European Agency for Safety and Health at Work

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Cognitive automation: implications for occupational safety and health

Report

European Agency for Safety and Health at Work

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1 Introduction and objectives

As a consequence of digitalisation, jobs and working tasks are continuously changing. The development of recent technologies, such as artificial intelligence (AI) and advanced robotics, has especially established new possibilities for task automation and revived the debate on work-related psychosocial and organisational aspects and on workers' safety and health. To address emerging risks and to highlight implications related to occupational safety and health (OSH) adequately, the European Agency for Safety and Health at Work (EU-OSHA) has launched the 4-year research programme 'OSH overview on digitalisation' with the aim to develop and disseminate further information on the challenges and opportunities for OSH associated with digitalisation. The OSH overview consists of four main projects on the following topics:

- The impact on OSH of advanced robotics and AI-based systems for automation of tasks;
- The impact on OSH of new forms of worker management through AI-based systems;
- OSH in digital platform work; and
- The opportunities for OSH of new systems for the monitoring of workers' safety and health.
- remote and virtual work.

Based on the taxonomy developed in the report: "Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health" (EU-OSHA, 2022), this report will present OSH challenges and opportunities related to the automation of cognitive tasks through AI-based systems. For definitions of automation and AI-based systems, refer to Chapter 3 of the report: "Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health" (EU-OSHA, 2022).

To support or substitute cognitive tasks where no physical handling of objects or persons is required, increasingly, modern information and communications technologies (ICT) and smart systems are deployed in many industries and sectors, and the scope of cognitive tasks and functions they can support has broadened steadily (EU-OSHA, 2022). Automation via the use of AI and advanced robotics has less induced entire job replacement than was initially feared, but has led to more modular task changes or task replacement via re-engineering and reorganisation (Brynjolfsson et al., 2018), which results in the redefining and relabelling of their descriptions and expectations. Thus, the focus on the support or possible replacement of tasks rather than jobs is an effective and valid approach (EU-OSHA, 2022).

The mentioned taxonomy (see Figure 1) not only allows us to classify the task's content but also the application of different types of technologies, as well as their critical assessment regarding implications for OSH. It is therefore used in the subsequent analysis and presentation of results. The current report additionally describes a variety of economic sectors and jobs in which cognitive tasks are fully or semi-automated. Finally, the impact of their automation through AI-based systems on work-related psychosocial and organisational OSH aspects are described and, therewith, the challenges as well as the opportunities for OSH to date and in the future.

Chapter 2 explains the methodological approach taken to gather relevant research findings on AI-based systems and advanced robotics for the automation of cognitive tasks. This builds the groundwork for **Chapter 3** in which, based on the conceptual taxonomy developed in the report "Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health" (EU-OSHA, 2022), the results of these systematic literature reviews are analysed and presented. The evaluation focuses on the task's content and the degree of automation. Specifically, it distinguishes between semi- and full automation of information-related, person-related and object-related cognitive tasks (Figure 1). In the presented taxonomy, the highlighted boxes represent the primary categorisation of the observed AI-based systems. While some categories are mutually exclusive, for example, regarding the frontend representation, an AI-based system either possesses the ability for physical manipulation or it does not, while in other categories several characteristics can be applicable. An example of this is that when observing the task characteristics of AI-based systems, one finds both routine and non-routine tasks. **Chapter 4** applies the findings obtained so far with regard to OSH dimensions. These include psychosocial implications, including fear of job loss, job transformation, and the risks of loss of trust, autonomy and privacy for information-related, person-related and object-related automation of cognitive tasks, respectively. Therewith, it presents opportunities and challenges for OSH associated with the automation of cognitive tasks. **Chapter 5** discusses organisational impacts when AI systems are integrated and recommends some methods to carry out change without unmanageable negative disruption. **Chapter 6** presents concluding remarks and an outlook to the next phases within this project.

Figure 1: Taxonomy for AI-based systems and advanced robotics for the automation of tasks with accentuation of categories relevant for cognitive task automation (EU-OSHA, 2022)

2 Methodology

This chapter presents an overview of the applied methodology and the major data sources used to depict the relevant areas of literature regarding AI-based systems for the automation of cognitive tasks. This includes systematic reviews and meta-analyses as well as a review of grey literature and forward citation search to identify additional scientific work. EU-OSHA's report "Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health" (EU-OSHA, 2022), identified state-of-the-art technologies and current trends as well as uses of systems for the automation of tasks. To complement the findings, an additional literature research on a variety of sectors was conducted.

The systematic literature searches were conducted in the following scientific and complementary databases, covering a wide range of research fields: *IEEEexplore*, *Ebscohost*, *Web of Science*, *PubMed* and, to a limited degree, Google Scholar. While the results of the first four databases are included to their full extent in the literature review, represented in the number of results, the first 20 pages of Google Scholar were examined complementarily to identify relevant studies that were not published in one of the other databases. For AI-based systems, the following search string was applied in the databases: *(‘artificial intelligence’ OR ‘AI’ OR ‘algorithmic learning’ OR ‘intelligent system’ OR ‘machine learning’)* ***AND*** *(‘systematic literature review’/‘meta-analysis’).*

Here, a total of 33 studies were screened for the interest areas (22 systematic literature reviews and 11 meta-analyses). From this, four papers included direct or indirect implications regarding OSH (three systematic literature reviews and one meta-analysis). The included systematic reviews and meta-analyses are listed in the annex of the report “Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health” (EU-OSHA, 2022). While the systematic literature reviews covered around 1,158 primary publications (not all papers mentioned the number of included primary papers), the meta-analyses included 815. Furthermore, some primary papers might be included in several systematic reviews and/or meta-analyses. Regarding advanced robotics literature for the automation of both physical and cognitive tasks, a total of 57 studies were screened for their areas of interest (46 systematic literature reviews and 11 meta-analyses). Sixteen papers included direct or indirect implications regarding OSH (10 systematic reviews and six meta-analyses). In this report, only results relevant to the automation of cognitive tasks will be further discussed. The results for the automation of physical tasks can be found in the report “Advanced robotics and automation: Implications for occupational safety and health” that will follow. The search string used was: *(‘HRI’ OR ‘Human-robot interaction’ OR ‘human robot interaction’ OR ‘cobot’ OR ‘robot collaboration’ OR ‘collaborative robot’ OR ‘robot cooperation’)* ***AND*** *(‘systematic literature review’/‘meta-analysis’).*

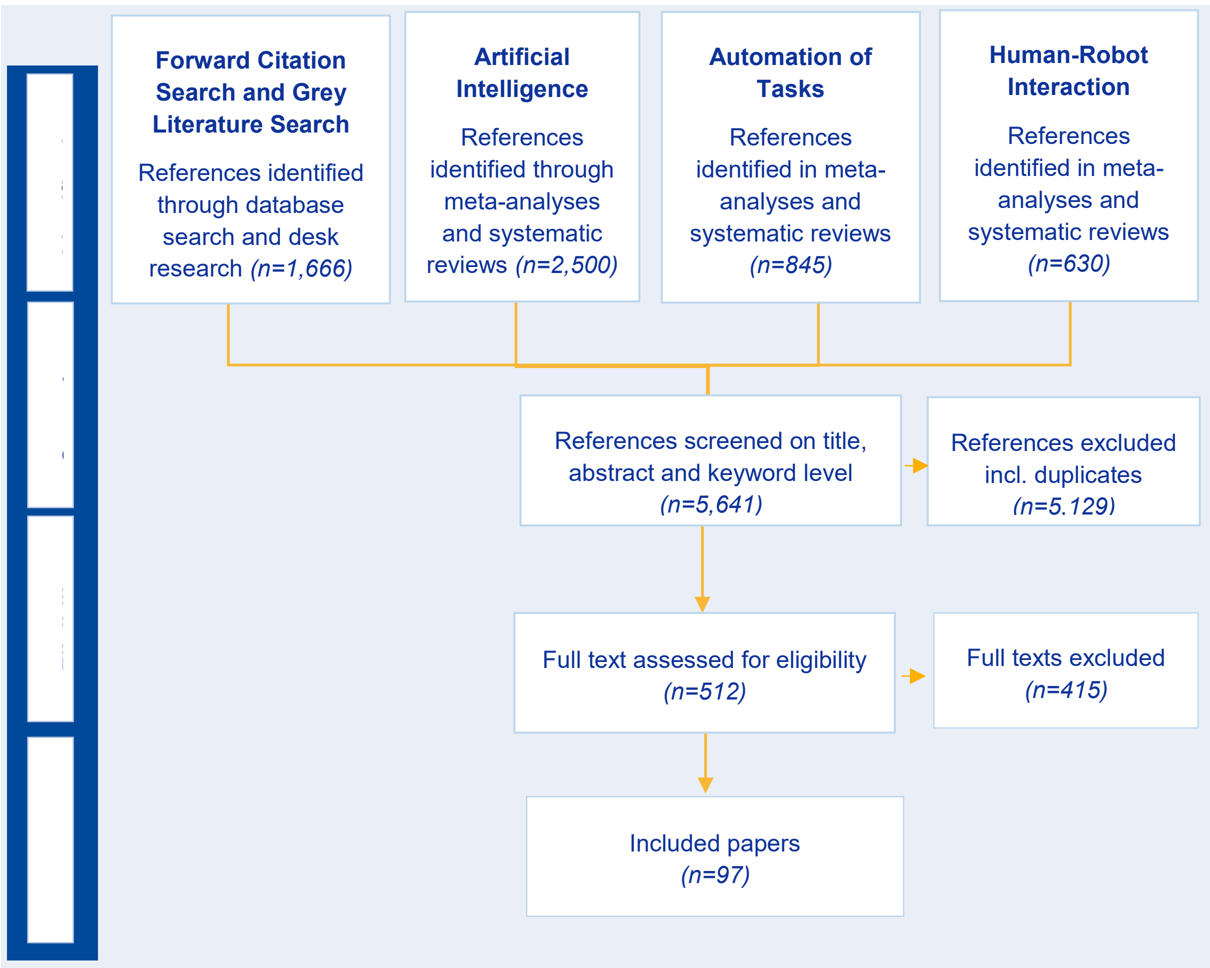
While the systematic reviews covered around 1,844 primary publications, the meta-analysis covered 343. It has to be noted that some primary papers might be included in several systematic reviews and/or meta-analyses. The additional systematic literature review focused on the automation of physical and cognitive tasks, independent from any specific technology. This allowed us to identify processes that the previous two reviews did not uncover. A new search string was constructed and applied in four different databases*: IEEEexplore*, *Ebscohost*, *Web of Science* and *PubMed*. In this review, Google Scholar was not used to supplement the results, as its mechanism does not accommodate the search string without substantial loss of detail and depth. The new search string contained the following keywords: *(‘automation of task*’ OR ‘automated work’ OR ‘task automation’ OR ‘automated task’ OR ‘work automation’ OR ‘job automation’ OR ‘Level* of automation’ OR ‘degree* of automation’ OR ‘systematic automation’ OR ‘automation system’ OR ‘system automation’ OR ‘test automation’ OR ‘automat* task’ OR ‘automate repetitive’ OR ‘workplace automation’ OR ‘automation tools’ OR ‘smart automation’ OR ‘automation in manufacturing’ OR ‘industrial automation’ OR ‘factory automation’ OR ‘automatic production’ OR ‘automation of industrial tasks’ OR ‘automation architecture’ OR ‘process automation’)* ***AND*** *(‘meta analysis’/‘systematic literature review’ OR ‘systematic review’).*

The literature research conducted for the report “Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health” (EU-OSHA, 2022) regarding task automation yielded a total of 845 results across all databases and both conditions via 596 meta-analyses and 249 systematic reviews. Those results were then screened on title and abstract base for eligibility and duplicates were removed. After that, the full text articles were screened if necessary to determine whether they were suitable for the final selection. For this report, only publications containing relevant information on the automation of cognitive tasks were selected. Regarding the meta-analysis, the final sample contained 45 studies, of which three contained direct OSH implications and one indirect. The remaining 41 form the additional base for the extraction of key information. The systematic literature review has a final sample size of 47, of which five have direct OSH implications and three indirect. This results in a final group of 11 papers with OSH implication. This group was then split, as only five focus on AI-based systems. Out of the three systematic literature searches, only 29 studies were then included in this report. They stem from all three result pools and contained valuable insight into the automation of cognitive tasks and OSH.

To identify appropriate pieces of work in the scientific, and to some extent grey literature, a series of terms in Boolean operator were selected. The term ‘artificial intelligence AND skill variety*’ resulted in 50 references but only one was selected for this review and ‘artificial intelligence AND autonomy AND work*’ yielded 142 references from which nine were selected. Two hundred and thirteen references were found with the search term ‘artificial intelligence AND legal AND work*’ from which seven were selected and 33 references from ‘artificial intelligence AND job characteristic*’ from which 10 were selected. The search term ‘artificial intelligence AND work* AND health and safety’ revealed 103 references of which 11 were selected. Three further publications were selected that were not directly from the search.

For an in-depth analysis of various job sectors and their specific OSH implications, additional searches in *Web of Science* were conducted. Two of them, regarding care work and education, are depicted exemplarily in the following. For the former, the term ‘artificial intelligence AND care work*’ revealed 684 references and ‘artificial intelligence AND elder care*’ 149. The search for ‘artificial intelligence AND caregiver*’ resulted in 121 references. From these results, 18 were considered as relevant. Regarding the education sector, the search term used was ‘educator AND artificial intelligence*’, which revealed 171 references. Of these, 13 references were considered as significant. Forward searches were used to find other explanatory research when necessary. A total of 68 publications were identified in the extended literature (see Figure 2).

Figure 2: Selection process for scientific literature

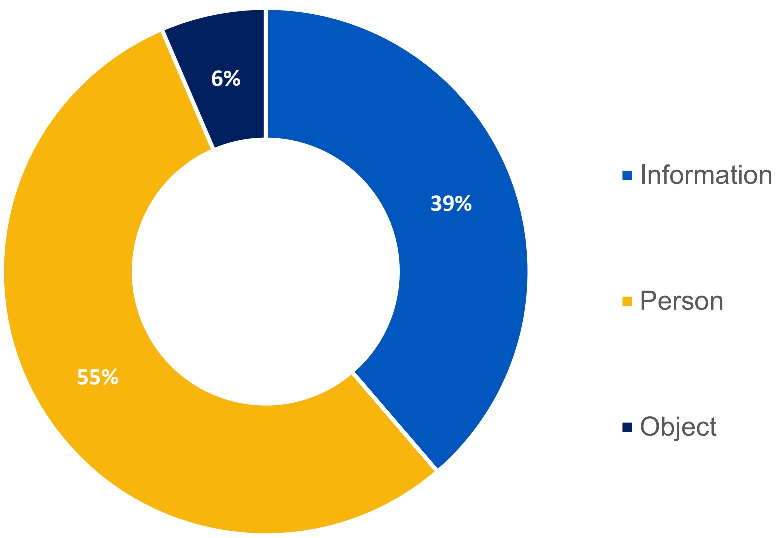


The following sections examine different OSH-related dimensions and outcomes of the identified literature. As many studies include more than one relevant outcome, these individual results are then presented separately in the relevant section below. Chapter 3 analyses the results regarding cognitive tasks' content and the degree of automation, based on the taxonomy developed in the report "Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health" (EU-OSHA, 2022). The taxonomy is also used in Chapter 4 when applying the findings on OSH implications. Additionally, opportunities and challenges for OSH associated with the automation of cognitive tasks, identified through the extensive literature search, are presented in Chapter 4. This structure elevates the findings of individual studies to a more global and comprehensive level.

3 AI-based systems and types of tasks

The following section presents the findings regarding the effects that automation of cognitive tasks can have on workers and their surroundings. This is based on the results extracted from the described literature research. First, tasks are divided into groups of fully automated and those that currently fall under a state of semi-automation. Within these two groups, each is further separated into the task being person-related, information-related or object-related, based on the object of work according to the focus programme 'Occupational Safety & Health in the Digital World of Work' established by the Federal Institute of Occupational Health and Safety in Germany (Tegtmeier et al., 2018). First, examples of person-related tasks include teaching, care work and customer service, where work takes place through a social interaction between two (or more) people. Second, information-related tasks typically involve processing data, such as software code generation, financial services and health monitoring. Third and finally, object-related tasks relate to a worker acting upon an object, like driving a car, flying a plane or making repairs via automatic maintenance alone. Each of these three subgroups then further differentiates between the task being either a routine task for the worker or a non-routine task. It must be said that within the screened literature, not every possible combination of categories is present. Such absences provide additional insight into which fields of application currently lean more heavily towards the automation of cognitive tasks, and where gaps are formed.

Figure 3: Task type distribution according to scientific literature



As already outlined in the report “Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health” (EU-OSHA, 2022), AI-based systems lean heavily towards being applied for the automation of information- or person-related cognitive tasks. The conducted literature research reflects this distribution (Figure 2). While in the reviewed literature person-related task applications are represented with a slightly higher frequency, this might be explained by publication bias. An application of AI for an object-related task was identified in the reviewed literature involving a car with intelligent driving assistance. However, this example can be argued to be an information-related task if one defines driving as much by its cognitive component as by its physical. This illustrates how the boundaries between physical and cognitive tasks are not always as clearly defined, and that advanced systems, such as cobots, can be applied even in these complex cases. A better representation of object-related cognitive tasks could be a robot supporting teaching personnel in schools. These kinds of tasks are not prominently present now in research.

In the following section we start with presenting fully automated cognitive tasks, where an AI-based system can substitute the human worker in the process, and then continue in section 3.2 with semi-automated cognitive tasks in which the system provides essential assistance to the worker during the task’s procedure. It is important to be aware of the nuanced differentiation between tasks that today are theoretically fully automatable, tasks that are currently implemented in practice, and systems where even though the technological capabilities could support full automation, they are not. Sections 3.1 and 3.2 categorise the tasks along the above-presented taxonomy into person-related, information-related and object-related cognitive tasks.

3.1 AI-based full automation (substitution) of cognitive tasks

In the following paragraphs, the results of our literature research regarding fully automated tasks are presented. According to the taxonomy (Figure 1), this group can be separated into the task being person-related, information-related or object-related. However, no object-related cognitive tasks were found through our literature research. Therefore, the results of both remaining categories are described.

3.1.1 Person-related tasks

Within the subgroup of person-related tasks, we differentiate according to the taxonomy between routine and non-routine tasks for the worker.

Routine tasks

Performing a routine task based on human-to-human interaction with an AI-based system could generate merit for a number of jobs. A primary technology to emulate this type of interaction is chatbots or AI-based conversation agents. The former refers to a system that uses natural language processing (NLP) in written form and the latter in spoken form, to interact with someone. These can be applied in a number of work settings such as telephone-based **customer support** (Bavaresco et al., 2020; Tuomi et al., 2020) or for patients’ **well-being management** through conversation-based health monitoring (Federici et al., 2020). Chatbots and conversational agents are interaction systems. In customer support they might fill the role through a telephone conversation with a customer where they are either able to resolve the presented issue or redirect the customer to a specialised human operator. The same can be said for chatbots in a digital environment. This means that, independent of their domain of application, their performance is measured in terms of the quality of interaction. This interaction emulates (or: gives the user the feeling of) direct human interaction; however, the technologies set limits since they are being developed for a specific domain. This implies that the system is capable of fully automating specific tasks, as long as the scope of interaction is limited to the area they have been designed to function in. Their base functionality allows them to theoretically be introduced into a plethora of work environments, only changing the domain knowledge they present. For example, conversational agents in business support are capable of emulating a straightforward *dialogue experience* (Bavaresco et al., 2020; Tuomi et al., 2020), which, as described, automates the task nearly completely. They emulate a conversation that would normally be performed by a human operator, but since in customer service there are commonly reoccurring interactions, they can be automated. It can be an organisational consideration to still employ a worker in case the conversational agent is not capable of fulfilling a given request. As these systems are increasingly based in AI, they start containing methods of NLP, self-learning and personalisation, and generative-based responses, instead of hardcoded output (Bavaresco et al., 2020). These developments create a system increasingly independent from a human operator.

While Bavaresco et al. (2020) do not explicitly state this, it is possible to speculate that this task, which is the central task to some jobs, like customer service workers, could in the future primarily be performed by AI-based systems.

Automating a **teaching** situation presents the challenge to create a system capable of teaching learners according to their skill level, and not solely based on a predetermined learning path. In recent years, many researchers have worked on so-called intelligent tutoring robots (ITRs) (Yang & Zhang, 2019), or intelligent tutoring systems (du Boulay, 2016; Sottilare et al., 2018) to automate specific teaching tasks, beginning with easily standardisable tasks, such as *vocabulary training.* More recent developments have focused on personalising interactions of ITRs to specific users. This is accomplished by the algorithm behind the tutoring systems adjusting the complexity of content to the capabilities of the learner by providing more complex problems only when easier problems have been mastered (Yang & Zhang, 2019). Hence, the system takes over a multi-step process, formally performed by a teacher or coach: the *assessment of a learner's state of domain knowledge*, the subsequent *planning and selecting of teaching* contents and strategies, and finally the *presentation of new information* to the learner. Hernández de Menéndez et al. (2020), for instance, describe how these systems are capable of 'helping students in their daily educational activities by interpreting their responses and learning as they operate' (p. 58). The algorithms can offer the student problems to solve, or specific videos based on their past or current interactions. Advanced versions can even provide a personalised learning experience by 'constantly monitor[ing] how students are acquiring knowledge to offer customized material' (Hernández de Menéndez et al., 2020, p. 58).

In some cases, intelligent tutoring systems (ITSs) led to greater learning success over teacher-led classroom instruction (Ma et al., 2014). According to Murphy (2019), the use of ITSs 'resulted in higher test scores than did traditional formats of teacher-led instruction and non-ITS online instruction and produced learning results similar to one-on-one tutoring and small-group instruction.' Additionally, we see educational robots providing learning support for students (Anwar et al., 2019; Cheng et al., 2018; Hein & Nathan-Roberts, 2018; Papadopoulos et al., 2020). Tasks regarding language education in the form of *vocabulary and grammatical education* (Cheng et al., 2018), *oral language skills assessment* (Hein & Nathan-Roberts, 2018), and teaching of *mathematics and science* (Papadopoulos et al., 2020) have all been successfully automated in applications through these systems. However, noticeably, the publications do not contain predictions of teaching jobs being replaced by ITRs, ITSs or educational robots. There also is limited description of how these systems handle situations in which the provided information for the learner is not sufficient for them to understand and solve the problem. While adjusting the teaching strategy sometimes is within the ability of a system, it normally targets lowering or raising the presented difficulty level, not changing the approach to teaching the problem. Adjusting the teaching method and aiding with problem solving appears to stay in the task area of human teachers. These highly complex and individualised facets of teaching are currently beyond the capabilities of AI-based systems. Rather, it has been suggested that when deployed, these systems grant teachers more opportunity to focus on individual learners who exhibit problems with the material (du Boulay, 2016). While previously the task of teaching and its more specific subsets were all contextualised within a school context, it is applicable beyond that. Specified teaching methods in the form of *cognitive training* for elderly people (Vogan et al., 2020) or *skill training* for people with special needs have been subject to automation, too (Federici et al., 2020). From a task perspective, these fall within the same range as a system teaching students as it involves the acquisition or training of information-based skills, such as memorising and recall.

Tools that teachers can use for students' assessment and supervision is another development made possible by AI-based systems that can improve efficacy in the classroom and reduce preparation time. The same dynamics that allow AI to provide new kinds of services for students – i.e. bulk data collection and machine learning – can similarly help teachers understand how to improve their own performance. Bryant et al. (2020) suggest that reducing the preparation time teachers currently undertake will be a major contribution of AI in the education sector. They report that, 'teachers spend an average of 11 hours a week in preparation activities. We estimate that effective use of technology could cut the time to just six hours' (p. 4). This estimation is based on the fact that several software providers offer mathematics packages to help teachers assess the current level of their students' understanding, group students according to learning needs, and suggest lesson plans, materials and problem sets for each group. In other subjects, collaboration platforms enable teachers to search and find relevant materials posted by other teachers or administrators. These examples show that the technology has the potential to reduce a teacher's workload. Possible risks within the educational sector are the increased loss of privacy and decrease in social interaction, as automation in the classroom increases.

Non-routine tasks

Some tasks that are automated include non-routine tasks. What defines a routine versus a non-routine task can differ depending on the perspective one takes. What can be considered a routine task from a technological point of view surely is far more restricted than what workers describe as a routine task in their job. As we focus on the human experience while working with AI-based systems, a non-routine task is a non-frequent or in its structure less foreseeable task for the worker. Some of them can be found in the field of **care work**. However, classifying the social component of care work into specific tasks can be challenging. They are undeniably part of the profession, but as they are intrinsically contained in every interaction between patient and caregiver, as well as active social engagement for the patient, describing it in the form of a routine can be difficult. It is a cognitive task to provide **social interaction** and we see technology of different complexity applied to fulfil this task (Bemelmans et al., 2012; Gongora et al., 2019; Kachouie et al., 2014; Shishehgar et al., 2018). As companion robots can improve the mental and emotional well-being of patients, it can possibly alleviate some emotional labour of caregivers. The literature is primarily focused on the benefit of patients and has yet to quantify the effects these types of technology can have on the worker once they are introduced to the workplace.

The introduction of new technologies, such as instructional and assistive technologies (IATs), are able to automate the need for caregivers to conduct independent research in the course of caregiving. For example, Li et al. (2020) found, 'preliminary evidence that it is feasible and effective to implement a voice-based virtual assistant to provide diet-related services to ADRD [Alzheimer's disease and related dementias] caregivers' (p. 8). They report that the voice assistant can support a variety of food and nutrition recommendations, education and planning services, including tips on proper diet, handling challenges in eating, food item and nutrition explanations, meal suggestions, and recall of daily and weekly diet histories. The administration of proper nutrition has been shown to slow the symptoms of Alzheimer's disease and dementia-related diseases. In a conversation, different service categories can be integrated to serve the user's requests. AI-supported voice recognition systems could help caregivers in completing documentation that might give them more time to spend with people in their care (Lernende Systeme, 2019) Similarly, the introduction of new technologies, such as IATs, is able to automate independent research in the course of caregiving, thus relieving caregivers from the need for them to conduct this during their time with the patient.

Mobile applications also show some promise in reducing the burden of caregiving, 'by providing convenient tools and resources to coordinate the demanding tasks and the complex networks of relationships involved in caring for others' (Grossman et al., 2018, p. 3). Indeed, as these authors point out, mobile phone technologies are a great opportunity to help manage caregiving needs. Grossman et al. (2018) found that applications are already proving to offer stress-reducing potential. Beyond instructional assistance and automation of tasks, some apps now contain, 'components to address caring for the caregiver, in the sense of providing emotional or social support or forms of stress relief, and respite' (p. 185). This kind of technology would be a primary example of AI-based systems developed for and deployed in a work environment with the targeted purpose of improving workers' mental health.

3.1.2 Information-related tasks

Within the subgroup of information-related tasks, the literature research did not reveal any fully automated cognitive tasks that fall under the category of non-routine tasks. Therefore, we will present solely routine tasks for the worker that include information as the object of work.

Routine tasks

Health monitoring of patients is a crucial part of medical procedures that is routinely performed by medical staff. The process often includes standardised health assessments to track a patient's condition, identify behaviour changes or screen for possible complications. A notable part of this data is either self-reported by the patient to a healthcare professional or based on a dialogue between the two parties. A variety of conversational agents using NLP and free text input have been developed to address these specific tasks, as their standardised nature allows for efficient automation. These types of conversational agents do focus on data collection and processing (Rheu et al., 2021). The collection itself can potentially be fully automated, however many of these systems are still in their development stage (Milne-Ives et al., 2020).

Health monitoring is set to be expanded considerably by AI systems, with revolutionary potential for industries that centre on relationships of care and dependency. The development of so-called smart appliances can fulfil both simplistic and complex functions. Simplistic devices, for example, monitor a single health indicator and collect 'wellness data' such as blood pressure of blood sugar levels. Ho (2020) explains, however, that the introduction of AI allows, 'health monitoring technologies [to] build upon these [simple] capabilities [and] go beyond collecting and tracking various indicators' (p. 2). AI-infused instruments are thus, '[e]ndowed with processes that mimic human intelligence, such as recognizing, learning, reasoning, adapting, predicting, and deciding' (Ho, 2020, p. 2), which means that they have the potential to play 'a novel and significant role in caring for older adults by complementing current care provision, reducing the burden on family caregivers, and improving the quality of care' (Ho, 2020, p. 2). Another possible application of health monitoring devices can be found in the industrial sector where smart sensors monitor the workers' posture and can generate notifications through smart watches when identified as being in a poorly ergonomic posture, thus trying to protect their physical health (Ispăşoiu et al., 2021).

Complex monitoring technologies may revolutionise home and residential facility care. These systems are paving the way for the scaled-up development of 'smart homes' that will, in effect, fully monitor the safety and health of elderly people who continue to live independently. According to Udupa and Yellampalli (2018), the smart home system is for the most part built majorly using three technology types. Physical components (sensors, actuators) that sense the data, the control system (AI system) that receives the data from the physical component and takes the decision, and, finally, the communication system (wired/wireless network) that connects the physical component and control system, completes the home automation system. The purpose of the smart home, can be to reduce the need for in-home caregivers and allow elderly people to live independently. The second component of a smart home, the control system, could in part diminish the need for a human caregiver with expertise to decide what steps should be taken to resolve problems as they arise.

Another task found in, but not exclusive to, the medical field is *notifying a patient, client or other person* of an appointment, test results or otherwise important information. This is a seemingly small task; however, it does require knowledge of the recipient, their means of contact and the content of the notification, among other things. Automation of these notifications has been done, especially in the medical field (Aardoom et al., 2020; Liebow et al., 2012). As it is in and of itself a small task without many steps, this form of notification is already fully automated in some cases.

Information-related task automation can also be found in the context of software development. We can see standardised tasks previously performed by software developers changing towards full automation. Examples of these are the generation of so-called release notes that contain information such as description of new features, bug fixes, license changes, deprecated libraries, a new application program interface (or API) and other changes made to the software. Manually, this process is described as prone to errors and time-consuming, even for skilled workers. Utilising NLP-based algorithms tools have been developed to automate this process; however, at this point the programs are not yet accurate enough to function without human supervision (Ali et al., 2020) and so not accurate enough to include in findings. Similarly, the generation of test cases in software development has seen steps towards automation. As the testing process can take up a significant amount of time, automating parts of it holds potential to increase efficiency. And, the generation process of test cases, which need to fulfil specific criteria, is being increasingly automated (Ali et al., 2020), as is the testing process itself (Kong et al., 2018).

Producing or writing text has been at the forefront of automated tasks. Constant improvements of NLP algorithms have led to efficient and accurate systems fulfilling this task (Ali et al., 2020). This enables some basic form of text generation to be fully automated. However, more complex forms of writing, like journalism-related articles, cannot be generated yet to the same quality as a human can produce. The AI-based system used specifically gives input to generate a text of specified length on the topic. This output can then either be used as written or further edited to suit the intended context more.

3.2 AI-based semi-automation (assistance) of tasks

In the following paragraphs, the results of our literature research regarding semi-automated tasks are presented. Again, this group can be separated into the task being person-related, information-related or object-related. However, the literature research did not reveal any person-related cognitive tasks that are semi-automated. Therefore, the results of both remaining categories are described.

3.2.1 Information-related tasks

In contrast to fully automated information-related tasks that all fall under the category of routine tasks, semi-automated cognitive tasks include routine as well as non-routine cognitive tasks. Therefore, the next paragraphs will focus first on the former and then on the latter.

Routine tasks

AI systems can automate routine tasks that in the past required human intervention, such as analysing a substantial amount of information to accelerate taking decisions. Researchers argue that 'AI for critical systems must combine real-time analysis with robust network communications structures to continually adapt to changing circumstances' (Laplante et al., 2020, p. 46). Correctly *identifying and diagnosing a medical condition* are important tasks assigned to medical health professionals. To be successful in this process, doctors need to have both extensive knowledge about their respective field and enough information about the patient and their condition to arrive at an accurate diagnosis. The subsequent treatment, too, is based on this decision process. In the medical field we see a large group of AI-based medical diagnosis tools, which support doctors in their **decision-making** and **diagnosis process**. In detail, this can among other functions entail the identification and classification of heart sounds (Dwivedi et al., 2019), procedural advice during pregnancy (Davidson & Boland, 2020), evaluating the imaging procedure and proposing suitable treatments (Lernende Systeme, 2019), pain management (Pombo et al., 2014), detection of sepsis, inflammatory response syndrome and septic shock (Wulff et al., 2019). Decision support systems are one form of AI-based technology that can be used as assistance by medical health professionals in their task. They analyse the patient's data and base recommendations on probability. While the final responsibility for diagnosing the patient and assigning them to a treatment plan is still performed by a medical professional, the surrounding tasks to arrive at these decisions can be automated. None of the publications gave a definitive indication whether these systems will one day perform diagnosis tasks without human supervision. This type of data analysis with subsequent assignment of probability for a diagnosis or procedural recommendation found in decision support systems can technically be applied to any decision-related situation that provides sufficient data. However, the medical sector is by far the most prevalent area of current application for it according to the reviewed literature. Other areas of routine decision-making include, but are not limited to, cost analysis (Altaf et al., 2020), recruitment for clinical trials (Köpcke & Prokosch, 2014), and optimised project scheduling (Desgagné-Lebeuf et al., 2020).

Supporting a decision process is not solely limited to the medical field. Advising someone on making investment decisions belongs to the core tasks of a financial adviser (Boughaci et al., 2020). Today, systems exist that provide similar advice on how investments should be made based on given funds, risk tolerance, accessible assets and so on. The construction of an investment strategy based on those indicators, in addition to surrounding financial market conditions, is a considerably complex task that, until now, only skilled, and experienced, advisors could perform. In the literature, this has been studied regarding business-to-business recommendations, as a way to support the process (Patil & Agarkar, 2019), but it is technically possible to apply this technology **to personal financial advice**. While the evaluation process is automated, once again, final evaluation and jurisdiction over the proceedings are still the responsibility of trained workers.

Data classification is a prime example of AI-based systems supporting workers in a variety of fields. Automated coding of medical data describes the transformation of natural language descriptions in clinical text into data that can subsequently be used for clinical care, research and other purposes (Stanfill et al., 2010). Similarly, software dealing with enriched metadata can be used for automatic indexing and classification in a variety of research work (Golub et al., 2016). A third example is automated instead of manual *assessment of bias risks* in clinical trials (Marshall et al., 2016). Some software vendors and experimental researchers claim that tools can replace manual subject indexing, while they currently aid researchers, as they are not yet reliable enough (Golub et al., 2016). While automated coding and classification systems cannot be generalised, as they are commonly trained for a specific field of application, it can be observed that in clinical research specifically (Standfill et al., 2010) and indexing-based processes for literature reviews in research (Golub et al., 2016), the software can assist researchers in a time-consuming task. Published research shows these systems hold promise, but these data must be considered in context, with performance relative to the complexity of the task and the desired outcome.

While the job of a software developer is a cognitively challenging and creative one, we can see that AI-based systems are being used to automate standardised or repetitive tasks relating to it. While on the organisational side this can prove to be cost-efficient and more accurate, this also frees up workers' time to devote to less monotonous tasks. A chronologically earlier task in the process of **software development** is **code generation**. This describes the process by which code has to be derived from previously set requirements in the form of a high-level software description. Automatic code generators *parse the input and map this description into executable code*. Automatic code generation is a well-known way of getting executable code of a system from a given design model (Batouta et al., 2016). While executable code meets the criteria of being functioning, automatic code generators currently do not replace skilled software developers who need to optimise the product according to further requirements (e.g. run time, failure rate). However, they do expedite a task that when done manually can be time consuming.

Closely related to automated code generation is **automated text generation** (Graefe & Bohlken, 2020). To an AI-based system, the difference between a coding language and natural language is less prevalent than to us humans; as both languages contain similar elements in the form of grammar, vocabulary, syntax and so on, Such systems could fulfil one of the most fundamental tasks of almost any job if they reach technological maturity. Text generators are commonly trained within a specific domain, to mimic the required writing style of it most accurately. However keyword-based text generation can also be performed by non-specialised systems. While creating the complete coherent text is effectively automated by an AI system, the pre- and post-processing steps remain with a skilled professional. For an output to be generated, selected and specific information must be researched and provided, and the text currently still has to be edited post-generation to match human quality.

Non-routine tasks

Organisational decision-making processes on an administrative level can take a variety of forms, changing widely from the area of application and job. This, however, is unified by the concepts that those who must make this critical decision typically need to process available situational information and base their decision on a number of criteria. In this context, the phrase 'social machine' has been used to describe working situations in which people perform the non-standardised, creative task and an algorithm does the administration (Santos Brito et al., 2020). Decision support systems are one possible form of automation to assist in this process. There are examples across several fields, such as *which parts of software testing to automate* (Garousi & Mäntylä, 2016), *which scheduling tools could provide the most efficient support during a planning process* (Desgagné-Lebeuf et al., 2020), or *support in assessing risks*, and *deciding on suitable control strategies* on an organisational level in distributed software development (Aslam et al., 2017). Having to decide how to structure, organise and manage a project is a complex task, not only due to the possibly continuously changing conditions but also for the multitude of factors that need to be considered. None of the presented systems currently have the capabilities to replace an organisational figure. Their application is to support these jobs in their decision-making process for very selective areas. They automate the task of gathering and evaluating relevant data, while the final decision is then made by a human.

Artistic and creative work is usually considered non-routine but is not seen to be in great danger of task replacement. There is not a lot of literature on this, but Gudkov (2020) explores the development of AI for generating literacy artistic work and its impact of creativity, originality and authorship as compared to human artists. AI-generated creative writing can appear authentic, where 'artificial work is an imitation of intellectual human efforts made by AI machines, in the context of human mental artistic inputs and coding work. A minimal degree of creativity is achieved by copying and mimicking human ideas and rules, existing in original works. The human involvement in the AI generation process can be active by instruction, or passive by a provision of a data source (Gudkov, 2020, p. 764).

Imagination and creativity are human mental processes however, the author notes, and therefore AI can only generate artist work with human intervention. AI programmers can arrange text and input words, but the end results of an artificial work could not be considered original vis-à-vis a machine. Furthermore, it would be difficult to claim copyright for artificial creative work.

3.2.2 Object-related tasks

Within the category of object-related tasks there were no non-routine cognitive tasks found in the literature. Therefore, this paragraph only discusses semi-automated routine tasks.

Routine tasks

A possible example of an object-related cognitive task for an AI-based system is its application in vehicles. It is also a prime example of task, not job, related applications of AI-based systems as the usage of vehicles is not reduced to either a specific sector or job, though the potential impact on transportation and delivery is clear. Within the task of **driving**, we find several ways an AI can be introduced to assist the driver in their task. These can be but are not limited to *smart intersection warning and rear-end warning, lane departure, driving takeovers and cruise control* with the specific focus on collision prevention (De Winter et al., 2014; McDonald et al., 2019; Wang et al., 2020). The presented data also allow developers and engineers to extract recommendations for which specific driving tasks, such as lane switching, should receive prioritised support by an AI, based on which country was evaluated. For all considered countries, introducing AI to support the driver significantly raises the safety effectiveness, as it reduces human errors (Wang et al., 2020). While adaptive cruise control was introduced in cars as early as 1995, highly automated driving, supported by smart systems, is a more recent development (De Winter et al., 2014). In their current form, these systems assist a driver. However, some systems already support a takeover of the car for specific tasks, one of them being automated vehicle takeovers (McDonald et al., 2019), based on generated braking and steering models. Findings suggest that this might increase post takeover control for the driver, a factor especially important in the context of common driving safety risks such as fatigue and exhaustion (McDonald et al., 2019).

The reviewed literature strongly focuses on AI-based systems supporting rather than replacing drivers. Increasing safety is a reoccurring goal; hence, if applied successfully, workers who drive in a professional context might see an increase in safety. When considering the publications providing technological development along a timeline, it reinforces the idea that cars are becoming increasingly automated, with recent technologies providing the option to fully automate subtasks of driving. There were no suggestions made when, or if, fully automated driving with no human driver present will be available, or how this could affect jobs like taxi drivers or delivery trucks, which is a major missing aspect in the literature.

3.3 Impact on jobs

Because AI is likely to eliminate specific tasks on a piecemeal basis, as opposed to entire occupations outright, the content of jobs is likely to change considerably over time. The majority of jobs are made up of a plethora of different tasks, some interdependent, some independent. Furthermore, some jobs have greater task diversity than others. However, not only the diversity of tasks performed by a worker determines the possible degree of change faced, but also the complexity of them. Hence, the impact of AI-based automation can vary considerably between jobs and sectors.

A primary group currently affected by either full or semi-automation of cognitive tasks through AI-based systems is that of **medical health professionals**. This group contains both medical doctors and nursing staff (note rehabilitation services are covered in T3). We can see that AI-based systems find application in numerous tasks relating to medical professions. These can focus on person-related tasks in the form of conversational agents (de Cock et al., 2020), but most AI-based automations currently focus on information-related tasks, specifically, decision support regarding diagnosis and treatment (Cresswell et al., 2020; Gurung et al., 2011; Moja et al., 2014, Pombo et al., 2014). Currently, when these systems are applied, the tasks should be considered semi-automated, as the AI analyses gathered data and provides an output, but it is however still the medical professional who makes the final decision. We can see that especially data-based processes in the medical field are being automated, while higher cognitive tasks like the final diagnosis or treatment plan are still made and designed by medical professionals. However, as the technology becomes more advanced, it is within reason that its assessment becomes less supervised. Some medical devices, blood pressure monitors for example, at this point include software that assesses the patient's state accurately enough that human reassessment is only necessary in outlier situations (Pappaccogli et al., 2019). In addition, automated health monitoring also affects the job of medical professionals; indeed, it has been described as an area that in the future can be completely automated (Milne-Ives et al., 2020; Rheu et al., 2021). Automation of these routine tasks do however hold the potential to free medical staff, to focus on less routine-based activities and more complex or human-centred work (Milne-Ives et al., 2020). While these systems show promise, partially due to their user satisfaction, their effectiveness in healthcare regarding workload reduction of medical staff, needs further research (Milne-Ives et al., 2020). However, some literature reports the reduction of mental workload through the implementation of AI-based screening systems (Rodriguez-Ruiz et al., 2019).

Another job group that already sees the effects of AI-based systems in their work is **teachers and other educators**. A variety of pedagogical agents, intelligent tutoring systems and virtual classroom assistants have been developed. These systems can be applied to several teaching tasks. While a number of publications identify these systems as an effective technology to support people during learning phases, they do not address the effect these systems have on the teacher. So, while they see potential for this technology to be used in classrooms in the future, there is an acute lack of scientific evaluation of the impact these systems might have on the teacher, their work environment, tasks and job structure. The profession of teaching is also not limited to the school environment. Education is, for many, an ongoing and necessary process throughout their work life. Teachers, or possibly, professional coaches and instructors, used to present information to their students, providing explanation and context for the new concepts. In these jobs there are some examples of possibly fully automated tasks. AI-based systems have successfully taught new information to learners by automatically adjusting difficulty levels to suit the individual learner, improving their learning progress (Nesbit et al., 2014; Yang & Zhang, 2019). However, while efficient, at least for school-based education, a teacher should be present, to support learners who show difficulties with the material beyond the algorithm's capabilities (du Boulay, 2016), which is interesting when the teacher is remotely based such as is the case during the COVID-19 pandemic.

One job group directly mentioned in the literature as a beneficiary from task automation through AI-based systems is that of **researchers**. Data classification is one way to apply an AI-based system in their work environment, extracting, classifying or indexing large bodies of literature. This previously time-consuming task being expedited allows researchers to focus on the transformative work with the results more quickly than if they had done these tasks manually (Matwin et al., 2010; Golub et al., 2015; Marshall et al., 2016). Crucial tasks, like results interpretation or contextualising the results, are currently areas where the screened literature does not place any specific AI-based automation, leaving it part of the researcher's primary job. The technology of data processing and indexing, however, can be useful for more than just researchers selecting suitable literature, yet they are the most prominently named group in published literature. This could be due to a publication bias, as researchers have a given interest in assessing and sharing information and technology that could improve research in general.

In a broader job category, we see that **administrative positions** can receive support from AI-based systems, too. Here, AI-based systems, a prominent candidate being decision support systems, pre-evaluate input about the current state of the situation or project and, based on these data, suggest a course of action or identify next planning steps (Aslam et al., 2017; Desgagné-Lebeuf et al., 2020; Garousi & Mäntylä, 2016). This kind of technology could be applied in almost any work context and job that requires planning and coordination. Noticeably, the information collection and evaluation parts of these decision processes have been automated, but final jurisdiction about the course of action still lies with the human supervisor. Jobs like project manager, team lead, business strategist and consultant could all benefit from this technology. If the systems analysis and recommendations prove to be effective and accurate enough that they are trusted and followed, these workers could potentially either supervise more projects or focus more on the human-centred side of their job. While in theory full automation of complex planning tasks is possible in the future, given that the system is provided with sufficient information and clear goal instructions, as is stands, a complete removal of workers in planning positions does not seem likely. Their job not only contains the aforementioned planning process but also a variety of communicative tasks between all parties involved.

Financial advisors and bankers are in a similar position as team leads. Their decisions need to take a variety of situation- and person-related information into account and derive a solid strategy from there. Specific financial recommender systems could support them in that task, today on a business-to-business level, but potentially also in the private investment sector (Patil & Agarkar, 2019). Currently, human advisors are still needed and wanted in these areas, as trust is an important component when making financial decisions (Ferrario et al., 2019). There is indication in the reviewed literature that for automated advisors, trust may increase incrementally over time, but for important financial decisions, human advice might still be preferred in the future. This would make the recommender system a technology to support the workers rather than replace them. Once again, recommender systems can find application in many jobs; the banking sector has however been explicitly mentioned in the literature.

While advising a decision or planning process is one way an AI-based system can generate output, another way is to generate specific work pieces that were formally created by a worker. An example of this is AI-based systems that find application relating to the jobs of **software developers**. The job of a software developer contains receiving information on what the client needs in a software, translating it to code and testing it. Within this process we see several tasks with the potential for automation, and some with already existing technology. Automated code generation, test case generation and testing itself relate specifically to workers within software development (Ali, 2020; Batouta et al., 2016; Kong et al., 2018). While in some work contexts these tasks might be addressed within the job requirements for a software developer, in larger corporations there can be departments focusing on only one of these. One example is a department for software testing, with employees who have special expertise in identifying root causes of problems revealed by a system test. In the current state of technical development and work procedures, these developers are still involved in the mentioned tasks to some extent. Be it for optimising pre-generated code towards a specific requirement (e.g. program size), creating the boundaries for test cases, or supervising, testing and analysing complex problems, the AI might have carried out discovery but was not able to resolve a problem. Given the current trajectory of technological improvement, many tasks could be fully automated in the future, pushing developers towards the problem solving-oriented or optimising aspects of software development.

Using a technology similar to that of automated code generators used for software development, automated text generators find application in jobs beyond them. So-called automated journalism might impact the job structure of **journalists** in the future (Graefe & Bohlken, 2020). These AI-based systems create text based on provided keywords and an established knowledge base, effectively being able to deliver usable pieces of writing within a fraction of the time a human writer could. However, when comparing human-written to AI-generated journalistic text, currently human written text is rated more readable and of generally higher quality (Graefe & Bohlken, 2020). Nonetheless, this technology, too, has improved over time, in terms of output quality, so it is within reason to assume that in the future the generated text could match a human writer's. Currently, the AI system needs selected and specific input that has been generated and researched by a journalist. And, as mentioned above, as long as the output quality is lower than a manually written text, it has to be edited and improved by a writer. While not currently at the level of journalists, these systems could speed up the writing process significantly in the future. In the field of journalism, however, this only represents one task of their job. Hence, they could move towards spending more time on researching the information or other related tasks. Another reason why journalists might be affected but not replaced by automated news generators is the facet of trust (Graefe & Bohlken, 2020). Human written articles are rated higher in credibility and quality. This effect however was measured regardless of whether the text was auto-generated or human-written. This helps illustrate the wish for human involvement in the journalistic process, but also highlights the need that AI-generated text in fields such as journalism should be made recognisable.

The technology of automated text generation can however be applied to many more jobs than just journalists. Every job that contains a writing element could eventually find use for such a system. This includes **authors, copywriters, content marketers and ghostwriters** down to **bloggers** and writing-related **freelancers**. The list goes far beyond that. The more focused a job is on the writing process itself, the more impactful this technology will be, to the point that standardisable text, such as technical descriptions, might not be human-written at all at some point. If a writing-related job does not contain significant pre- or post-processing steps, these jobs could potentially decrease in the future.

Another one of the possibly most affected job groups is customer support. The increasing capabilities of AI-based conversational agents through NLP replaces a main task in their job, potentially reducing the number of **customer support workers**. This could lead to human workers only being employed to handle any special cases that the chatbot could not sufficiently process (Bavaresco et al., 2020).

Commercial drivers form another group likely to experience work routine changes in their work routine instigated by AI-based systems. Currently, AI-based systems are applied in a supportive role while driving, increasing the driver's safety. However, when looking at some state-of-the-art technology, we do see the first versions of theoretically fully automated driving. For various reasons, we currently don't see this technology rolled out commercially yet. However, small automations, like lane assistance, or fully automated parking, show how not only private but also commercial drivers can be assisted. When considering technological development along a timeline, it reinforces the idea that cars are becoming increasingly automated, possibly to the point that commercial drivers might move into a supervisory role for the system, overseeing the automated driving process and only intervening in select situations.. In scientific literature, there are currently no estimations on when, or if, fully automated driving with no human driver present will be available, even though in practice there are currently trials being carried out of automated tracks and truck 'trains'[1]. As we see that the technology is becoming capable of this set of tasks, we also observe that reasons beyond the technological capabilities can influence whether something is automated. The ethics behind a vehicle piloted by an AI raises ethical questions that should be addressed before using the technology commercially. However, as being a commercial driver does include other subsets of tasks (stocktake, product handover, etc.), they are likely to primarily benefit from the next smaller automations in the form of driving assistance, while still performing other tasks related to their job manually.

Care providers, especially in elder care settings, are likely to experience considerable job transformation. Indeed, AI is viewed by researchers as a promising development that can help to resolve the care shortages caused by an ageing population. Advances in life expectancy, coupled with declining birth rates in post-industrial nations, have led to major increases in the percentage of people over the age of 65, particularly in post-industrial nations. According to the European Commission (2020), the old-age dependency ratio has gone, 'From about 29% in 2010… to 34% in 2019 and is projected to rise further, to 59% in 2070' (p. 3). This demographic trend implies an ever-increasing number of people in need of care and decreasing numbers of people able to provide it (Vollmer Dahlke & Ory, 2020). It is hypothesised by some that AI will play a major role in managing the rising old-age dependency ratio by optimising care systems through the automation of tasks. Efficiency gains in the provision of care will be necessary to compensate for the lack of caregivers relative to care recipients. A key expectation is that AI will economise care work by transforming it from a 'high-touch' interactive process to a 'low- or no-touch' experience. Saxena and Cheriton (2020) point out that conventional 'approaches to senior care are high-cost and greater risk,' because they 'require[e] close physical contact with trained caregivers' (p. 1). Presently, care workers are responsible for physically, emotionally and psychologically assisting and monitoring clients, which entails a wide-ranging set of duties that make caregiving extremely cost-intensive. AI offers 'an opportunity, if not an urgency, to… dramatically reduc[e] risk and cost inherent to care work by enhancing the capacity of devices and systems to automate aspects of elder care' (Saxena & Cheriton, 2020, p. 1).

The spectre of automated or 'low-touch' care work poses considerable OSH-related benefits for care workers. The possibility of offloading some of the duties associated with caring for elderly people – especially those who often suffer from terminal ailments – can reduce the physical, mental and emotional stress that caregivers experience. However, there are concerns surrounding the dehumanisation of highly automated care work.

3.4 Impact on sectors

The sectoral analysis presented in the "Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health" (EU-OSHA, 2022) report, already revealed the area of **human health and social work** as a prime sector for automation through AI, followed by **education and professional, scientific and technical activities**. While these results give an indication of which sectors the scientific literature focuses on, they do not represent the

[1] https://www.automotiveit.eu/technology/autonomes-fahren/wie-lkw-autonomes-fahren-in-die-praxis-bringen-92-405.html

entirety of affected sectors. In an additional literature analysis focusing specifically on sectoral impact, a variety of additional sectors have been identified.

The **human health and care sector** sees the largest number of publications. Most of them focus on automating only specific tasks, such as diagnosis, patient notification or collection of patient data. As the jobs in this sector are very complex and contain a great variety of tasks that so far are not automated, we could not identify a specific job group that would face reduction caused by automation. But as this sector offers such a diverse field of tasks, it is likely that in the future more will be automated, for the benefit of efficiency, patient care and possibly the workers' well-being.

The **education sector** is the second most mentioned sector when it comes to AI-based systems. A variety of tasks, such as basic language training or teaching math, can be automated by an AI-based system. This does not only apply to school-based education but can also be used in adult education. Noticeably, publications position themselves towards these systems as a support for a teacher, giving them more time to spend on individual student support. Technology is being more and more employed in the classroom, but at this point the teacher's job is not seen as at risk of full automation. Hence, it is likely that in the future we will see more AI-based automation in the education sector, but not necessarily a reduction in teachers.

Some groups of the **service sector** will face changes due to automation through specific AI-based systems. Customer support is increasingly automated, as systems successfully aid clients. This will likely lead to lshrinking employment in this sector, while a select group of workers will stay employed to deal with more individualised customer issues. Similarly, as text and code generation become higher in quality, jobs like journalist and software developer will feel the impact of these systems automating a crucial task in their work field. While in journalism there is a preference for human-written narrative, the same cannot be said for writing software code. Both of them are in the information and communication sector yet might be affected differently. This helps illustrate that the effect of an AI-based system cannot always be generalised to an entire sector, as the jobs covered by it are held to different expectations and standards.

There are mentions of systems in the **finance sector**, however these are currently so limited that no reasonable conclusions on how this will impact the sector can be drawn. Noticeably, sectors such as the **judicial, trade, arts, agriculture and construction have been underrepresented** on the meta-level of scientific literature. This should not be interpreted as these sectors having no need or no opportunity to apply AI-based systems, but rather that the current state of scientific literature is still comparatively narrow, as it is a new technology. This is also supported as the interviewed experts have stated sectors such as the agricultural one as an area of interest for increased automation.

The previous chapter illustrates that while some AI-based systems have the potential to affect jobs across a wide spectrum, some are developed to be employed for a specific purpose. Technologies such as AI-supported driving is the kind of technology that in the future might be observed in many different sectors. As long as the sector involves some form of transportation, this technology might find purchase potential. Similarly, a variety of sectors can benefit from AI-based organisational decision support systems.

While contextually assigned to benefit researchers, data classification software, too, can find application in many fields. Other AI-based systems are in their application more limited. Automated code generation will primarily affect the sector of ICT. An important observation is that despite a large body of literature being reviewed, predictions of technological impact on the demand for a specific job or impact on the applied sector were not central to any of the publications. They focus on either the technological limitations or applications of the systems, how they impact efficiency of a workplace or how the possible beneficiaries of the system are affected. Those, however, are often a different group from users, like medical patients versus nurses. How AI-based technology impacts workers, their environment and their mental state in the present and in the future is not yet a central focus of published literature. The technology in question only recently reached maturity for wider-spread application and is in many sectors still only being tested and not a common appearance.

4 OSH implications

The use of AI based systems for the automation of cognitive tasks, could present a number of opportunities for OSH but risks as well. Based on the literature reviewed we can identify certain areas of interest regarding the current scientific discourse and the OSH-related topics discussed most when it comes to the automation of tasks through AI-based systems. According to the presented taxonomy, they can relate to physical, psychosocial or organisational aspects. It can happen that a specific implication is primarily discussed in a, for example, person-related context, as it is especially relevant for those kinds of tasks. In addition to that, the implications are assigned to their specific area of effect. These areas are psychosocial, physical or organisational. Furthermore, some AI-based systems have the potential to be applied so broadly that they should not be limited to a singular field of application, such as risk analysis of the working environment performed by an AI. Here, we look at the psychosocial and organisational effects of actual or perceived/possible task transformation emerging from AI-based systems at work and the associated risks and opportunities for OSH. While not as prevalent in the literature, there are also some possible physical consequences of automating some cognitive tasks, in specific areas.

4.1 Psychosocial effects

The most commonly discussed psychosocial factors are issues of: feared job loss; job transformation reflected in required or forced deskilling, reskilling and upskilling; trust; loss of autonomy; and loss of privacy. All of these experiences of what can be called digitalised ‘psychosocial violence’ (Moore, 2018) result in workers’ anxiety, depression, work disengagement, lack of attention, incompliance and withdrawal, and while this report does not discuss worker responses, can lead to sabotage and other forms of situational leveraging indicating a lack of psychosocial stability. This section reports on our findings relating to psychosocial impacts of AI cognitive systems as they have begun to impact workers’ tasks. These impacts are transversal to industries, but the following sections draw out some specific impacts that are observable and known in existing literature.

4.1.1 Workload

AI in the workplace can change the workload experienced in many jobs, both in terms of quality and quantity. While it is hard to predict precisely how an individual workplace will change once an AI-based system is introduced, there is the general expectation that the (cognitive) workload will be impacted. This often includes a reduction of repetitive or dull tasks. That does not necessarily mean that the overall workload reduces in the long run. More so, that the type of task changes towards more creative, supervisory or otherwise focussed tasks.

In the educational sector, using AI-based system has been considered a chance to free up teachers, as the system is being used by students and the teacher gets to focus on singular students to support them with specific questions or struggles regarding the material. In several other job groups we see a shift of workload from producing output to supervising or working off of AI-output. Pre-generated text in journalism, ghost writing etc. or automatically created code provide a basis for the human to work upon, instead of creating everything from scratch. A similar change can be observed for jobs performing some form of data classification when the AI is placed in charge of extracting, classifying or indexing large bodies of data. These are time consuming tasks, that need the worker to stay focussed for extended periods of time, and having them automated provides relieve to cognitive load. Similarly, administrative positions are anticipated to shift in focus. If the AIs analysis and recommendations prove to be effective, these workers could potentially either supervise more projects or focus more on the human-centred side of their job. Overlapping to a degree with physical workload, the cognitive workload of care workers is likely to decrease as well. The possibility of offloading some of the duties associated with caring for elderly or sick people can reduce the physical, mental and emotional strain that caregivers experience (Saxena & Cheriton, 2020).

These are only a handful of examples of how a shift in task focus can impact workers and their workload. AI-based technology can take over tasks that need elongated periods of concentration, repetitive information processing, or scheduling etc. and that way reduce a certain type of cognitive workload. This however will likely not leave workers with less to do, but rather have them perform more creative, human-centred or complex tasks.

4.1.2 Job loss

The fear of job loss is one of the most discussed factors among research papers when it comes to the automation of cognitive tasks. In recent years, several shocking headlines have circulated proclaiming the onset of major job losses in the coming decades, in part due to the rise of AI. Perhaps the most famous example of this is an Oxford University-based paper titled 'The Future of Employment: How Susceptible Are Jobs to Computerisation?' that estimated that 47% of jobs in the United States are at risk of automation. Since the publication of that 2013 study by Carl Frey and Michael Osborne, dozens more studies have attempted to decipher the amount of job destruction that can be expected due to AI and automation. The MIT Technology Review has attempted to catalogue studies dealing with this question and their findings. That effort is reproduced in Table 1.

Table 1: Predicted jobs automation will create and destroy

When	Where	Jobs Destroyed	Jobs Created	Predictor
2016	worldwide		900,000 to 1,500,000	Metra Martech
2018	US jobs	13,852,530*	3,078,340*	Forrester
2020	worldwide		1,000,000 to 2,000,000	Metra Martech
2020	worldwide	1,800,000	2,300,000	Gartner
2020	sampling of 15 countries	7,100,000	2,000,000	World Economic Forum (WEF)
2021	worldwide		1,900,000 to 3,500,000	The International Federation of Robotics
2021	US jobs	9,108,900*		Forrester
2022	worldwide	1,000,000,000		Thomas Frey
2025	US jobs	24,186,240*	13,604,760*	Forrester
2025	US jobs	3,400,000		ScienceAlert
2027	US jobs	24,700,000	14,900,000	Forrester
2030	worldwide	2,000,000,000		Thomas Frey
2030	worldwide	400,000,000 to 800,000,000	555,000,000 to 890,000,000	McKinsey
2030	US jobs	58,164,320*		PWC
2035	US jobs	80,000,000		Bank of England
2035	UK jobs	15,000,000		Bank of England
No Date	US jobs	13,594,320*		OECD

When	Where	Jobs Destroyed	Jobs Created	Predictor
No Date	UK jobs	13,700,000		IPPR

To be sure, these headline numbers offer cause for sincere concerns about the state of future labour markets. However, they must be contextualised by important epistemological and methodological considerations. For instance, Frey and Osborne (2018) have since clarified that: ‘Our estimates – particularly the 47% figure – have often been taken to imply an employment apocalypse. Yet that is not what we were saying’ (Frey & Osborne, 2018, para.3). Instead, they claim that their study ‘simply looked at the susceptibility of existing jobs – 702 occupations, comprising 97% of the US workforce – to recent developments in emerging technologies such as artificial intelligence (AI) and mobile robotics. It did not predict a timeframe, and it did not explore the new sectors and roles that will undoubtedly arise in the years and decades to come (Frey & Osborne, 2018, para.3).

As Ernst et al. (2020) point out, studies that attempt to make broad forecasts about overall job destruction, ‘focus on potential gross job destruction and cannot provide an answer to actual job destruction, net job displacements, or labour market turnover, which would be necessary to assess the challenge of automation from a policy perspective’ (p. 5). Part of the inability for these studies to calculate the ‘actual’ job destruction is because they cannot account for new jobs that will be created alongside the elimination of current occupations. This limitation is, however, at the centre of heated debate about the degree to which the AI revolution will, like other technological revolutions, produce new forms of work.

On the one hand, there are the optimists, who argue that fears of job destruction are overstated if not factually baseless. This perspective benefits from a long historical record of repeated cycles of fears over new technologies that will supposedly herald a new age of idleness, but they never seem to arrive. Mishel and Bivens (2017) note that: ‘The media are full of stories about robots and automation destroying the jobs of the past and leaving us jobless in the future; call it the coming Robot Apocalypse (p. 1). They bemoan the fact that, ‘there is a strong desire to believe [this media narrative] despite so little evidence to support these claims (p. 1). In fact, they explicitly state that ‘automation has led to job displacements in particular occupations and industries in the past, but there is no basis for claiming that automation has led - or will lead - to increased joblessness, unemployment, or wage stagnation overall’ (p. 1).

On the other hand are the pessimists, who do believe in the so-called Robot Apocalypse and that AI will eventually result in mass job loss. They argue that one need only subscribe to a very simple and plausible thesis: that, at some point, machines will outperform humans at every imaginable task. This is certainly not a new idea. Nobel Prize winning economist Herbert Simon proclaimed in 1956 that: ‘Machines will be capable, within twenty years of doing any work a man can do’ (p. 96). Of course, Simon’s prediction has proven untrue, but that may be because Simon was mistaken not about what machines will be capable of, but when.

The AI ‘revolution’ poses new reasons why widespread job loss may be a reality in the not-too-distant future. Such a possibility is associated with profound OSH concerns. First, if mass (long-term) unemployment does materialise, the devastating impacts hardly need spelling out. As this development unfolds, workers will be forced to function under the constant psychological stress that they could be automated next. Moreover, this concern is anything but a far-out issue that can be put aside as widespread fear of redundancy via automation is already taking hold. Survey data indicate that workers already nurture fears that their jobs will be automated, particularly younger workers (Mercer, 2020). Mercer’s 2020 Global Talent Trends survey found that one in three workers believe their job will be automated within three years.

The fear of job loss is a serious OSH risk. The literature consistently finds a strong link between job insecurity and poorer mental health outcomes. Indeed, this connection has received heightened attention in recent decades due to the shift in industrial strategy away from long-term full employment to flexible and competitive marketplaces. Thus, it is no surprise to find Ferrie's (2001) paper documenting how 'most researchers who have examined the effects of perceived job insecurity on health have looked at psychological morbidity as an outcome, often as the only outcome. Every published study has documented consistent adverse effects on psychological morbidity' (p. 72).

More recent literature confirms these findings. Watson and Osberg's (2018) robust regression analyses of social data from Canada found that: 'After controlling for a host of factors thought to influence psychological distress, our key results suggest that job insecurity, measured in either subjective (perceived job insecurity) or objective (probability of joblessness) terms, is associated with greater psychological distress for working age males and females' (p. 2). It is worth remembering that the 'invisibility' of mental health problems makes their recognition and treatment more difficult. This challenge must be seriously addressed given that the OSH implications related to AI advancements will be predominantly cognitive in nature.

4.1.3 Job transformation

Regardless of whether AI does bring forth incredible levels of job destruction, it is indisputable that developments in this kind of technology will dramatically alter the world of work and the nature of current jobs. There is a tendency to emphasise that low-skill work is at risk of being automated, but this is somewhat misleading – professional jobs are at risk of being transformed by AI as well. As evidenced in previous chapters of this report, the tasks that AI systems are capable of completing are increasingly cognitive-based. This means that professional work, typically thought of as safe from automation, is also at risk of being transformed by the spread of AI. Indeed, some argue that 'The emergence of technologies that are able to automate, enable substitution of, or substantially reduce the time spent on even quite complex professional tasks is, however, likely to have a more direct impact on professional occupations, at least in the medium term' (Lester, 2020, p. 6).

Deskilling

The impact of AI on the skills of workers bears important OSH implications. As AI continues to augment the execution of tasks, or even replace the need for specific human contributions altogether, aspects of a worker's job may be entirely eliminated. To be sure, this may, in certain cases, be an entirely positive development by eliminating the necessity of a worker having to complete mundane, routinery and repetitive tasks. For example, the elimination of clerical and secretarial tasks that can bog down administrators in public services may allow for better benefits provisioning. Similar possibilities abound in the healthcare sector, wherein administrative processes are considerable and direct resources away from patient care. This mode of redundancy is to be celebrated, as it can open up time and resources for new kinds of work that may be more stimulating, challenging and impactful. However, this development of automating particular tasks and aspects of one's job may negatively impact workers who experience what is 'sometimes referred to as deskilling: The skills and knowledge needed to perform a job that are lost when automation takes over' (Joh, 2019, p. 136). The possibility, or inevitability, of deskilling as a result of automation poses OSH concerns. Automation can have a 'polarisation effect' by forcing displaced workers into lower- or higher-skilled occupations. Certain demographics are more likely to suffer a downward trajectory into lower-skilled jobs. Autor (2019) explains that across recent decades, almost all occupational change among non-college workers reflects a movement from the middle toward the bottom of the occupational distribution. Thus, not only has technological change been transformational, it has led to deskilling, by which the current authors mean that it has narrowed the set of jobs in which non-college workers perform specialised work that historically (and currently, as we show below) commanded higher pay levels (p. 9). Kunst (2019) similarly notes that 'automation since the 1950s has been deskilling among manufacturing production workers around the world' (p. 3). Kunst's research shows that 'most manufacturing employees worked in medium-skilled craftsman occupations, jobs which required handicraft skills and a good understanding of the entire production process' (p. 4). However, in large part due to automation, there has been a 'pervasive reduction in the relative demand for craftsmen in countries of all income levels and world regions over the subsequent decades' (p. 4).

The outcome of this transformation has spelt declining wages, occupational prestige and marketable skills for so-called blue-collar as well as skilled white-collar workers and employees. The prospect of such decline can induce psychological morbidity, stress and fears over lost status. In addition to these psychological harms, deskilling can exacerbate troublesome labour market trends like long-term unemployment, a growing reality especially for men in prime working ages.

There is another dimension of deskilling, made possible by AI that is raising concern among researchers: namely, the possibility (or inevitability) of moral deskilling. Green (2019) defines this phenomenon as 'the loss of skill at making moral decisions due to lack of experience and practice'. They argue that '[a]s we develop artificial intelligence technologies which will make decisions for us, we will delegate decision-making capacities to these technologies, and humans will become deskilled at making moral decisions, unless we endeavour not to be so'. This again brings out Foucauldian themes, like the disciplinary society: the prospect that individual actions are no longer guided by moral reasoning but by simply following directions as operators in a larger system. The loss of skills with enhanced automation poses risks if, for some reason, those systems breakdown and individuals can no longer complete those automated tasks.

This is particularly concerning with skills related to working through moral dilemmas. An example of this could be related to the programming of self-driving vehicles. When confronted with a trade-off between two unfortunate outcomes, such as veering off the road to avoid a pedestrian, how should cars be programmed to act in such circumstances? Green (2019) argues that we should resist AI making too many morally significant 'decisions for us, thus fostering dependency; the key is to promote these skills in humanity, helping us to become independent moral decision-makers'. Failure to do so has potentially detrimental implications in the workplace. This aligns with the experts' opinion that the 'human in command' principle should always be prevalent when working with these systems. As expectations of individuals to be capable of moral reason declines due to deferment to an artificial intelligence, the possibility for exploitation increases. That is, workers can more easily be manipulated into acting against their moral interests or preferences because they are unable to understand artificially intelligent processes guiding their actions.

Examples are beginning to abound of managers employing algorithms to make managerial decisions like who should be terminated during mass layoffs for company downsizing objectives. When confronted by workers about the reasons for their selection for termination by the algorithm, managers are unable to provide clear and satisfactory explanations. Managers can thus find themselves in the position of having to execute morally significant duties without knowing the full contextual details surrounding the act. If, unbeknownst to them, these algorithms are biased or discriminatory, then managers are being manipulated into propagating an act of discrimination without knowing it – thereby being subjected to a serious occupational hazard and risk. This highlights the need for transparency from the manager's perspective in their decision-making process, informing workers that an AI-based system was involved in this process, as well as, and more so, from the side of developers regarding the working mechanisms in their algorithms. This from of transparency can help in discovering hidden biases and reduce unintentional discrimination.

Reskilling/upskilling

To manage or compensate for the problem of deskilling, workers have been instructed – and in some cases aided by industrial policy – to 'reskill' or 'upskill' to obtain skills that are desirable to employers. This solution, however, is not without its problems. First, it is not clear that it yields the assumed results. Kunst's (2019) analysis concluded that 'while increasing human capital investments may be necessary, they do not guarantee success on the labour market: in spite of the substantial skills that they had acquired, manufacturing craftsmen have experienced pervasive declines in relative wages and employment opportunities since the 1950s' (p. 28). Second, the pressure to upskill can amount to an oppressive burden that leads to rising stress levels. This is particularly true with more advanced AI systems. Surya (2019) explains that increased uptake of AI would 'radically revise a certain kind of training required during the next era' (p. 9). As Surya point out, it 'is challenging to acquire the requisite skills to implement AI technological innovations' (p. 9), and therefore workers may not 'feel confident interacting with technology or be aware of current regulations, like privacy and data legislation that directly impact AI ventures' (p. 10). Thus, deskilling at the hands of automation gives rise to the necessity of upskilling that can induce stress and a lack of confidence in the workplace. A final concern worth noting in relation to the phenomenon of deskilling is the reduction of craftsmanship itself. This will be experienced more acutely in certain industries more than others. For instance, the craft of teaching is exemplary of a social good that may be crowded out by increasing instruction by AI systems. It is worth acknowledging that AI will not replace teachers anytime soon. As Bryant et al. (2020) put it: ‘Many of the attributes that make good teachers great are the very things that AI or other technology fails to emulate: inspiring students, building positive school and class climates, resolving conflicts, creating connection and belonging, seeing the world from the perspective of individual students, and mentoring and coaching students.’ These things represent the heart of a teacher’s work and cannot – and should not – be automated. In other words, our traditional understanding of the education process is that ‘teaching is a craft and, like all craftsmanship, is to be taken very seriously’ (Goodwin, 1987, p. 15). Yet, the craftsmanship aspect of teaching may be under threat by the growing automation of tasks completed by educators. To be sure, some AI developers claim to be guided by the principle ‘Put the teacher in charge, not the computer’ (Heffernan & Heffernan, 2014, p. 470). In other words, AI technologies will empower teachers and serve a complementary role. Whilst this may be true in some respects, there are reasons to be concerned that such technologies will endanger the autonomy of educators over their craft.

We are, however, beginning to witness that some systems are already taking the next step of putting, ‘teachers into an arguably lower-level role of facilitating computer systems and managing student social and emotional needs’ (Schiff, 2021, p. 340). Schiff (2021) describes a digital educational platform that ‘has registered over a million students in more than 200 cities and is growing. For both students and instructors, the laptop is the main vehicle of learning’ (p. 340). The founder of this platform has expressly stated that ‘human teachers will be like a pilot’ as they will ultimately play ‘a passive role, monitoring computer dashboards until a student is fagged, and even then focusing on emotional (not academic) communication’ (p. 340). The displacement of teachers from crafts(wo)men to pilots of an automated system is liable to produce intense feelings of alienation and purposelessness – subjectivities that have serious OSH implications (Wogu et al., 2018).

4.1.4 Trust

Trusting a technology while working with it is known to be an influential factor on safety (Mosher, 2013). Hence, the impact of trust in the system should be considered when discussing AI-based systems and OSH, outside of specific task or job application. Trust can play a role in multiple aspects of system use, depending on the task it is being used for and the user themselves. For the specific case of AI-generated team instructions, trust in the AI system is a significant antecedent to effective team learning and team performance; however, the consequences of trusting or not trusting the AI one works with also apply outside of this example. Gaining benefits from the AI system comes with a set of prerequisites. For example, for AI-based team tutoring to be effective, the AI-tutor needs a model of each learner’s domain competency (Sottilare et al., 2018). Additionally, the system must be reactive to changes in the environment and learners on a team and should be proactive in taking initiative to progress towards team goals. A well-adjusted and trusted system in education can improve learning results and enhance the learning experience (Sottilare et al., 2018). While not the central focus of the publication, trust in a system is highlighted as an important factor to benefit from it. Without trust, any mental or physical gain intended by introducing the system could be influenced negatively. This general conclusion can be found for other types of AI systems and other tasks, such as conversational agents (Rheu et al., 2021). A system that is trusted is more likely to be used and thereby reduce the workload of the user. The skill level of the agent is critical in building trust; however, anthropomorphic design features were found to influence how people assess an appropriate level of trust towards the system and could even nullify performance-related factors (Rheu et al., 2021). However, enhancing trust redundantly may result in safety issues due to overreliance (Rheu et al., 2021). This ties into automation bias. It describes the overreliance on a provided assistive technology provided, or the tendency to overvalue machine-provided information over manual information. It is associated with the degree of cognitive load experienced in decision tasks, while not being directly associated with multitasking (Goddard et al., 2012; Lyell & Coiera, 2017). If a systems operator exhibits automation bias, the consequences can be an overreliance on or misuse of the AI-based system (Goddard et al., 2012). Overreliance can manifest in several ways, decreasing OSH, for example by neglecting supervision or maintenance routines, or operating the system above its capacities. In areas such as medicine this would not pose a primary risk for the using healthcare professional but rather the patient (Goddard et al., 2012).

While the possible gravity of insufficient trust or unregulated automation bias can vary from workplace to workplace, it is advised to always consider it. A general take-away is that for any user to fully benefit from the system they need a sufficient level of trust towards it. This can result in direct effects, like fully benefiting from the system's intended effect of cognitive support, to more indirect effects by avoiding the consequences of automation bias, in form of overreliance or loss of skill. When introducing a new system to a workplace, everyone in contact with it should be made aware of the capabilities and realistic limitations of the system. Users should be given training to not only understand the technology but also see how their work changes due to it.

4.1.5 Loss of autonomy

Autonomy is regarded as a constituent feature of meaningful work, and, therefore, encouraging its preservation and expansion should be a goal of policy-makers (where appropriate). In this respect, the dispersion of AI into workplaces presents complications and challenges. First and foremost, new technologies can have a constricting effect on the totality of the work execution process. Smids et al. (2020) explain that some robotic applications in the workplace may require working according to a very strict protocol that leaves little room for human creativity, judgment and decision-making. For the same reasons, workers' opportunities to engage in job crafting may be severely restricted. Their tasks and work environment may be so tightly structured by the robots that there is little room for restructuring in ways that make the job more meaningful. If robots had that kind of impact, worker autonomy would be undermined, and consequently the jobs' meaningfulness as well (p. 514).

This dynamic is likely to unfold in a number of industrial sectors, ranging from care work to the delivery of parcels. The economisation of work is a central aim of implementing intelligent systems, and any worker discretions that diverge from the maximally efficient action might be eliminated. In other words, workers who currently face daily choices in their work over which they have some discretionary power might see their work reorganised such that those discretions are removed. One such example is the structuring of delivery routes in the courier industry. Currently, some parcel deliverers still have the autonomy to structure their routes each day. This entails a freedom to plan stops in such a way that they may feel most comfortable with or that allows them to stop for lunch in a preferred area. The onset of 'timed deliveries', having to deliver a parcel within a specific time frame, is causing that freedom to recede, with algorithms increasingly planning routes. Indeed, the use of algorithmic decision-making by employers, especially in the digital platform economy, is a phenomenon that is receiving a lot of attention by industrial sociologists. Posada (2020) notes that '[o]ne of the biggest concerns regarding the deployment of artificial intelligence in the workplace is the use of algorithmic management and its implications for workers' agency and privacy' (p. 6). As Posada notes, one of the biggest concerns surrounding the proliferation of algorithmic management is the constant surveillance and monitoring associated with it. Heightened surveillance, and loss of privacy, is an OSH threat in its own right, as explained in another section. EU-OSHA also investigates these issues in more depth in two further projects on OSH in relation to digital platform work (EU-OSHA, 2021a) and OSH in relation to new forms of worker management through AI-based systems (ongoing).

The negative association between monitoring and workplace freedom has to do with the phenomenon of self-censorship. When an individual is aware that they are being watched, they may feel an innately arising pressure to act in what they believe is the most desirable manner in the eyes of the observer. This dynamic harkens back to Jeremy Bentham's notorious attempts to build the 'panopticon' that would give incarcerated persons reasons to believe they are under surveillance at any moment. In contemporary workplaces, this could encourage working practices that are unreasonable and even unsafe. According to Rosenblat et al. (2014), 'direct and active electronic monitoring can create rigid technological control over standardized work activities … For example, stockers in warehouses sometimes have their movements tracked as they load and unload products from docks, and their minutes and distance are catalogued as they crisscross the lengths of the warehouse' (p. 6). All these are efforts to study and produce the most efficient methods for completing tasks, but the bottom line for the workers is that they will be fired if they don't hustle. An employee under constant monitoring may believe they must work with greater intensity than they actually have to, knowing that if they are observed moving 'too slowly' they could be accused of time theft and punished. This brings us to another related concern surrounding algorithmic management, the lack of transparency inherent to this mode of workplace governance. In workplaces overseen by human managers, exercises of managerial discretion can be observed, analysed and investigated by workers and external authorities. However, the implementation of management by AI algorithms renders managerial discretion non-observable and even non-intelligible.

Ajunwa (2020) elaborates on how this development affects the workplace: 'The faithful reliance on big data-driven algorithmic decision-making systems ... create[s] the paradoxical "black box" at work ... the "black box" demands a higher level of transparency from the worker in regard to data collection, it shrouds the decision-making derived from the data in mystery, making employer decisions, which have now been algorithmically derived, even more inscrutable to the worker ... the worker is commanded to be supplicant, by divulging highly personal information to oracular hiring systems ... and, once hired, the worker must submit further still to algorithmic processes of evaluations which will make authoritative claims as to the workers' productivity. Furthermore, said worker is governed by an invisible data-created leash comprised of wearable technology that collect data as to the worker's movements in the workplace, their interactions, as well as, their communications' (p. 2).

Additionally, this could be associated with a number of health related issues. For instance, previous research provides enough evidence for causal relationships between a number of psychosocial risk factors and musculoskeletal MSDs (EU-OSHA, 2021b). However, examining the associations between psychosocial risks and MSDs in more detail, it is not possible to establish specific associations between different types of MSDs and different types of psychosocial risk.

The expression 'black box' is used in the literature to signify that algorithms, by their very nature, are often inscrutable. It is difficult, if not impossible in some cases, to understand how decision-making algorithms make a given choice. To therefore be governed by the decisions of an algorithm that embodies the properties of a 'black box' is to be subjected to a decision-maker that, as Ajunwa points out, is not transparent, accountable or explainable. Such an arrangement is an assault on the liberty of a working person, because freedom requires that insulation from (and the capacity to resist) subjection to the arbitrary will of another. Neither of these demands of freedom can be realised in a relationship where the motivations, aims and goals of the governing power are beyond the understanding of its subjects. If, for instance, a worker is dismissed at the recommendation of an algorithm, how can they prove that the grounds for such a dismissal are arbitrary or unfair? Similarly, if a prospective interviewee is not selected for a position based on algorithmic feedback, how can they challenge potential bias or discrimination if they sense it was at play? In short, the capacity for individuals to exercise their basic (workplace) liberties can be undermined by a system of algorithmic management, a system that is increasing with the growth of AI.

Task automation through AI-based systems is more commonly associated with cognitive task assistance or substitution, rather than its impact on the environment of workers in meaningful, OSH-related ways. While not in direct contact with a worker, but rather the work environment as a whole, there are ways to benefit workers. Occupational accident analysis via an AI-based system in the work environment can take different forms and impact the workplace accordingly. An advanced decision support system can be used for real-time data analysis and safety-related decision-making. A cloud-based model can be embedded into the system for the storage of big data, which aids in efficient data analysis, and quick decision-making. A video surveillance system can also be implemented in the workplace to monitor the safety violation or anomaly detection and, accordingly, proper actions can be taken to mitigate or even prevent the occurrence of incidents (Sarkar & Maiti, 2020). All systems utilise workplace and worker-related data to improve OSH. Hence, AI-based systems can very tangibly be applied to increase the safety of workers in many different work environments.

4.1.6 Loss of privacy

A central OSH concern associated with the spread of AI is the potential loss of privacy in the workplace. Privacy protection in the workplace is a fundamental right, which is a set of technical, legal and organisational procedures intended to protect personal data in order to prevent and eliminate violations of their rights to privacy. However, privacy protection and some system performances have conflicting requirements. A system with more person related data can potentially perform its task better, than one without any personal data that could also impact OSH. However, the right to privacy is protected under the EU General Data Protection Regulation. Therefore, it is important to investigate cases in which person related data is OSH relevant, to determine an adequate balance between safety and privacy. Protocols need to be in place to protect any logged personal data from unwanted collection, analysis or distribution. This also highlights the need for transparency (Köbis & Mehner, 2021) when working with AI-based systems. Workers need to know if, and if so what kind of data a system potentially collects.

Without sufficient transparency this could lead to mistrust towards the system; the negative OSH consequences of which are detailed above.

Additionally, a perceived loss of privacy might result in the feeling of being under constant surveillance. This can impact employee well-being, work culture, productivity, creativity and motivation (Ball, 2010). Studies deemed relevant in meta-analyses of the educational sector effectively bring this issue to light. It is consistently noted that in the field of education, the development of AI systems will require copious amounts of data, which technology firms currently do not have. This raises questions as to how firms will be able to acquire the data needed to build models in order to facilitate machine learning. As Murphy (2019) explains, 'most developers interested in applying machine-learning techniques to develop intelligent, adaptive instruction products for the classroom lack access to the large digital data sets needed to train the models' (p. 11). Whilst educational institutions retain large student information systems, they 'do not include the fine-grained information on instruction and learning that is required to train a machine learning–based adaptive instruction system' (p. 11). That kind of data is only available from 'online instructional platforms, and access to these metadata is restricted to the district and the platform provider' (p. 11).

This data access issue raises privacy concerns for students and teachers alike. Any forthcoming push to obtain the currently restricted metadata may endanger the privacy rights of educators. Sweeping data collection – a necessity for AI systems – involves numerous and complex questions of consent, selection, transparency, representation and accountability, among other considerations (Köbis & Mehner, 2021). Failure to develop and enforce ethics guidelines for the collection and utilisation of instruction-related data could result in widespread rights violations for educators.

A related OSH concern is the heightened monitoring of education by surveillance systems. At present, this possibility is described in positive terms: it will allow for helpful feedback, student customisation potential, time saving and so on. But greater surveillance opens up the possibility for the collection of incriminating information as well – information that could be used to bring forward more frequent disciplinary sanctions against poor performance. In this sense, the site of educational instruction would, like other highly digitalised spaces, become increasingly panoptic (Manokha, 2018). The rising rate of teacher observation as a means to improve education outcomes demonstrates a tolerance and willingness for classroom monitoring, something that AI could take to whole new levels (Neumerski et al., 2018).

While prominent in the literature and real life application, it is not exclusively educators affected by possible loss of privacy. The collection of person-related data offers the potential for individualised systems; however, there needs to be a balance between that and the possible loss of privacy. Possibly any job working with an adaptive AI-based systems can be affected by this phenomenon. When an AI-based system requires person-related data to adapt or improve its performance, perceived and actual loss of privacy is an inherent risk. It is important to be transparent towards the worker how the AI-based system functions, what kind of information it is collecting and utilising, and if possible to provide the worker with the ability to adapt the level of detail in the system. In addition to that, all systems need to consider the current status of data privacy laws applicable to them.

4.1.7 Depersonalisation

The literature surveyed for this report, particularly findings from the care and education industries, suggest that the uptake of AI could induce a process of depersonalisation. The introduction of AI into the care industry is uniquely illustrative. Rubeis (2020) explains that the expansion of smart 'technology leads to the distinction between patients as bodies and patients as subjects' (p. 2) because the central focal point of care becomes 'easily measurable indicators that are usually bodily in nature' (p. 2). In other words, growing involvement of monitoring systems and instructional assistants in the caregiving process transforms the relationship between the carer and patient, ultimately by turning the latter into an object for the former. The patient no longer represents needs as a subject, rather, needs are directly observed by the carer through technological devices.

Although the literature tends to focus on the potential benefits and harms of AI technologies for patients, we can reasonably assume that depersonalisation in the nursing relationship may promote a form of alienation for caregivers. As more aspects of care work become automated, the care worker's responsibilities are revolutionised from actively assessing patient needs and prescribing a course of action to responding to alerts and following machine-generated recommendations. This reconfiguration from active assessment and prescription to following mechanical commands alienates and limits the projection of the carer into their work. Put another way, the worker no longer extends themself into the decision-making processes, effectively limiting the need to utilise their emotional and cognitive capacities whilst providing care.

Another related concern is the dehumanisation of an increasingly automated work environment. As more tasks are offloaded onto computer systems, all types of robots, IATs and so on, care workers are increasingly surrounded by, and reacting to, 'data' and 'devices' more than interacting with human beings. For those who enter this line of work because they value the socially interactive element of caring for others, this will become a less central feature of these workplaces, thus depriving them of that opportunity. While care work seems to be the primary area affected by this, other social jobs, such as teachers, as well as therapists or customer service workers are also being affected. Such deprivation amounts to harm as it effectively blocks an individual from participating in an activity linked to their own self-actualisation and fulfilment from work.

4.2 Organisational effects

Introducing an AI-based system into the work environment can impact the organisational structure of a workplace in disruptive ways that can be seen as both negative and positive, depending on the context and depending on which stage of the implementation life cycle one considers. There are a number of methods to integrate technologies effectively into workplaces, but to reduce possibilities for ineffective outcomes, good dialogue with worker representatives is typically recommended.

Two issues must be addressed at the organisational level when integrating AI-based systems: firstly, the optimal situation whereby trained algorithms only provide accurate results and thus a reduction of any potential for bias. AI designers and users should, thus, when employing multiple systems, look for ways to 'solve volatile, uncertain, complex, and ambiguous challenges' (Laplante et al., 2020, p. 46). Potential challenges with the use of AI-based systems, furthermore, are found in the overrepresentation or underrepresentation of a case within data that create biased conclusions. Further to this, data insecurity can arise where attackers could also modify new inputs; therefore, security protocols need to be implemented when introducing AI-based systems.

Usually, when AI-based systems are introduced into organisations, data must be collected from what the General Data Protection Regulation (GDPR) calls 'data subjects'. The GDPR makes it very clear that data subjects should not suffer a loss of privacy and data security just because there are possibilities to advance optimisation of a system that would include the introduction of an AI system into workplaces. GDPR Art. 32, which focuses on the security of processing personal data, emphasises that 'the [data] Controller and the processor shall implement appropriate technical and organisational measures to ensure a level of security appropriate to the risk, including, inter alia, as appropriate':

> (a) the pseudonymisation and encryption of personal data;
> (b) the ability to ensure the ongoing confidentiality, integrity, availability and resilience of processing systems and services;
> (c) the ability to restore the availability and access to personal data in a timely manner in the event of a physical or technical incident;
> (d) a process for regularly testing, assessing and evaluating the effectiveness of technical and organisational measures for ensuring the security of the processing. (Art. 32)

In proportion to the AI introduced in a company, the data it processes and collects, as well as the outwards communication about the system, it demands organisational changes. It is important that during the introduction process transparency about data privacy is prioritised as to not introduce mistrust or the feeling of unnecessary surveillance to the workplace, both of which can have a negative impact on OSH.

Thus, there is an important role for the Data Protection Officer (DPO) when integrating AI systems into organisations. Moore's (2020) European Parliament Science and Technology Office (STOA)-commissioned report recommends the full inclusion of workers and managers in all technology implementation. She recommends that all DPOs should be proactive and include not only trade unions but also employer associations. Indeed, to demonstrate good practice, for insurance of lawfulness and workers' rights protections, DPOs should work with employer associations and, as also recommended in the new European Commission AI Act, write codes of conduct to accompany any system processing data. This will ensure that employers understand the wider context within which their activities function, and that consultation has occurred. This could even operate at the level of international standards, where, for example, the International Standards Organisation is currently developing a standard that looks at the use of dashboards in such places as warehouses, which takes into account the variety of usages in various countries and the legal frameworks and organisational cultures within which they are operating.

4.2.1 Communication and organisation

Particularly in large companies, communication becomes a crucial tool for effective and successful work when AI systems are integrated. The literature presents the case that a lack of uniform processes among different system users in communication and coordination problems, may themselves lead to negative social situations creating OSH risks of stress. A suitable AI-based system such as a decision support system can be useful to help mediate those risks. Decision support systems can be linked to different stages of planning in a project. They can improve the quality of cooperation, and mitigate possible negative impacts, such as stress, due to failed communication (Aslam et al., 2017). In this case, the AI-based system does not introduce a new form of risk to the workplace, but rather reduces organisational risk of conflict.

Some AI-based systems are applied in a more supervisory position, being involved in structuring the work process and supporting communication within teams. This is a noticeable difference to the automation of physical tasks that is discussed in EU-OSHA's report for “Advanced robotics and automation: Implications for occupational safety and health” that will follow, where the automation leads to workers moving towards supervisory roles.

4.2.2 Cybersecurity

The topic of cybersecurity needs also to be addressed on an organisational and legislative level to ensure OSH at the workplace when using AI-based systems. Beyond a legal framework on how to process data safely and responsibly, protecting the data and systems themselves is a concern. As systems become more interconnected and increasingly reliant on data exchange, the need for cybersecurity increases. Especially, if the AI-based system is handling sensitive data, such as personal data, or in case of cobots if the system is interacting directly with a worker. However, cybersecurity is sometimes treated as an afterthought, instead of already being integrated at the initial design stage (Burgess, 2020). It is recognised that AI creates significant concerns about cybersecurity (Oancea, 2015) AI-based systems might find themselves as both target and executing force of cyberattacks, as their capabilities increases, putting personal data at risk. However, it can also play a key role in protecting said data (Oancea, 2015). The exact impact of a breach in security measures of AI-based systems is highly variable depending on the type of system, the kind of data it processes or has access to, or the environment it is implemented in. Risk assessment could help gage the possible consequences of a breach in that area. AI will increasingly handle these kinds of threats as well (Oancea, 2015). It can potentially take over tasks like high accuracy threat detection with higher efficiency compared to human intervention (Tschider, 2018), effectively supporting IT-workers and cybersecurity specialists. However, it is noticeable that there is a distinct lack of discussion around this topic in the primary data sources consulted for this report. Where and how to use AI in the context of cybersecurity, including how to protect an AI-based system and the data it processes form potential outside intervention, is an organisational consideration companies will likely phase in the future.

4.2.3 Risk assessment

The specific OSH impact of introducing an AI-based system into a workplace is often hard to gage and varies dependent on the specific system, automated task and environment. So is the overall risk assessment of implementing an AI-based system into the workplace. While there are AI-based tools to perform risk assessment on other areas of application, like medical conditions (Grossi, 2006) or lending (Thiel & van Raaij, 2019) risk assessment tools for AI-based systems and their impact on OSH are currently an area which lacks in options. Within the research of this project, AI specific OSH risks have been identified as well, specifically psychosocial risks. Recently the EU-OSHA also published a policy brief titled „Impact of artificial intelligence on occupational safety and health“ (2021), outlining AI specific risks associated with the processing and collection of large amounts of real-time data through AI like surveillance, bias and discrimination, or increased stress. So while there are risks specifically attached to the use of AI, appropriate risk assessment tools that cover both risk identification and risk analysis are often not available. While there are some guidelines and regulations for the safety limits of machinery (e.g. ISO 12100) and even technical specifications for robotic systems (e.g. ISO 15066) to ensure safety, when it comes to AI these are currently missing. The European commission acknowledges in a recent white paper (2020a) that the ‚EU has a strict legal framework in place to ensure inter alia consumer protection, to address unfair commercial practices and to protect personal data and privacy.‘ (p.16). However, they add that ‚these existing provisions of EU law will continue to apply in relation to AI, […] certain updates to that framework may be necessary to reflect the digital transformation and the use of AI.‘ (p.16). As part of the digital strategy, the European Commission (2021) has also proposed a regulatory framework on artificial intelligence, which defines four levels of risk in AI, spanning unacceptable to no risk options. The publication itself states that ‚2024 is the earliest time the regulation could become applicable to operators with the standards ready and the first conformity assessments carried out‘ (European Commission, 2021, para.3). At its current state, the framework only provides an indicator on which level of risk an AI would fall under, that companies can use to orient themselves, however it does not cover specific risk identification or analysis. So while the proposal provides a timeline for more concrete publications, currently it provides only general information.

Accurate and in depth risk assessment of a technology in the workplace is vital to ensure OSH, and the lack of assessment tool capable of providing this for AI-based systems needs to be considered going forward.

4.3 Physical effects

Physical object-related tasks are likely the most well-known form of application for robotic systems. Physical effects, if they appear in the context of automation through AI-based systems, are often a secondary effect. An example would be more effective scheduling in a nursing home, might result in reduction of daily walking distance for nurses. However, these effects are not the primary focus of the reviewed literature relating to AI-based systems applications. Further investigation of these secondary effects could provide inside into how the new technology impacts a workplace on a larger scale, overlapping with OSH related topics like elongated sitting in digitized workspaces.

Nevertheless, there are already cases in which AI-based systems have a direct impact on physical OSH.

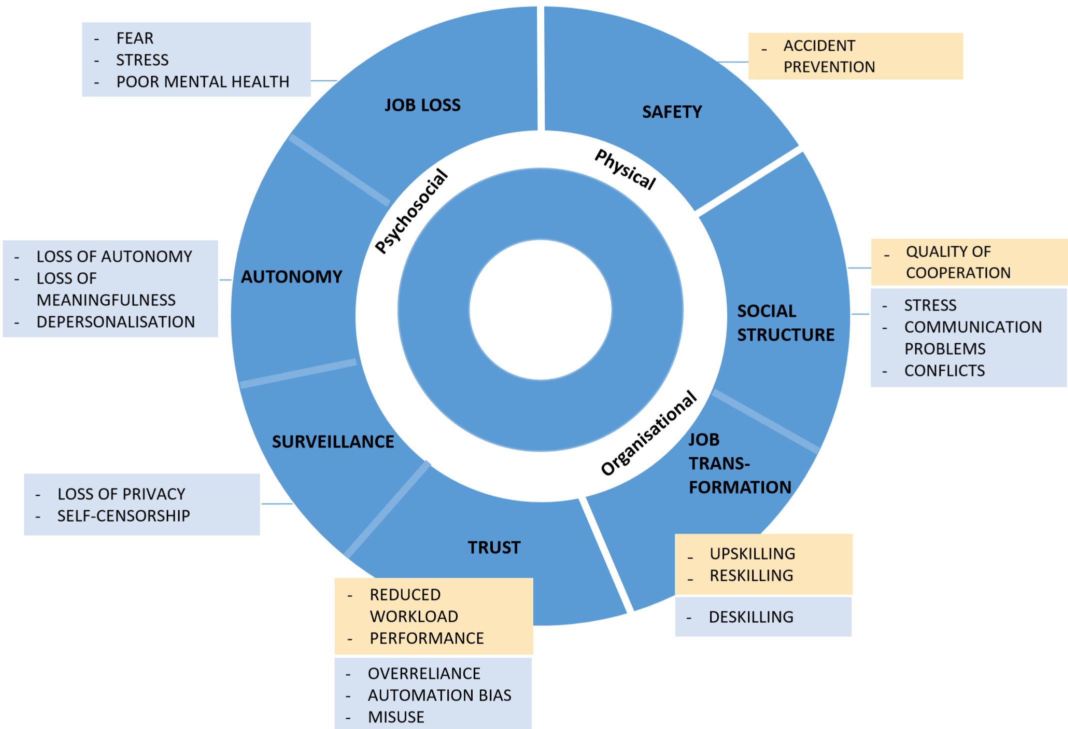
Occupational accident analysis via an AI-based system in the work environment can result in improved physical safety. Real-time data analysis via a decision support system can be used for safety-related decision-making. A more specific example for this could be a surveillance system that could analyse safety violations or utilise anomaly detection enabling supervisors and workers to take actions that can mitigate or even prevent the occurrence of workplace accidents (Sarkar & Maiti, 2020).

Many are confident that advancements in AI will continue the historical trend of eliminating dangerous jobs, or reducing the mist high risk task performed by humans to a minimum. One of the most comprehensive example of how the automation of a cognitive task can have physical implications would be the advent of self-driving vehicles. Approximately 9.3 individuals per 100,000 die each year in traffic-related fatalities in Europe. A considerable proportion of people on the road at any given time are commuters driving to work, ride service providers or truck drivers transporting goods and services. It is widely believed that the rise of self-driving vehicles could dramatically minimise this cause of premature death. While driving has prominent physical components, the inbuilt AI-based systems primarily automate perception-based tasks of a driver and based on their analysis trigger the appropriate physical response (e.g. braking) in the vehicle. Investments in life-saving technologies have a great deal of potential upside both in terms of preventing premature and needless deaths, but also limiting healthcare costs associated with accidents.

In both cases, we see an AI-based system automating a cognitive task, which improves physical safety for workers and their surroundings. As mentioned above it is also likely that systems which do not have a primary focus on physical tasks or safety still passively impact the workers physical state. The extent of such secondary effects could be included in future studies.

Figure 4 summarises the found OSH-relevant factors.

Figure 4: Overview of OSH relevant factors and effects



5 Summary and Conclusion

In the continuous process of task automation perhaps starting with the industrial revolution, automation of cognitive tasks is very much alive and well today. Automation of the tasks discussed in this report, however, has been a comparatively recent development, largely progressed by the development of increasingly capable AI-based systems in the workplace. This new technology has led to changes within how work is structured and will continue to change this in the future, as the technology is still in various developmental stages, depending on the application sector and task complexity. While not yet widespread into every workplace, we do see AI-based systems increase in numbers, with no indication of stopping this trend. We see technology assisting and semi-automating tasks to various degrees, as well as some fully automated tasks in specific jobs. Some sectors, like the medical and educational sectors, are currently a major focus of research. The issue is not only how these systems can make the work more efficient, but also how the brought changes and interaction with the system might impact workers. And rightfully, OSH should be considered early in the development and application process of a new technology.

For this report, we reviewed literature concerning the automation of cognitive tasks, consulted experts in the form of interviews, and extracted numerous implications regarding the tasks affected by the technology, the jobs and possible implications for future development of jobs in specific sectors, as well as an array of OSH implications, either specific to certain tasks or sectors or other more generally applicable. A possible line to divide some implications of automation is whether the task at hand has been fully automated or semi-automated. Interestingly, some publications include predictions that, while currently semi-automated, as the technology progresses, many tasks will most likely become fully automated in the future.

We see full automation of some cognitive tasks already. Here, the focus tends heavily towards repetitive standardised data input, like teaching routines and medical data gathering. In these tasks, heavily affecting medical personnel and teachers, according to the literature, work tasks are predicted to shift towards individual attending of cases that the system cannot currently deal with. In areas such as teaching, this might take the form of more intentional teacher-student interaction to specifically support their learning journey, or one specialised customer support worker supervising special requests. In addition, it is notable that object-related tasks currently find very little representation in the literature, neither in semi- nor fully automated tasks. This does not necessarily imply that there is no room for automation in this area, but simply that they currently do not fall under the more active fields of application for AI-based systems.

In the area of semi-automated tasks, a reoccurring pattern is that AI-based systems perform previously conducted manual tasks, technically completely, but that a human worker then needs to adjust the produced output. This can be either for quality assurance, or in case of the medical field, ethical reasons. Many of these systems are currently held back from full automation by the quality of their output; however, as this is bound to improve over time, human involvement in these tasks might shrink further. While areas like software development move quicker towards this development, areas such as journalism, even though they utilise similar technology, might hold on longer to human-created output or heavy human supervision of the output, as concerns of style and quality are more present.

The majority of OSH implications arising when AI-based systems are integrated into workplaces lie within the psychosocial realm. As this report focuses on the automation of cognitive tasks, this result is not entirely surprising. Major risks that are listed independently of any given sector, job or tasks are the fear of job loss, negative impacts of job transformations and mismatched trust in the system as well as the possible loss of autonomy through it. In addition to that, while discussed most prominently in the area of teaching, the loss of privacy is a noticeable concern that can be applied to the more general usage of AI-based systems. The potential for increased loss of privacy is in particular different from previous automation fears, because AI-based systems by design often gather and to some extent analyse data. For ethical reasons, workers need to be aware if this is happening, and if it is, what data is being collected and what this data is used for (see section 4.2 on organisational effects). Furthermore, any AI-based system in the workplace that collects data should abide by the most recent ethics and privacy and data protection regulations.

While the fear of job loss is a psychosocial experience and therefore can be considered ‘subjective’, the actual risk of task replacement and thus aspects of job loss because of the introduction of AI-based systems, is not. However, there is no consensus among experts as to the actual extent of it, where there is an imbalanced ratio between jobs destroyed and jobs created, in this climate.

Historically, it has been difficult to accurately project the real impact a technology has had or will have on jobs, workplaces and sectors. AI-based systems continue an ongoing trend of automating standardised routine-based tasks. However, as these systems grow in their self-learning capabilities and sensory complexity, the threshold of how standardised a task must be to be successfully automated seems to lower. Some AI-based systems, built into mobile robots, are capable of navigation outside a predefined, hardcoded path, others can at this point successfully navigate a social interaction or teaching situation, individually adjusting to the user. While currently a lack of flexibility from some systems might cause hindrances in the use or introduction to the workplace, technology can develop the possibilities. With regard to that, accurate predictions of how or where AI-based systems and the automation of cognitive tasks will impact workers become less certain. Regarding their application, we see a trend in the medical and education fields, as well as tasks and jobs that deal with either data classification or data generation. The underlying technology can, however, be applied to a plethora of jobs. Both the time frame and absolute impact of automation on the job market vary noticeably depending on which source is looked at. The overarching consensus is that by 2035 automation will likely have rendered millions of jobs obsolete, and, however, it will also lead to the creation of new jobs. Whether this balance is considered overall positive or negative varies heavily. This uncertainty in a changing job environment will impact workers. Noticeably, AI systems will introduce the need for specific job transformations. Ideally, this would happen in the form of upskilling or reskilling of the worker, but if not addressed properly, deskilling is also possible.

Next to the risks of applying AI-based systems in a workplace, there can also be a variety of benefits. Similar to the risks, they often fall under psychosocial benefits. The alleviation of mental workload and stress are by far the most prevalent benefits discussed. However, the actual effect that task automation has on the mental capacities of a worker is often not researched in depth; while mental workload and stress are two aspects of psychosocial effects caused by the system, the longevity of the effect should be researched in greater depth. As workers might get used to the new workload, they may fill their capacities with new tasks that arise from using the AI system. Additional benefits can be an improved communication within the company, when an AI supports teams in working together. And beyond the borders of job categories the introduction of automation in a workplace provides a chance for re- or upskilling workers. These new skill sets can have a number of benefits and possibly allow workers to perform more interesting or creative tasks. While some positive impact of AI-based systems on physical OSH have been mentioned in the literature, they were mostly a peripheral effect. Examples include improved safety surveillance systems and decision support systems that support a worker during a crisis situation. The most common tangible physical OSH benefit is through AI being used to reduce accidents. While not directly related to a specific job, using it can be potentially live saving for a significant amount of workers.

When it comes to the impact of AI-based systems on a job or sector level, the medical and educational sectors are among the most highly researched ones, based on current literature. Both sectors also show distinct preferences as to which kind of AI-based system is most prominently used - a form of decision support system in the medical sector and intelligent teaching assistants for educators. While these systems are often specialised towards these jobs, their underlying function is applicable to a wider array of jobs. We see decision support systems used in other contexts, such as process planning and financial advisory, to name two examples. This, however, leads to a broader view that, often, technology is developed for a fundamental task, and then the data used is specialised for the desired output. This is the reason why jobs like journalist and software developer can all benefit from similar output-generating technology. Hence, for future research, continuing the task-based approach can allow us to draw more fundamental insights about the application of AI-based systems, which are applicable to a wider variety of jobs. On that basis, specific differences between how the automation of cognitive tasks affects a group of workers differently from others who have automated the same tasks can be highlighted.

Besides the conclusions based on topics reported in the literature, this report has presented an opportunity to observe which topics of workplace development and OSH are not sufficiently represented. While it is often acknowledged that, especially during the stage of semi-automation, the task a worker performs changes, there is an acute lack of discussing how this affects the task design. Changes in the decision latitude, pace of the work, or interaction medium and feedback hold potential to be beneficial on OSH if considered during the introduction and development of the AI-based system; however, they might also contain some risks to reduce human control over their workplace. Similarly, how the system is designed plays a considerable role in the way that people interact with it. Considerations towards the impact of anthropomorphism, especially when the system is deployed in any sort of social context, such as a teaching environment, should be considered, as a more or less human-like presentation is impactful on how users perceive the system. In the same vein, the interaction mode design of a new AI-based system has not been researched to any great degree. Factors such as dialogue principles and system transparency are known to impact interaction with non-AI-based systems, hence they should not be neglected for this new type of technology.

While trust is one of the most discussed factors, when it comes to introducing an AI-based or robotic system, with the agreeance that it is a prerequisite for successful and safe usage of the system, the actual process to achieve sufficient trust has not been extensively outlined. Questions regarding the introduction process and the assessment of worker attitudes towards robotic and AI-based systems need to be asked so as to facilitate a successful introduction and long-term working conditions. The fear of job loss has been acknowledged as present due to continuous automation, however how to successfully mitigate this fear specifically for AI-based systems is (if ever) only vaguely acknowledged in current publications. There also is a noticeable need in the literature for more in-depth assessments of the mid- to long-term effects that working with AI-based systems can have on workers. Given that the systems are comparatively new, this lack is not surprising, however accounting for these effects should not be forgotten.

Two topics that are not currently in the focus of scientific discourse, but to impact OSH regarding AI-based systems are cybersecurity as well as in general the effective inclusion of AI based systems in the workplace risk assessment. The area of cybersecurity is likely to be impacted by increasing AI use and capabilities both in ensuring data protection as well as posing a risk to it. Additionally, assessing what risks a specific AI poses to a workplace is an important step of introducing a technology to a workplace. This needs adequate assessment tools and guidelines, and while there are already some publications on EU level providing general guidance, more is needed to ensure OSH when working with AI-based systems.

The field of AI in the workplace is diverse and rich in detail. While it is possible to categorise some of it along the lines of degree of automation, task category and current state of research on AI-based systems, it is equally important to acknowledge the complexity within each system that is unique to its application. There are some challenges and opportunities shared among systems, which need to be considered, and many work contexts create unique factors to consider when implementing the system. As the automation of cognitive tasks progresses with rapid speed, researchers and policy-makers need to focus on OSH-relevant topics, while also addressing the current gaps in research, to ensure a human-centred or ‘human in command’ approach to the development and integration of AI-based systems in the workplace.

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