologies, and, hence, could more often try to mitigate negative OSH effects.

Table I-5: Workplaces by type of measures undertaken to prevent psychosocial risks in the last three years, by type of digital technology used (EU-27, %)

Use of technologies (Q310)		Reorganisation of work to reduce job demands and work pressure	Confidential counselling for employees	Training on conflict resolution	Intervention in case of excessively long or irregular hours	Allowing employees more decisions on how to do their jobs
Personal computers at fixed workplaces	Yes	44.0%	42.5%	34.5%	29.8%	67.3%
	No	38.5%	38.6%	30.7%	24.9%	69.9%
Laptops, tablets, smartphones or other mobile devices	Yes	45.8%	44.5%	36.2%	31.2%	69.3%
	No	35.2%	33.7%	26.8%	22.4%	62.2%
Robots interacting with workers	Yes	48.1%	48.2%	42.4%	36.2%	70.8%
	No	43.1%	41.7%	33.7%	28.9%	67.6%
Machines, systems or computers determining the content or pace of work	Yes	50.3%	47.3%	40.0%	37.3%	69.3%
	No	42.4%	41.2%	33.2%	28.0%	67.5%
Machines, systems or computers monitoring workers' performance	Yes	50.7%	52.0%	44.0%	37.8%	70.0%
	No	42.6%	41.1%	33.1%	28.4%	67.5%
Wearable devices, such as smart watches, data glasses or other (embedded) sensors	Yes	51.1%	48.4%	43.8%	40.7%	73.2%
	No	42.9%	41.7%	33.5%	28.5%	67.4%
Total	Yes	43.3%	42.0%	34.0%	29.1%	67.7%
	No	54.8%	56.2%	64.7%	67.9%	30.5%

Source: Authors' elaboration on ESENER-3 data.
Note: establishment proportional weighting factor *estprop* applied that corrects for the disproportionalities of the sample with regard to size and country and adjusts for unequal responses by size, sector and country.

Barriers to the management of psychosocial risks

A bivariate analysis of questions on barriers to the management of psychosocial risks was carried out to examine whether certain barriers are more often associated with some technologies than with others (see Table I-11). Though the analysis shows some differences between those using a particular technology and those not using it, these differences are mostly relatively small. The fact that most of the establishments used not just one particular digital technology, but several of these, further complicates the analysis. Nevertheless, this might imply that digital technologies do not create any additional barriers for managing psychosocial risks.

Table I-11: Workplaces by type of barriers for the management of psychosocial risks, by type of digital technologies used (EU-27, %)

Use of technologies (Q310)		Lack of awareness among staff	Lack of awareness among management	Lack of expertise or support	Reluctance to openly talk about psychosocial risks
Personal computers at fixed workplaces	Yes	44.2%	33.5%	45.2%	60.7%
	No	40.5%	30.2%	46.8%	53.4%
Laptops, tablets, smartphones, or other mobile devices	Yes	44.3%	33.6%	45.4%	61.3%
	No	41.5%	30.9%	45.0%	53.2%
Robots interacting with workers	Yes	49.5%	40.8%	46.3%	58.6%
	No	43.6%	32.8%	45.3%	60.0%
Machines, systems or computers determining the content or pace of work	Yes	48.5%	40.6%	48.9%	64.7%
	No	43.1%	31.9%	44.8%	59.2%
Machines, systems or computers monitoring workers' performance	Yes	46.2%	37.8%	50.8%	63.9%
	No	43.6%	32.6%	44.6%	59.4%
Wearable devices, such as smart watches, data glasses or other (embedded) sensors	Yes	47.4%	33.9%	38.9%	54.4%
	No	43.7%	33.1%	45.7%	60.3%

Source: Authors' elaboration on ESENER-3 data.
Note: establishment proportional weighting factor *estprop* applied that corrects for the disproportionalities of the sample with regard to size and country and adjusts for unequal responses by size, sector and country.

Annex II – Experts interview questionnaire

Name of interviewee	
Institutional affiliation	
Level of representation (national and/or EU)	
Relevant experience (OSH, AI-based worker management, other)	
Date of interview	
Name of interviewer	

Effects on occupational safety and health of the use and implementation of AI-based worker management systems

Q1. *Does the introduction of AI-based worker management (AIWM) practices have positive and/or negative effects on the* ***safety*** *as well as* ***mental or physical health*** *of workers? What are the* ***key occupational safety and health (OSH) risks*** *presented by these systems (e.g. impact on worker autonomy, job control, loss of social support/relationships with peers or managers, not being able to take a break when needed, impact on ergonomics, safety, stress, mental health issues, impact of such systems not taken into account in the workplace risk assessment, incl. aspects such as ethics, data protection, worker consent, consultation and involvement of workers and their representatives in the choice of systems or decision-making process, etc. that may be relevant to workers' safety and health*)?

………

What are the **opportunities** these systems present for OSH (e.g. AI-based solutions are perceived to be less biased than humans with the assignment of tasks and evaluation of workers; such solutions more accurately take into account the physical capabilities of workers when assigning physical tasks)?

………

Q2. *Which worker groups are more/less subject to the negative impacts of such systems, and which benefit more from the OSH opportunities presented by such systems? If such worker management practices will become wider spread, <u>who</u> will be subject to the negative effects the most, and who will benefit the most?*

………

Q3. *What could be considered as 'success factors' (e.g. taking the system into consideration in the workplace risk assessment and OSH management system of the company, provision of adequate information for workers (e.g. on objective of the AIWM system, on the data collected, etc.), involving workers in the choice of system, adequate training of workers and managers, using the right data to train algorithms, a good design of algorithms, choosing a well-tailored system, co-governance and human oversight over algorithmic systems, transparent application of the systems) that lead to the identified positive effects?*

What could be considered 'failure factors' (e.g. poorly trained discriminative and biased algorithms, absence of human oversight, inscrutable systems, excessive application of AI tools, lack of transparency about the systems) that often lead to the identified negative effects? Are there any other ways in which the introduction of such systems might positively/negatively affect the OSH of workers?

………

Q4. *What features of AI-based management systems could be introduced to reduce the negative OSH effects on particular sectors/jobs/types of companies/worker groups, etc.? And to maximise OSH benefits?*

………

Q5. *What should be done during the implementation/usage stage of the system (not only technically, but also from a work organisation point of view/in relation to OSH management) in order to reduce the negative effects on OSH and maximise the benefits?*

………

Discuss the challenges of managing and evaluating the fast-changing AI-based systems underlying these new forms of worker management and formulate recommendations as to how to overcome these + overview the opportunities for OSH in such management systems

Q6. *Are AIWM systems properly taken into account in the workplace risk assessment? What are the risk assessment practices that companies employ to evaluate OSH-related risks connected to AI-based tools/practices? Are they sufficient? If yes, why? If not, how can the existing risk assessment approaches be improved?*

………

Q7. *Is there sufficient awareness within organisations of the potential impacts of these systems on OSH and the need to consider these systems in the risk assessment? If yes, are organisations concerned about the negative impacts these systems might have on OSH? What measures, if any, are taken to prevent the negative effects on OSH? If not, what can be done to raise this awareness?*

………

Q8. *Are OSH risks considered during the development/design stages of these systems? Does the consideration for OSH risks differ when these systems are developed by companies internally and when the development/design of these systems is outsourced to external developers? How are OSH-related challenges taken into account?*

………

Q9. *Do you think these systems can be used to improve OSH? If yes, how? If not, why?*
………

Q10. *What are the trigger factors (and gaps and needs) for organisations to implement or properly take the AIWM systems into account in their prevention/OSH management systems, risk assessment (ex ante/ex post), etc.?*

Q11. *How do organisations manage these systems? Do they hold consultations with workers or their representatives? Are workers or their representatives included in the decision-making process regarding the use of these systems? Do organisations raise awareness/provide training for workers and managers on the risks and potential negative effects on OSH related to the use of these systems?*

………

Identify gaps, limitations and needs in the research

Q12. *Could you recommend some academic and other kind of research that could help to answer questions on how AIWM solutions would affect OSH?*

………

Q13. *In your opinion, are there any large gaps in the research on the effects of AIWM solutions and OSH? Are there any specific types of companies (e.g. company size, sector) and/or workers (e.g. type of job, place of work, workers' demographic characteristics) that are insufficiently covered in the research on the effects of such solutions?*

………

Q14. *In your opinion, what are the most important aspects of AIWM practices and their effect on OSH that should be addressed in the research? Why do you believe so?*

……

Q15. *In your opinion, how can the knowledge that specific actors (e.g. policy-makers, workers' representatives, employers, HR managers, designers/developers of AI-based tools) have on AIWM practices and their influence on OHS be improved?*

……….

Q16. *Are you aware of any organisations/workplaces that use AIWM systems that could be interesting for a case study (e.g. in terms of the design, development, implementation and use of these new forms of worker management, and how related OSH issues are addressed)?*

……….

TE-RO-22-010-EN-N

The European Agency for Safety and Health at Work (EU-OSHA) contributes to making Europe a safer, healthier and more productive place to work. The Agency researches, develops, and distributes reliable, balanced, and impartial safety and health information and organises pan-European awareness raising campaigns. Set up by the European Union in 1994 and based in Bilbao, Spain, the Agency brings together representatives from the European Commission, Member State governments, employers' and workers' organisations, as well as leading experts in each of the EU Member States and beyond.

European Agency for Safety and Health at Work

Santiago de Compostela 12, 5th floor

48003 Bilbao, Spain

Tel. +34 944358400

Fax +34 944358401

E-mail: information@osha.europa.eu

Publications Office