European Agency for Safety and Health at Work

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Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and Occupational Safety and Health

Report

European Agency for Safety and Health at Work

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

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1 Introduction and objectives

Digital technologies play an important role in our everyday lives, as well as in our workplaces. The introduction of new systems and technologies, such as artificial intelligence (AI) or advanced robotics, hold the potential to change a number of aspects related to the way human labour is designed and performed. 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 been undertaking extensive foresight research on Digitalisation and OSH since 2016. EU-OSHA's portfolio on this topic holds a number of activities, like a scenario-based foresight study or expert discussion paper to address the main challenges for OSH associated with digitalisation. Building on this groundwork, EU-OSHA has launched the four-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 five main projects investigating OSH implications on the following topics:

- advanced robotics and AI-based systems for automation of tasks,
- new forms of worker management through AI-based systems,
- online platform work,
- new systems for the monitoring of workers' safety and health, and
- remote and virtual work.

The four-year research programme will be followed by an EU-wide Healthy Workplace Campaign starting in 2023.

The aim of this report is to set the scene, presenting types and definitions of AI-based systems and advanced robotics for the automation of tasks. For this purpose, a comprehensive taxonomy was developed and provides a framework for the analysis of OSH implications throughout further project activities. Furthermore, this report presents current and potential uses of AI-based systems and advanced robotics, their sectoral distribution as well as a description of the primarily impacted tasks. Finally, this report gives an overview of policies and strategies on a national and international level regarding the automation of tasks by AI-based systems and advanced robotics.

Chapter 2 briefly explains the methodological approach. A more detailed description of the methodological approach is given in the **Annex**. **Chapter 3** presents a model-based definition of AI-based systems and advanced robotics for the automation of tasks, leading to a comprehensive taxonomy functioning as a conceptual framework for the following project tasks. The development of such a taxonomy enables embedding the application of different types of technologies as well as their critical assessment regarding OSH, which will be done in the following phases of the project. To map current and potential uses, **chapter 4** presents the results of systematic literature reviews, the results from EU-OSHA's national focal points (FOP)[1] consultation as well as in-depth expert interviews. Based on these activities, **chapter 5** presents an overview of relevant European and national regulation. It also looks at international, European and national policies, strategies initiatives, programmes and campaigns regarding AI-based systems and advanced robotics for the automation of tasks and OSH as well as gaps and needs in that matter. **Chapter 6** presents concluding remarks and an outlook to the next phases within this project.

[1] EU-OSHA has a national focal point in each Member State and EFTA country. They are nominated by each government as EU-OSHA's official representative in that country and typically are the national authority for safety and health at work and primary contributors for the implementation of EU-OSHA's work programmes.

2 Methodology

This chapter presents a brief overview of the applied methodology and the major data sources. For this work, systematic reviews of scientific literature in three specific topics relevant to this project and a review of grey literature were performed. The selected areas of the literature review were relevant to artificial intelligence and advanced robotics, while a task focused approach was also followed. Furthermore, consultation with EU-OSHA's national focal points was performed as well as in-depth interviews with dedicated experts. A detailed description of each data gathering method is presented in the Annex. The systematic reviews of scientific literature were mainly used to identify technologies, current trends as well as uses of systems for the automation of tasks. The reviews were based on the categorisation of tasks into **physical** and **cognitive tasks** (a more detailed description is presented in section 3.1). AI-based systems (non-embodied) such as smart information and communication technologies (ICT) are used for the automation of cognitive tasks, while advanced robotics (including cobots[2]) are mainly, but not exclusively, used for the automation of physical tasks. Therefore, the main areas that were covered in the reviews were artificial intelligence (AI), human-robot interaction (HRI) and automation of tasks (AOT). A number of in-depth interviews were conducted in order to complement these findings, along with a consultation of EU-OSHA´s network of focal points[3] which provided information on regulation, policies, strategies, initiatives and programmes in relation to AI-based systems and advanced robotics for the automation of tasks and OSH. Remaining gaps were completed, when possible, with grey literature.

The three **systematic literature searches** were conducted in the following scientific and complementary databases, covering interdisciplinary research fields: ieeeXplore, EBSCOHOST, ScienceDirect, Web of Science, PubMed and to a limited degree Google Scholar. The results of the first five databases are included to their full extent in the literature review, represented in the number of results. Google Scholar results were selected on a complementary basis to identify relevant studies that were not published in one of the other databases. For each search request, an individualised search string was designed reflecting the scope of the review. The reviews addressed the topics artificial intelligence (AI), human-robot interaction (HRI) and automation of tasks (AOT). For example, for the review on human-robot interaction the following search string was used:

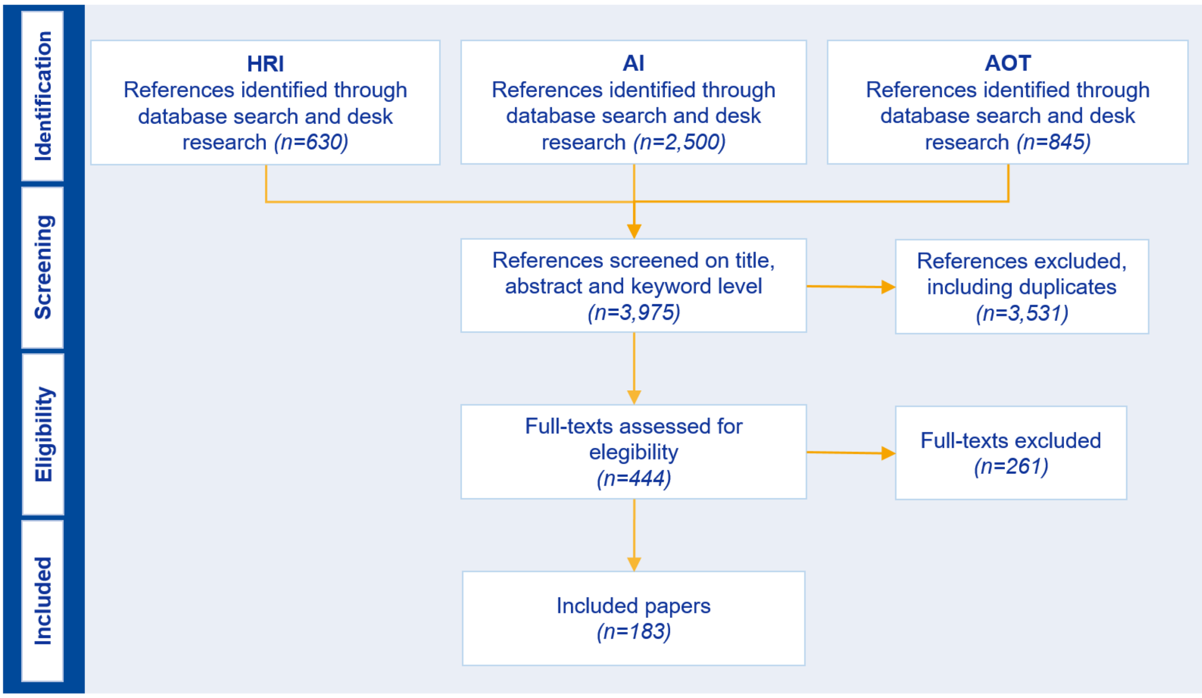
("HRI" OR "human-robot interaction" OR "human robot interaction" OR "cobot" OR "robot collaboration" OR "collaborative robot" OR "robot cooperation") AND ("systematic literature review"/"meta-analysis").

All results were firstly screened on bases of their title, abstract and keywords and if included for further analysis screened on full-text level. The results were screened according to predefined inclusion and exclusion criteria (listed in the Annex). Figure 1 illustrates the process of the three independent literature searches and their results. It should be noted that some references might have appeared more than once in the different searches. The final sample was checked for duplicates.

The final sample of studies was then further analysed and information on the categories relevant to the scope of the project were extracted. The relevant categories that were extracted were: 'type of technology,' 'affected sector,' 'affected task' and 'affected occupation' by the technology. The review results were also clustered according to the presented taxonomy (see section 3.4) in cognitive and physical tasks. Most studies from the search on HRI yielded results on physical tasks, whereas the search on AI mainly yielded results on cognitive tasks. This purely system-based approach was purposely used for the systematic literature search as both topics (AI & HRI) provide powerful keywords in scientific databases. However, the following analyses and categorisation was guided by a task-based approach allowing any system to fall into any category of task depending on the automation scope.

[2] An abbreviation for collaborative robot in human-robot interaction (see section 3.3).
[3] https://osha.europa.eu/en/about-eu-osha/national-focal-points

Figure 1: Selection process for scientific literature



Source: Author

The **focal point (FOP) consultation** was used to assess the regulatory and policy landscape regarding AI-based systems and advanced robotics for the automation of tasks and their implications on OSH. For this purpose an online questionnaire was developed, which served to identify national occupational safety and health objectives and programmes associated with AI-based systems and advanced robotics for the automation of tasks and OSH in each European country. The questionnaire was then distributed to the national focal points of the 27 Member States as well as to the 4 countries in the European Free Trade Association (EFTA). The focal points then circulated the questionnaire among their national experts and handed in their feedback within five weeks after the initial distribution. The FOPs were asked to hand in one completed questionnaire per country and to upload it. The questionnaire was designed to ensure that all issues experienced by national stakeholders, like authorities and labour inspectorates, social partners or research organisations that monitor and regulate the implementation of AI-based ICT systems and advanced robots for the automation of tasks and their association with OSH, were addressed. A data privacy statement and the informed consent were also included to the questionnaire. The following aspects were addressed within the questionnaire, using a combination of multiple choice and open-ended questions:

- legally binding regulations,
- not legally binding initiatives or programmes,
- recommendations by major stakeholders,
- national campaigns and activities,
- national public funding,
- main contributors on AI-based systems and OSH,
- gaps and needs on a national level regarding legal binding regulations, recommendations by major stakeholders, national public research, initiatives, programmes, guidelines or others,
- gaps and needs on the European level,
- key issues/challenges and tasks/sectors with widespread use,
- case studies and best practices.

Thirteen countries answered the questionnaire: eleven via EU survey (France, Portugal, Belgium, the Netherlands, Slovak Republic, Finland, Croatia, Sweden, Ireland, Hungary and Germany) and two by email

(Austria and Greece). Two more countries stated that they did not have any policies or research relevant for this request at the time.
Apart from the literature reviews and the FOP consultation, **in-depth interviews** with dedicated experts from EU Member States, international and EU bodies and associations, academics and the private sector were conducted on the automation of tasks with AI-based systems and advanced robotics. Their aim was to complement findings from scientific literature as well as the FOP consultation. They also addressed gaps and needs, especially regarding legal and policy frameworks. Seven interviews were completed by telephone or video conference. Data privacy information and informed consent were distributed in advance. The semi-structured interview addressed four focus areas regarding AI-based systems and advanced robotics for the automation of tasks and OSH. The interviewers were guided by 23 questions in total. The focus areas were: 'The development of AI-based systems and advanced robotics for workplaces in Europe,' 'Sectors and tasks,' 'OSH' and 'Legal and policy framework.' The Annex shows the complete interview guide including all questions. After the interviews were completed the answers were transcribed and summarized. Chapters 4 and 5 of this report include the analysis and synthesis of the results stemming from the three different data sources: literature reviews (including grey literature), FOP consultation and expert interviews.

3 Types and definitions of AI-based systems for the automation of tasks

The world of work is facing constant changes. Technological developments and innovations have been and still are key drivers in changing jobs and work tasks in many ways, such as context, complexity, required skills and so on. However, using (digital) technologies for automation processes has always presented two sides. On the one hand, positive effects for workers are intended, for example by removing them from hazardous environments, optimising workload or allowing greater task variety. On the other hand, this goal may not always be achieved and a number of potential challenges can occur, like the loss of human situation awareness, overreliance or possible loss of specific skills. Overreliance may occur when an operator's expectations of what the system is capable of doing are exceeding its actual capabilities, leading to a neglect of supervisory duties or misuse of the system. The intended benefits of automation as well as the challenges are both related to which and how many functions are automated (Manzey et al., 2012; Parasuraman et al., 2000). A highly accepted definition of automation in scientific literature can be found in the information box.

> Automation can be defined as 'a device or system that accomplishes (partially or fully) a function that was previously, or conceivably could be, carried out (partially or fully) by a human' (Parasuraman et al., 2000).

The appearance and rapid evolution of new technologies such as robotic systems that can closely interact with humans have led to a revival of the debate on the automation potential of jobs and tasks as well as their consequences, in part started by Frey and Osborne (2013). Some rather pessimistic foresights emerged in terms of automation potential for different jobs or work activities by AI-based systems and advanced robotics, predicting redundancy of the human work force and creating job loss scenarios. However, there are also more optimistic interpretations in which new jobs might emerge and the job loss is less significant.

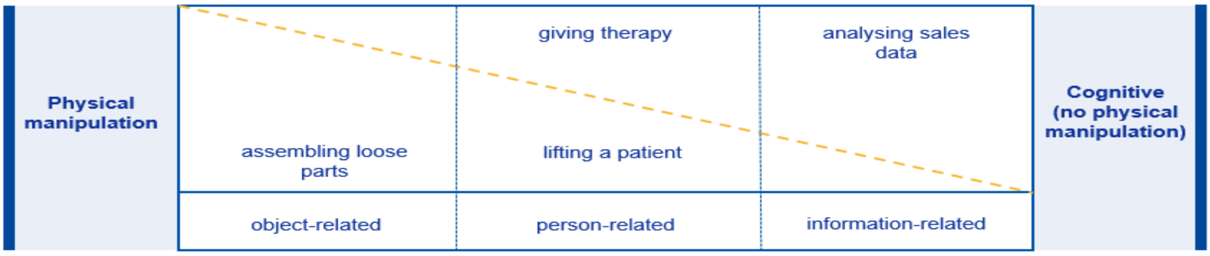
Taking a look back in history shows 'automation and technological progress have not made human labour obsolete' (Autor, 2015, p. 5). Furthermore, a major criticism addressed towards Frey and Osborne, as well as towards radical theses about job loss, is the disregarded fact that 'it is tasks that are automated, not usually whole jobs, and these tasks exist within a broader role alongside other tasks that will not be automated' (Parker & Grote, 2020, p. 2). There are also a number of voices raised, stating that the increasing automation of tasks will create a number of new jobs. They will differ in their nature of job quality and, as presented in the 'polarisation-hypothesis,' lead to an increase in low-skilled jobs and high-skilled jobs likewise (Goos &Manning, 2007; Goose et al., 2009). As a result, a growth of high-education, high-wage jobs like professional, managerial and technical occupations could be visible. Simultaneously, the number of low-education and low-wage jobs like service and labourer occupations could rise (David, 2015). However, changes in tasks caused by automation technologies can be drastic and may have major consequences on occupational safety and health (OSH), for example by automating physically strenuous tasks with high-injury potential, such as heavy lifting. To understand the effects, and to characterise opportunities and challenges for OSH that the automation of tasks through AI-based systems and advanced robotics has, it is important not to consider technology characteristics or task characteristics separately, but jointly. This approach will be the groundwork for this project and the according activities. This chapter will introduce a taxonomy incorporating a task-approach, a definition of AI-based systems and OSH implications. The resulting taxonomy has been developed as there is currently no definition or concept available taking all three aspects into adequate account.

3.1 The task approach

A focus on tasks rather than jobs is a valid approach as (automation) technologies assist or substitute individual functions in specific tasks. The joint European Commission – Joint Research Centre (JRC) / Eurofound report on 'How computerisation is transforming jobs – Evidence from Eurofound's European Working Conditions Survey' (2019) also supports this argument: 'Tasks are a better unit of analysis when investigating the impact of automation potential. The task approach allows a more nuanced and detailed understanding of which specific aspects of human work can be more easily automated' (Bisello et al., 2019, p. 3). Therefore, a reflection on opportunities and challenges associated with automation as well as the assessment of implications for occupational safety and health (OSH) should approach task and technology characteristics likewise.

The JRC / Eurofound report reviews different task classifications outlining their strength and weaknesses and concludes with a comprehensive and detailed framework. According to the European Commission / JRC / Eurofound task framework, tasks can be described based on their content as well as methods and tools. The task content can be defined as *what* is being produced or transformed in the work process (Bisello et al., 2019). Methods and tools are defined as *how* tasks are completed. The framework categorises content in physical tasks, intellectual tasks and social tasks (Bisello et al., 2019). The ideas of content and tool are included in this project framework. However, the content categorisation of tasks has been adjusted as the category 'intellectual tasks' already provides an appraisal of the task quality to some extent. Therefore, we will use the categories **object-related**, **information-related** and **person-related**, being purely based on the object of work according to the focus programme 'Occupational Safety & Health in the Digital World of Work' established by the German Federal Institute of Occupational Safety and Health (Tegtmeier et al., 2019). Following the idea *how* tasks are performed accentuates two additional dimensions of tasks, which we also include in our taxonomy: cognitive and manual (physical) tasks. To accomplish different tasks, cognitive functions, like information processing, and physical actions, like object manipulation, are necessary. As a result, our taxonomy includes the second more abstract layer of **cognitive** or **physical tasks**, which can be object-related, information-related and person-related to a variable extent. Within each category, routine and non-routine tasks can occur likewise. However, physical tasks will mainly be object-related and the least information-related, whereas an information-related object of work is mainly dominated by cognitive tasks. For example, the assembly of parts is a typical object-related physical task, whereas analysing sales data is a typical information-related cognitive task. Person-related tasks can be either cognitive or physical. For example, one can perform a cognitive task, such as giving a person therapy, or a physical task, such as lifting a person (see also figure 2).

Figure 2: Task categorisation with example tasks



Source: Author

In addition to the tasks being cognitive or physical in nature, or differentiating them by their focused subject matter, it is possible to categorise tasks as either routine or non-routine. Routine tasks are typically repetitive in nature, with identical procedures in every cycle; non-routine tasks occur irregularly and do not necessarily follow the same trajectory every time. While previously only very rigid routine patterns could be automated, the introduction of AI-based systems holds the potential to expand this to more complex tasks.

The concept of **routine tasks** 'has become prominent in research and policy debates on the future of work' (Bisello et al., 2019, p. 3). Tasks have been described by means of five categories: routine cognitive, routine manual, non-routine cognitive analytic, non-routine cognitive interpersonal and non-routine manual (Autor & Price, 2013). Whereas traditional automation technologies are mostly used for routine tasks, AI-based systems may also perform non-routine tasks. Differentiating between **routine** and **non-routine** comprises the first task categorisation layer within the developed taxonomy presented in section 3.4 of this report (figure 4).

3.2 Definitions of AI-based systems

The assistance or substitution of functions to complete different tasks requires AI-based systems that entail various technological characteristics. When it comes to the definition of AI or AI-based systems, there is no single definition that is commonly accepted among scholars, practitioners or policy-makers. Different stakeholders and disciplines put forward various definitions. Especially in scientific literature, a larger number of different definitions can be found. They can either be related to a specific application such as 'intelligent tutoring systems' or provide a very broad definition of AI. Visualising the scope of this project to address the automation of tasks by AI-based systems and advanced robotics and the implications on OSH, we incorporate definitions by two major stakeholders: the Organisation for Economic Co-operation and Development (OECD) and the EU Commission, who each have put forward a definition created by high-level expert groups. The OECD definition of AI-based systems was especially designed in a technology-neutral way, being applicable to short as well as long-term time horizons. The OECD (2019) defines AI-based systems as follows:

> An AI system is a machine-based system that is capable of influencing the environment by making recommendations, predictions or decisions for a given set of objectives. It uses machine and/or human-based inputs/data to: i) perceive environments; ii) abstract these perceptions into models; and iii) interpret the models to formulate options for outcomes. AI systems are designed to operate with varying levels of autonomy.[4]

The independent high-level expert group on artificial intelligence, set up by the European Commission (2019), presents the following definition:

> Artificial intelligence (AI) refers to systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals. AI-based systems can be purely software-based, acting in the virtual world (e.g., voice assistants, image analysis software, search engines, speech and face recognition systems) or AI can be embedded in hardware devices (e.g., advanced robots, autonomous cars, drones or Internet of Things applications).[5]

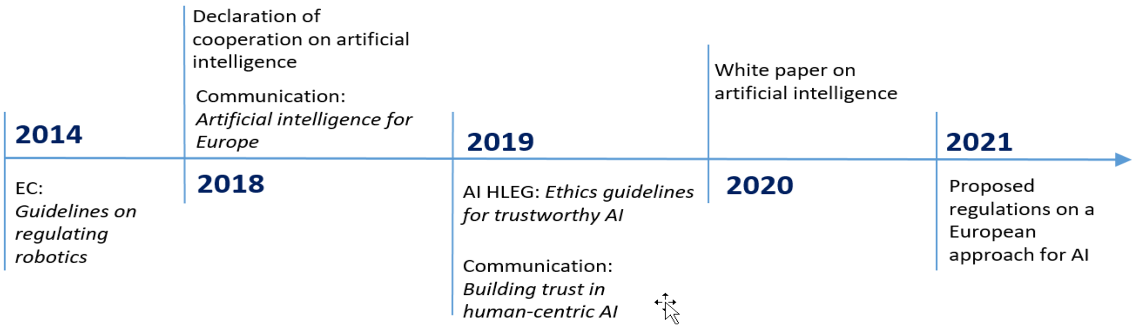
Both concepts of AI-based systems show similarities. They commonly state that AI-based systems perceive their environments in some way, analyse the information and act in response. The advantage of the European Commission's definition is further in that it gives examples of specific applications. However, neither definition addresses the specific aspect of the automation of tasks. In relation to the assistance and/or substitution of cognitive and physical tasks and their different level of occurrence in object-related, information-related and person-related tasks, a major differentiating aspect among AI-based systems lies in their ability to perform physical manipulations or actions in their environment. Therefore, we include these system characteristics in our taxonomy. The perception and analysis models within the OECD and EU Commission concepts are symbolised by the level of technology backend, that is, the specific software of a system, in the taxonomy. Perception, analysis and action models themselves can be further described according to their individual method of data analytics and thus their overall capability. The application of **methods or techniques for data analytics** such as **machine learning**, **artificial neural networks, deep learning** or other enable a range of system capabilities. While narrow AI can only do the specific task that it was designed for, the idea of general AI is having a single system that can solve multiple problems or perform tasks as well as create new questions and ideas for new tasks. Eventually, machine learning and other applications and processes will introduce systems that can be described as narrow artificial intelligence or general artificial intelligence.

[4] https://www.oecd.ai/wonk/a-first-look-at-the-oecds-framework-for-the-classification-of-ai-systems-for-policymakers
[5] https://digital-strategy.ec.europa.eu/en/library/definition-artificial-intelligence-main-capabilities-and-scientific-disciplines

However, the AI-based systems that are now available can only be described as narrow AI. These concepts and terminology are frequently used around the topic of AI and certainly deserve their own discussion. Yet, when we link algorithmic performance to workplace relevant assistance systems and OSH, the specific data analytics techniques become subsidiary and therefore will not be included in detail in our taxonomy. Furthermore, we aim to broaden our taxonomy for some technologies that are under the scope when addressing the issue of automation of tasks that are not strictly AI-based. These technologies often show very advanced abilities, but from a strictly technical perspective they have no real AI embedded. They solely perform their programmed task, which could be advanced, yet every action is predetermined and defined in the system's programming architecture from the beginning. This is, for example, quite often the case for collaborative robotic systems. Hence, we have labelled the possible categories of the backend level in our taxonomy as **AI-based** and **complex, not AI-based**.

As AI and AI-based systems continue to develop and change, we consider this progress reflected in a continuation and expansion regarding the policy of the EU. Over the last few years, there have been several new and updated policies, guidelines and regulations as shown in figure 3. These publications address continuing and important issues regarding AI, such as ethical facets and trust. For these policies to be as impactful and accurate as possible, it is vital they be informed by precise definitions on what AI is and what its capabilities are.

Figure 3: Evolution of EU policy on AI and advanced robotic systems[6]



Source: Author

3.3 Major technologies for the automation of cognitive and physical tasks

When it comes to investigating the effects of the automation of tasks and its effects on OSH, a closer look at specific technological developments is useful. One main area that has introduced many innovations to support physical manipulations and actions in recent years is the field of robotics. The range of robot types has expanded. Traditional caged and fixed robots capable of lifting heavy payloads and designed for speed and precision are no longer the mainstay in robotics (IFR, 2018). These systems are mostly found in fully-automated production environments such as spray-paint booths in car manufacturing plants. Systems with less payload as well as new generations of sensors and actuators have enabled innovative types of robots to emerge. They allow closer forms of human-robot interaction (HRI) in less structured and more complex environments outside traditional manufacturing industries. These types of systems are often referred to as cobots, yet they only include the interaction form of cooperation and collaboration (Onnasch et al., 2016). According to this taxonomy and the one presented by Bauer and colleagues (2016), the interaction between humans and robots can be categorised according to their shared task and actions. In the **interaction form** of **co-existence**, the actions of the human and robot are close, but time-wise unrelated. The interaction form of **cooperation** shows humans and robots working closely together, their actions are time dependable but not simultaneous. The third interaction form, **collaboration**, can be seen as the closest interaction form. The actions of the human and robot occur at the same time on the same object. For example, the support of lifting people creates a collaborative interaction form, whereas supporting assembly tasks might create cooperative forms of interaction. As an example, one can picture a robot prepositioning heavy parts, where

[6] https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence

a final assembly of non-rigid parts is performed by the human. The use of robotic systems for transportation tasks, for example, often leads to the interaction form of co-existence. As we include any kind of interaction form between human and robotic systems, we will refer to these systems as **intelligent or advanced robots.**

To support or substitute cognitive tasks where no physical handling of objects or persons is required, modern (non-embodied) information and communications technologies (ICT) are mainly deployed. The entities can range from super-computers, cloud computing and distributed systems, **desktop computers** and **mobile devices (smartphones, tablets)** to **wearables** like **smartwatches** or **smart glasses**. Many of these technologies have found their way into everyday life, not only in many workplaces but also in private lives. The smartphone is largely used for different purposes, having transcended its original function as a mobile telephone for a long time. It is now the device we also use to play music, take pictures, check our bank balance, interact with friends on social media, navigate, play games, and more. Quite often our smartphone is linked and communicating with other devices like a web server or a smartwatch for example. We exchange data on how many steps we have performed in a day, add information on additional exercises or our sleep quality. Our smartwatch detects longer periods of inactivity and encourages us to move about. Our web serving behaviour is analysed and paired with those of others. Consequently, we find matching recommendations when entering an on-demand streaming service to watch television, shopping recommendations based on our latest purchases or individualised content in our social-media or news feed. The scope of cognitive functions that ICT are able to support is steadily broadening. Along with displaying information, innovative systems are easily capable of monitoring actions as well as providing context-sensitive information in real-time.

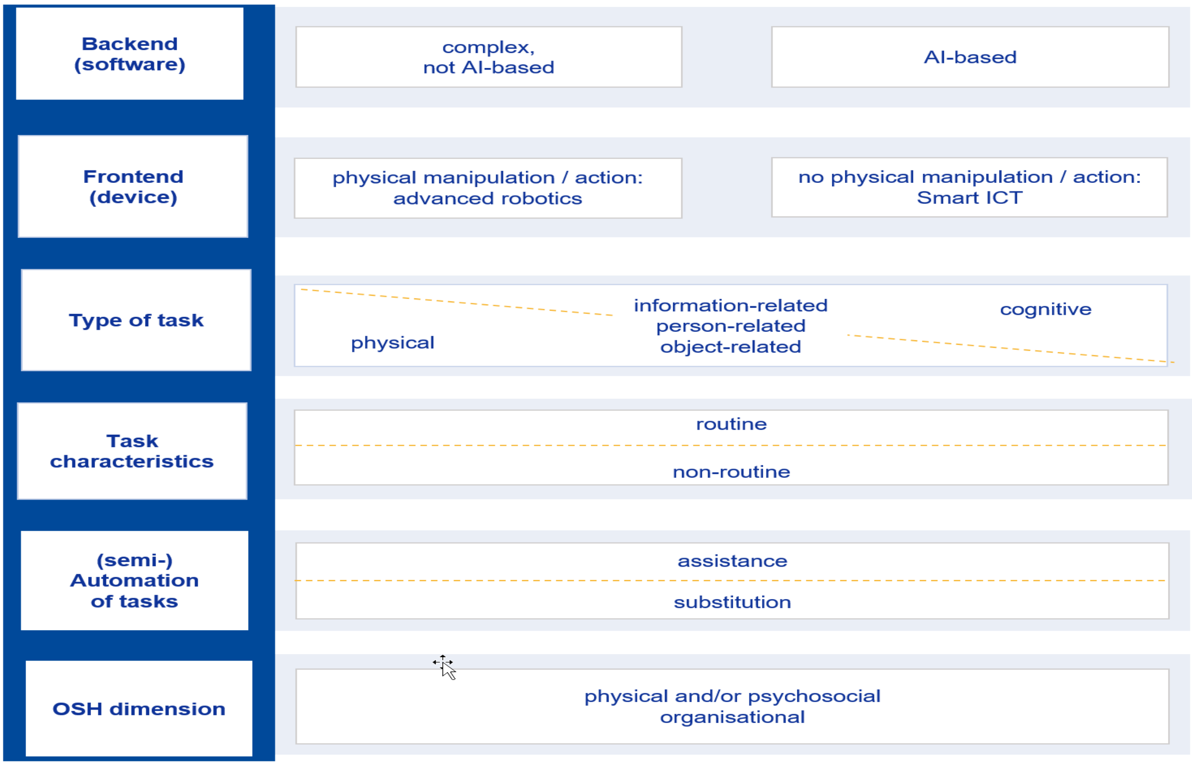
However, the analysis of existing technologies and applications will reveal that not only ICTs are used to support cognitive tasks, but a number of robotic systems also partly or wholly support cognitive tasks. For both robotic applications and ICT, the algorithms (or backend according to our taxonomy) that are implemented within these systems determine their scope of capabilities and usage potential (Hämäläinen et al., 2018). Depending on the algorithms' complexity or the degree of artificial intelligence, both systems are able to support different degrees and levels of functions as well as actions necessary to complete the task in question. Combining artificial intelligence methods with advanced machinery and hardware allows new forms of AI-based systems to emerge. These can range from larger systems like advanced robotics to very small nanotechnologies in computer chips with high performance integrated into smart devices. Hence, it is not the hardware technology that creates substantial changes in workplaces and in the interaction between workers and systems. It is the combination of the specific backend with the individual technological frontend that creates new challenges and opportunities for OSH.

3.4 Taxonomy for AI-based systems and the automation of tasks

It is not only technologies themselves that affect workplaces on potentially different levels, but the use of AI-based systems and advanced robotics for the automation of tasks that creates new or changes in existing working systems. The integration of AI-based systems and advanced robotics may hold significant positive possibilities for workplace progress and growth in productivity as well as for OSH. However, important OSH related concerns may also arise. Stress, discrimination in decision-making processes in human resources, and work intensification as well as job insecurity and potential job loss are some of the risks workers can face in most, if not all, sectors. A more detailed and in-depth analysis of these factors is presented in EU-OSHA's forthcoming reports, “Artificial Intelligence and automation of cognitive tasks: Implications for occupational safety and health” and “Robots, cobots and Artificial Intelligence for the automation of physical tasks: Implications for occupational safety and health”. The integration of new technologies and machines into workplaces can add to these stressors and have already been shown to especially pose psychosocial OSH risks (Moore, 2018). These risks are exacerbated when AI augments already-existing technological tools or are newly introduced for workplace management and design. Indeed, AI can exaggerate OSH risks in digitalised workplaces for a variety of reasons. Any introduction of unprecedented machinery may lead workers to fear automation of their own work tasks, and thus creates difficulties in integration. Agarwal and colleagues (2018) label some aspects of AI in workplaces as the integration of ‘prediction machines,’ where robotics and algorithmic processes at work are used to forecast talent, performance and, in general, to monitor and track workers' activity. In turn, this can lead to fears of micro-management, a major cause of stress and anxiety. But it is worth noting that it is not technology alone that creates OSH benefits or risks; it is also the implementation of technologies which creates negative or positive conditions.

To get a better understanding of the implications that AI-based systems for the automation of tasks have for workers' safety and health in the next phase of the project, the relevant OSH dimensions are considered in the proposed taxonomy. To provide meaningful advice for prevention, policy and practice regarding AI-based ICT systems and intelligent robots in the workplace, all relevant components of a work system are considered. This includes the physical and psychosocial work environment as well as the social and organisational context (Leka & Jain, 2010). Potential OSH risks and benefits can be aligned to these dimensions accordingly. Therefore, the three global **OSH dimensions** of **physical**, **psychosocial** and **organisational aspects** are included in the proposed taxonomy. Physical aspects include outcomes related to physical health like collisions and the occurrence of musculoskeletal disorders. Outcomes related to the psychosocial dimension include, for example, factors like wellbeing, motivation, stress or fatigue. Outcomes from the organisational dimension are, for example, related to health indices, such as productivity or absence. Each dimension can be broadened when investigated in detail throughout the project activities. The combination of each task type with each technology can potentially affect any of the three OSH dimensions. As the scope of this work is AI-based systems and advanced robotics, non AI-based ICT systems have been excluded. However, non AI-based robotic systems are included, as many advanced robotics (like cobots), which can already be found in workplaces today, operate without AI. The specific OSH related challenges and opportunities associated with these systems will be investigated in the following project activities. The complete taxonomy developed for this project, providing a comprehensive framework for the analysis of AI-based systems and advanced robotics for the automation of tasks and OSH is illustrated in figure 4.

Figure 4: Taxonomy for AI-based systems and advanced robotics for the automation of tasks



Source: Author

This taxonomy provides both a structural and visual overview of important factors to consider when categorising or analysing AI-based systems and advanced robotics. This includes the differentiation of the backend and frontend representation of the system, the type of task assigned as well as key characteristics of that task and the degree of automation the systems provides. Lastly, it represents which OSH dimensions can be impacted by these systems. The taxonomy illustrates that these factors can appear in a variety of combinations in the workplace, and while some categories are mutually exclusive, like a system being AI-based or deterministic, other categories do not benefit from complete separation. The taxonomy therefore helps to structure and visualise, what kind of system one is focusing on and what characteristics it is primarily associated with.

4 Mapping of current and potential uses

The exploration of technology diffusion reveals a high variety of available systems and applications that are not always assigned to perform a specific task. Therefore, a purely technology-based approach when addressing associated risks and benefits for OSH is not sufficient. Considering the nature of a task in combination with AI-based systems and advanced robotics enables a better categorisation of the different technologies. When exploring the distribution of AI-based systems for the automation or support of cognitive tasks within scientific literature, it becomes evident that according to the presented taxonomy, the majority of applications refer to software tools that can be implemented into different screen devices like stationary desktop computers, tablets or smartphones. These systems are not able to manipulate or perform any physical actions. The technology of advanced robotics, however, is not solely used to support physical tasks. Advanced robotics are also used for the automation of cognitive tasks, mainly person-related, but to some extent also information-related. A more detailed description of the different technologies is presented below. Current and potential uses of AI-based systems and advanced robotics are discussed in the context of automation of cognitive tasks and the automation of physical tasks separately.

4.1 Automation of cognitive tasks

A number of technology innovations and improvements regarding systems used for the automation of cognitive tasks have led to the development of new systems and enable more complex applications. Especially improvements in computing power have led to advances in AI-based methods and introduced a number of innovative systems. There are a number of powerful enabling technologies that can be mentioned in relation to AI-based systems for the automation of cognitive tasks. They include, for example, high speed networks, such as the **fifth generation standard for broadband cellular networks (5G)**, **radio-frequency identification (RFID)**, where digital encoded data from tags is received by readers over radio waves, or the advances in **microprocessors**, capable of providing incredible processing power compared to the past. Also worth mentioning are pattern recognition technologies that help to cluster and classify data, such as **neural networks**, **adaptive and predictive algorithms**, **natural language processing** techniques and data handling technologies like **big data**. Another technology class with the potential to especially influence the finance sector is **blockchain** technology, allowing digital information to be recorded and distributed, but not edited. Also quite relevant to the occupational context are the technology classes of **virtual reality**, **augmented reality** and the combination – **mixed reality**. With virtual reality, the experience of completely virtual and artificial environments becomes possible, whereas augmented reality allows the placement of virtual objects, information or images in actual real-life surroundings with the help of adequate devices like smartphones.

4.1.1 Distribution of technologies and applications

AI-based systems for the automation of cognitive tasks

For the automation of cognitive tasks with AI-based systems, the systematic review of high quality scientific literature reveals that most studies focus on the exploration of different types of **automated software**. Automated software tools refer to various applications in different domains like online examination (Butler-Henderson & Crawford, 2020) and learning applications (e.g., Davis, 2018), feedback systems for learners (Deeva et al., 2021), software testing tools (Garousi & Mantyla, 2016), automated retrieval and indexing of scientific information (e.g., Golub et al., 2016), clinical information systems (Govindan et al., 2010) or business processing modelling tools (Zafar et al., 2018). This finding is supported by the experts' view, as they report that software is often easier to deploy than hardware, thus widespread use is noticeable. Nearly every AI-based system for the automation of cognitive tasks can be defined as some form of automated software, but there are systems which can be distinguished further.

In the field of medicine in particular, a lot of high quality research is dedicated to **automated medical devices** such as closed-loop systems, which, for example, are used for vital parameter monitoring or systems related to automated diagnosis generation. Another remarkable group of technologies that can be found are **decision support systems (DSS)**. As with automated software, their application purposes are diverse. Many uses can be found in medical health, primarily used at the point-of-care to combine the clinician's knowledge with system information (Sutton et al., 2020). Others support remote health monitoring (Shanmathi & Jagannath, 2018) or treatment choices (Davidson & Boland, 2020; Triantafyllidis et al., 2020).

Beyond health services, DSS in other domains support risk assessment and management (Aslam et al., 2017; de Almeida et al., 2017), scheduling (Desgagné-Lebeuf et al., 2020) or recruitment for clinical trials (Köpcke & Prokosch, 2014). Not quite as many as for DSS, but still a noticeable number of studies address some type of **natural language processing (NLP)** system. The use of NLP systems can either be related to the automated processing of speech (Greenwood et al., 2018; McKechnie et al., 2018) or the automated processing of textual data (Argolo et al., 2020; Deng et al., 2020). Other systems that are described, but to a significant lesser degree, are **conversational agents, also called chatbots**, and **data mining**. The application of conversational agents, which are in fact systems capable of performing dialogue using human language, takes place in different areas. Many of the above mentioned technologies can theoretically find applications in a variety of different sectors, as only the content of the automated task changes, but the tasks itself essentially stays the same. For example, chatbots are used in customer support (Bavaresco et al., 2020) or in health care where they can support treatment, health monitoring, training or screening (Milne-Ives et al., 2020). Data mining systems refer to systems that discover patterns, trends or relations in data, such as text data or business data (Abbe et al., 2016; Patil & Agarkar, 2019). **AI-based analytics tools** are also found in marketing (Verma et al., 2021). They can, for example, support marketers in strategy and planning marketing activities or help to design products tailored to customer needs. Deep learning applications can help to personalise and customise offers and point of interest recommendations. Furthermore, pricing management can be supported by these systems as they can dynamically adjust prices in real time based on customer choices, competitor strategies and supplies (Verma et al., 2021).

Robotic systems for the automation of cognitive tasks

Apart from the large number of software applications, another remarkable category of systems used for the automation of cognitive tasks, addressed both in scientific literature as well as by the interviewed experts, are **educational** and **social robots**. Educational robots, for example, aid learning through social interactive abilities (Hein & Nathan-Roberts, 2018), enhance students' learning and transfer skills as well as increase creativity and motivation (Anwar et al., 2019). Educational robots are mostly used in informal settings like summer schools rather than formal settings like classrooms (Anwar et al., 2019), whereas socially assistive robots are currently used in areas such as elderly care to increase positive emotions or therapy engagement (Bemelmans et al., 2012). Furthermore, they are used to support caregivers when nursing patients with dementia or cognitive impairment, taking over reminding functions (like when to take medicine) or cognitive stimulation exercises (like singing) through video calls with caregivers (Góngora et al., 2019). Consultation tasks can even be performed by **telepresence robots**. However, these systems are not studied extensively within the analysed literature. Especially within social robots, the issue of **anthropomorphism** in **humanoid systems** is considered. The question of a robotic outward appearance is not only relevant to its functionality, but also to its effect on the human while the human is interacting with the system (Erich et al., 2017; Vogan et al., 2020). There are robotic systems purposely designed, not only to embody human features like eyes and ears, but also to imitate human behaviour like eye-blinking or body orientation towards a speaking person. Such systems are useful for investigating the effect of humanoid forms on humans' perception and interaction quality. Some of the aforementioned robotic systems can also be described as **service robots**. According to the International Federation of Robotics (IFR), a service robot 'performs useful tasks for humans or equipment excluding industrial automation applications' (ISO 8373; IFR, 2021). Humanoid systems are frequently found in service applications, as they are especially designed for direct interaction purposes. For example, they can be found in malls, department stores, hotels or airports where they reply to minor customer requests or navigate customers to certain products in a different aisle or to their hotel room.

AI techniques and future uses

As pointed out by the interviewed experts, many of the described systems are not entirely new and some have existed for a long time. New developments can be seen as refinements of older systems, where the specific form of AI becomes secondary. However, within scientific literature related to AI-based systems, there are some specific (statistical) procedures that can be identified as noteworthy clusters. The most common techniques addressed in high quality scientific literature are **neural networks**, among them convolutional neural networks, which are neural networks primarily used for the classification of images like photos, appear most frequently (Dallora, 2019; Wäldchen & Mäder, 2018; Xiao et al., 2018). Other AI methods, which bear mentioning in relation to the automation of cognitive tasks, are support vector machines, decision trees, genetic or clustering algorithms, deep learning or self-supervised learning.

As stated by the interviewed experts, new systems for the automation of cognitive tasks are being adopted very quickly and are very focused on **data processing and analysis.** Industries that accumulate a huge amount of data (insurance companies, financial companies, online retail, web search platforms) are drivers of AI-based systems for the automation of cognitive tasks. They are the leaders when it comes to the readiness of new systems and invest in research and development, especially regarding specific applications such as smart scheduling systems in warehousing. Based on the experts' opinion, the **Internet of Things (IoT)**, the interconnection of devices and systems, is considered the most disruptive technology.

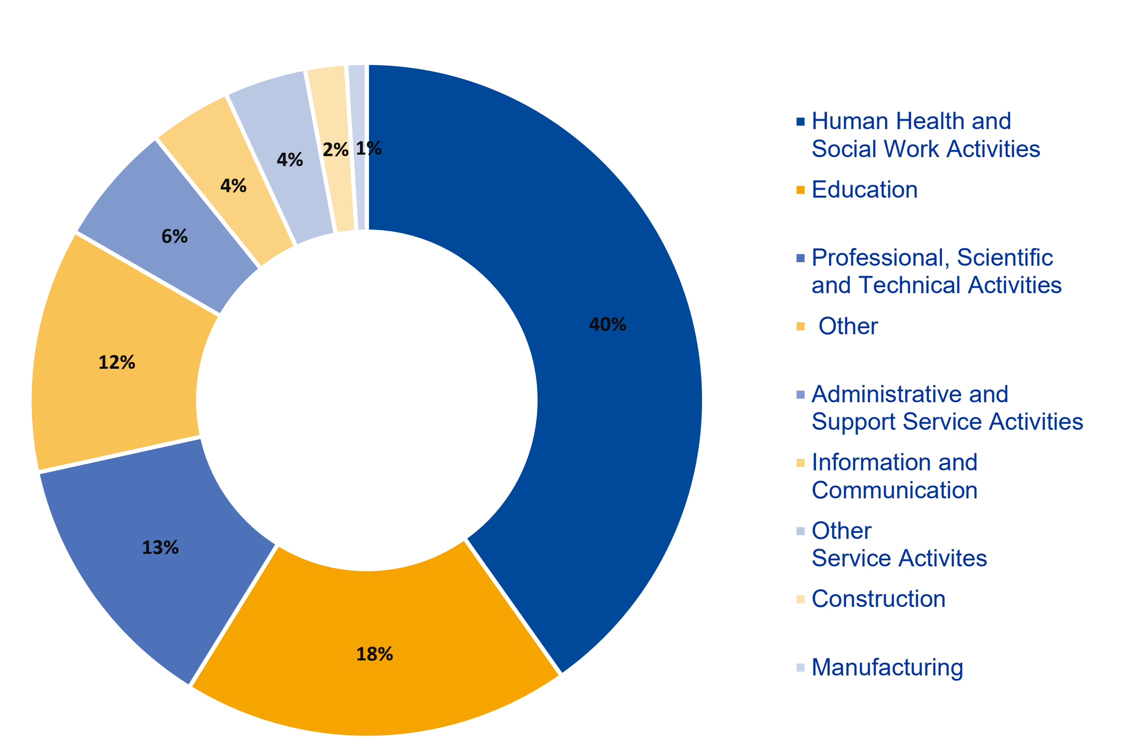
For **future uses**, the experts see the next milestone in **logging information / data from a long-term deployment** of a system to generate broader datasets. Extracting patterns from larger datasets to anticipate changing conditions is foreseen as a real-world application. For instance, you can monitor the motor torques, joint positions and the manipulator position of an individual robotic manipulator in a particular work cell, which may have the task of welding parts together. Some mechanical parts may degrade with time. This progress can be monitored, enabling intervening actions at appropriate times. This is based on a model, where it is understood how the machine changes over time, to predict failure. This process of prognostics is already applied across different industries. Or, a free model using a machine learning algorithm can train the correlation between details of each sensor signal and the overall status of the system or particular components over time.

4.1.2 Sectoral distribution

When analysing the appearance of AI-based systems for the automation of cognitive tasks regarding their sectoral distribution, the most outstanding category according to the NACE Rev. 2.0 (Nomenclature of Economic Activities) code is the sector of **human health and social work activities**. The analysed body of scientific literature supports this finding, as do the experts' opinions and the results from the focal point consultation. The majority of analysed studies address systems from the human health and social sector and, in particular, the field of medicine is frequently mentioned by the experts as well as the FOPs. A more diverse picture presents itself regarding other sectors. An extensive body of scientific literature is dedicated to the **education** sector. The experts point out the relevance of this sector, however, the answers from the FOP consultation do not explicitly mention this sector. The high frequency in which these two sectors appear in literature does not necessarily reflect the current usage of AI-based systems in the sectors. Both have high academic activities, which could lead to a form of publication bias. Nonetheless, these sectors do hold a great variety of tasks that can potentially be automated, hence the scientific interest is justified. In the experts' opinion as well as indicated by the FOPs, the **financial and insurance activities** sector plays an important role. They explicitly state that automation activities in banking are noticeable and expected to increase. In contrast, this sector is not represented strikingly in scientific literature. Mainly addressed in scientific literature, to a noteworthy degree, is the sector of **professional, scientific and technical activities**. This is to some extent supported by the experts, and the pervasiveness of AI-based systems in this sector is in line with the above-described findings regarding the broad distribution of automated software systems. To a lesser degree than the others, the **information and communication** sector is covered by scientific literature. It is, however, mentioned by the FOP consultation. Figure 5 summarises the sectoral distribution of AI-based systems for the automation of cognitive tasks according to the analysed scientific literature. In addition, the literature also mentions some specific applications for the automation of cognitive tasks in the sectors of manufacturing and construction work.

While there are some sectors that have only been highlighted by either the FOPs or the literature review, it has merit to also investigate which sectors are distinctly absent in both sources. The sector of **administrative and support service activities**, which includes tasks relating to security systems services and employment activities, is poorly covered regarding the possible role of AI-based systems. The wholesale and retail trade sector is also poorly covered. This sector also includes retail sale through mail order houses or Internet, a growing area with apparent potential for AI application. The absence of these sectors can have a multitude of reasons. It should not be assumed that simply because they do not currently appear in the forefront of experts or literature that there is no potential for the automation of cognitive tasks through AI-based systems. This absence is more likely due to the fact that other sectors present less complex tasks to automate or have a higher potential for automation. In the case of the **arts, entertainment and recreation** sector, it might also be an active decision against technological interference in the work process to preserve the human expression.

Figure 5: Automation of cognitive tasks – NACE sector distribution according to scientific literature



Source: Author

4.1.3 Impacted tasks (and jobs)

A variety of cognitive tasks that AI-based systems fulfil is found in scientific literature. As the nature of cognitive tasks implies, most cognitive tasks impacted by the automation of AI-based systems are information-related. However, there is also a noteworthy number of cognitive tasks affected by the automation that are person-related. There are two types of tasks prominently represented in the body of scientific literature. The first task frequently supported by AI-based systems is **giving a medical diagnosis** and is strongly information-related. This finding mirrors the above-mentioned results regarding the high prevalence of DSS systems in the human health and social work activities sector. Cognitive tasks such as giving a diagnosis can be partially done by AI-based systems; however, the experts state that it will be complementary to the doctor's work. One field, for example, where AI-based systems have taken over humans is the interpretation of X-rays and MRI imaging. Nevertheless, they will always be paired with a human radiologist. In this case, the technology only replaces parts of a task. Yet it complements the job, and makes it more accurate. This is the same principle that can be observed in air traffic controls, where the human is highly dependent on the technology for completing the task.

The second frequently reported task is some form of **learning support** in teaching activities. Currently most systems support **teaching-facilitating** tasks like **increasing learners' interest, motivation and engagement** to learn a certain subject. While some systems are designed to support children in **building programming and computer skills**, others, for example in early language learning, support **vocabulary learning** or **language production**. Furthermore, the person-related task learning support is often assisted by automated software or natural language processing (NLP) systems. Overall, the majority of these applications are currently observable outside of traditional classroom learning situations. However, as learning environments may change and become more digitalised, more teaching tasks may become supported by AI-based systems or advanced robotics. As stated by the experts, especially learning tasks require adaptable systems that have high predictive capacities. The experts further state that in order to automate tasks, they need to be standardised. Present AI-based systems have difficulties in performing non-routine and non-standardised tasks. However, if cognitive tasks to some degree are routine or repetitive, AI-based systems are capable of performing these. This type of task characteristic can be found in **communication tasks**. As reported in the FOP consultation, stated by the experts and addressed in a number of scientific papers, AI-based systems often support communication tasks in the form of conversational agents or chatbots, supporting for example customer requests. Language can be formalised and the task of giving information that is related to a distinct topic is repetitive and standardised to some extent. As stated by the experts, in order to be automated, at present, standardisation is a core requirement; thus, current AI-based systems cannot replace non-routine and non-standardised tasks. In addition, a number of single tasks related to **language and textual processing** are addressed in scientific literature. Among them, **information coding**, **indexing** or **classification** are mentioned frequently. Recently, the number of AI-based systems capable of language production like textual content creation, speech production like reading, or even real-time language production like translation has increased. However, these systems are not covered extensively in scientific literature yet.

Although there are a number of systems available aiming at supporting social interaction tasks, such as patient therapy engagement, the experts point out that person-related cognitive tasks, or social interaction tasks, will be more difficult to automate. Apart from the degree of standardisation, interpersonal actions have qualitative elements that will hardly ever be achievable by a machine. The attempts currently observed address only a fraction of a complex interaction situation. However, especially the automation of social interaction tasks has the potential to raise ethical issues. As AI-based systems and advanced robotics improve in performing social interaction tasks to some degree but at the same time lack important qualitative elements, the questions arises as to whether these systems should be used for assistance. On the one hand, a solely human-to-human interaction might be more favourable. On the other hand, AI-based systems and advanced robotics have the potential to widen the access to services like therapy, support or care for patients and clients. This could especially be the case in understaffed areas.

As the nature of tasks often is strongly associated with a certain job profile, most of the above-mentioned tasks represent a specific job. According to scientific literature, jobs of medical health professionals are most frequently affected by the introduction of AI-based systems, closely followed by teaching personnel. Caretakers, administrative workers and coaches/ trainers find equal mention in the literature. The fewest mentioned are mental health workers, team leaders (here specified in the field of IT), dieticians and customer support. The experts stress a phenomenon, which is also prominently addressed in scientific literature, under the term ‘polarisation of employment structure’: within jobs, tasks which require a mid-skilled profile are impacted by automation, leaving jobs to change in a way that automation will create an increasing number of higher-skilled jobs and low-skilled jobs likewise (Goos &Manning, 2007; Goose et al., 2009). While the experts stressed the impact and presence of this process, the translation to a worker’s reality might be more complex. Recent findings suggest that the job structure in Europe has upgraded in quality and education in the last three decades rather than become polarized. Some labour market opportunities expanded for the mid-skilled worker group, while automation affected low-paid and low-skilled occupations the strongest (Oesch, & Piccitto, 2020).

4.2 Automation of physical tasks

For the automation of physical tasks with AI-based systems and advanced robotics, several of the technologies mentioned in section 4.1 also apply. Furthermore, many applications are strongly influenced by advances in **sensors**, **actuators**, **material** or **gripper technologies**. Innovations in sensor and actuator technologies, for example, allow the identification of obstacles and an appropriate response like stopping or redirecting movements. Innovative materials, for example, allow equipping robotic systems with tactile surfaces, and intelligent gripper technologies are able to simulate the functionalities of the human hand. Technologies like **light-weight robots** combine some of these technologies, such as tactile surfaces, intelligent sensors and grippers. Robotic systems can further be linked to other sensory environments, such as wireless sensor networks **(WSN)** that are able to monitor and record the physical conditions of the environment, or even be part of the Internet of things (IoT). Also to be mentioned here is the technology of **3-D printing**, which enables the construction of three-dimensional objects based on digital models.

4.2.1 Distribution of technologies and applications

For the automation of physical tasks with AI-based systems, a strong focus is placed on robotic systems. In the automotive industry, robotic systems have been deployed for many years, since the early 1960s. They were large, heavy, and required significant programming, and they needed to be attached to the factory floor. They were not very intelligent, and they were dangerous in terms of workers’ safety as accidents occurred. There has been an evolution towards smaller, more intelligent systems with less programming required. Some even imitate human operators and do not require as much safety protection as the larger systems do. The reason is that these systems have remarkably less payload than traditional industrial robotics and some have sensors or tactile surfaces that are able to detect collisions, thus already supporting safety requirements by nature.

AI meets robotics

The combination of artificial intelligence or smart algorithms with robotic devices accelerates the level of autonomy and functionalities. However, many advanced robotic applications are not equipped with genuinely AI-based software in their control system yet. Nevertheless, advanced capabilities are also integrated into traditionally programmed systems. Whether or not AI is implemented within a robotic system is often not even noticeable to the end-user. Only when setting up robotic systems does it become clear which supposedly easy functions a robotic system is capable of doing and which it is not. For example, object identification and grasping an identified object can be programmed with some effort. AI-based software integrated into robotic hardware will perform this task more easily. If traditional programming was performed well, the difference between both systems will most likely be unobservable to the user in a defined task. What will be noticeable though, as the usage of such systems increases, will be the robustness of performance, a broadened range of capabilities and a smoothness in actions, which will further incentivise the inclusion of AI. The more we find AI-based software integrated into robotic hardware, the more we observe, for example, an elaborate moving behaviour, especially in unstructured environments or natural language processing. However, these game-changing technologies are still at an earlier stage. But once developed to their full extent, as the experts predict, robots incorporating AI software will be able to interpret human movement or emotions and will thus be able to adapt and to react to the human adequately. A number of different advanced robotics capable of interacting with humans are addressed in scientific literature. They can be categorised according to their intended purpose as well as by distinct features like mobility.

Types of robots

For the automation of physical tasks, **industrial robots** appear most frequently. According to Standard ISO 8373:2012 of the International Organisation for Standardisation (ISO), an industrial robot is an 'automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes,' which can be either fixed or mobile. This definition is also adopted by the International Federation of Robotics (IFR), a global acting focal point in the field of robotics. According to the IFR, **collaborative industrial robots** 'are a class of robots designed to perform tasks in collaboration with workers in industrial sectors' (IFR, 2021). Based on sales figures of robot suppliers, the IFR states that in 2019, 4.8 % of installed industrial robot units were **cobots**. They further report an increase in cobots of over 11 % from 2018 to 2019 (IFR, 2020, 'Demystifying Collaborative Industrial Robots'). These figures are in line with results from the latest European Survey of Enterprises on New and Emerging Risks (ESENER) data. Within the sample of ESENER-3, in 2019, 3.5 % of all interviewed enterprises (n=1,611) reported using robots with direct interaction capabilities (EU-OSHA, 2019a). In this third wave of the ESENER survey, most robotic applications with direct interaction capabilities were found in Slovakia (8.7 %), followed by Denmark (6.9 %) and the Czech Republic (6.7 %) (Wischniewski et al., 2021).

However, as described above, the term 'cobot' can also be applicable to other systems in other sectors and environments. The interviewed experts describe how cobots are used today. Conventional automation technologies are accompanied by large IT infrastructure and serve the purpose to output high numbers of products. Within these large scale production lines, product variations require a modification of the assembly line, which is very costly. However, as markets develop, the need for more customised products, fewer units and a more agile production grows. Rather than investing in costly assembly line modifications, human workforce is needed. Assisted by cobots, changing production requirements can be met. In less heavily standardised environments, cobots can assist in assembly or other applications like cleaning or logistics. The allocation of subtasks takes into account individual capabilities of the collaborating parties and allocation costs. Programming manipulation tasks for the cobot is currently difficult and creates high costs. In work systems where speed and accuracy are the primary automation criteria, it is unlikely that state of the art collaborative robots will be as economically viable as fenced industrial robots (IFR, 2020). The cobot may instead retrieve an item from storage, or guide the human to the product as it is easier for the human to handle. A human and robot **cooperating** is the most likely route forward, with the robot doing the simple, repetitive part of the task. The human accomplishes the more precise tasks and takes advantage of his higher dexterity and cognitive understanding. However, as stated by the interviewed experts, without the permission for the workers to experiment with the cobot's flexibility to find ideal ways of working, it is not likely to be efficient. This is closely linked to the level of standardisation of the working tasks and related processes. If, for example, tasks or cycle times are very short and the workers only have limited to no time in between tasks (Rafnsdottir & Gudmundsdottir, 2004), it is very unlikely that they will test different assistive functions of the robotic system. Also, as the working environment becomes more standardised, as in the example case of mass production scenarios compared to small-series production, their use becomes less valuable. This is strongly linked to the degree of autonomy a worker has within the working systems. In most cases, high level of standardisation is reversely related to the workers' freedom in how to perform a certain task and how or what assistive system to use. As the choice of use becomes less flexible, the added value of cobots with high flexibility decreases. Real **collaboration** between humans and robots, where both parties work on the same object at the same time, occurs very rarely. As stated by the IFR, today we mostly see the interaction form of co-existence, where human and robot share their workspace but do not operate on the same object at the same time or sequentially (IFR, 2020). However, the interaction form of collaboration can be observed in the handling and lifting of heavy parts, for example, in welding tasks. With **teleoperating robotics** used in remote maintenance operations, for example, we also find scenarios where human and robot collaborate. Though sometimes separated by large distances, they still can work on the same task at the same time. Similar uses can be found within the technology class of **construction robots**. These systems often also support heavy lifting and are operated remotely, especially in very large construction undertakings like building a reservoir dam. Further, they are used to explore natural resources, such as inside mines, and also in smaller forms, such as when painting walls. A different system category, which is sometimes mentioned in line with robotic systems, is **exoskeletons**. These systems are not used for full automation but support physical tasks that require, for example, heavy lifting or awkward posture. They can be categorised into passive and active systems supporting either the upper or lower body, or single joints. Passive exoskeletons use spring and locking mechanisms to support human movement, whereas active exoskeletons use sensors and actuators to support human movement. It is questionable whether these systems shall be placed in the category of robotic systems, especially passive systems. However, at least active systems must be mentioned when considering the impact of AI-based systems on physical tasks. Another important aspect differentiating exoskeletons from truly robotic systems is that exoskeletons can potentially be certified as personal protection equipment (PPE), although there is no agreement so far regarding this issue (EU-OSHA, 2019b).

A second noticeable group that is addressed in scientific literature is medical robots. As mentioned in the section for the automation of cognitive tasks, there are robotic systems that are used for medical care, for example, by supporting therapy commitment or therapeutic training. **Medical robots** for the automation of physical tasks refer to systems like robotic rollators (Werner et al., 2016; Werner et al., 2018) in the care of the elderly or impaired as well as robot-assisted therapy for balance function rehabilitation after stroke (Zheng et al., 2019). Still in the earlier development stage are medical robots designed for carrying and lifting patients, sometimes referred to as nursing robots. Other, already more frequently found medical robots that are fully automated navigate through hospitals performing transportation tasks. Surgical robots are also found for the automation of tasks. They support the surgeon during operational tasks with light, reducing jitter or magnifying structures.

Within scientific literature, the aspect of mobility is often addressed separately and independently from the actual robot's purpose. This fact, however, is not surprising as the integration of **mobile robots** in any environment raises a number of issues. Quite commonly these systems can be found for automated cleaning tasks in different environments like department stores, shop floors or hospitals. Especially in logistics and warehousing, robots are highly automated. Nevertheless, they still follow pre-programmed general routes and are programmed in collision avoidance – so there is some intelligence, but this is limited to a specific context. The integration of AI-based software could optimise the distribution of merchandise, so pathways for humans or robots within the warehouse, for example, to pick up the most popular purchased goods, are improved and time-saving. An algorithm would analyse orders, anticipate how different goods are disposed and change the arrangement of the items to reduce the distance travelled. As also pointed out by the experts, some companies even build new warehouses from scratch with the intention of having everything automated. Already very well-developed, highly automated robotic applications can be found in the agricultural industry. Examples are tracker systems, satellite guidance for weather, humidity monitoring, and systems indicating when to irrigate or to harvest (EU-OSHA, 2020).

Robotics and future uses

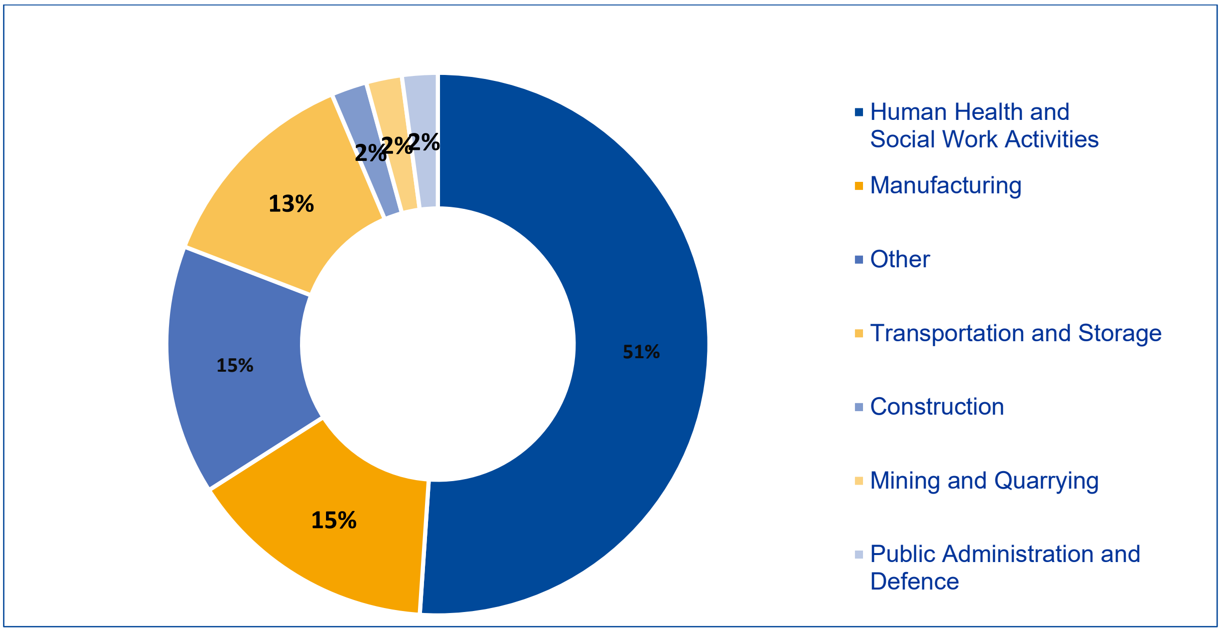
The experts predict that in areas such as **driving** there will likely be semi-automation of the task in the next ten years, rather than full automation. The experts see too much complexity in driving situations as a reason to allow for full automation, when considered in large dimensions such as a whole country. The variety of roads and landscapes create many challenges for autonomous vehicles. Further, there is not sufficient clarity on the legal situation if an accident were to occur. However, the experts do see the potential for **future uses** in the area of autonomous vehicles in general, partly triggered by the COVID-19 pandemic crisis. Compared to autonomously driving cars, these vehicles could instead be unmanned systems or **drones**. They see an increasing need for delivery, in particular regarding end-customer delivery. Companies have started developing delivery robots that move in the streets to cover these **last-mile deliveries**. This future solution does cause some challenges in European city centres though, as the systems need capacity and space for their movement. However, in the long term, the experts even see the potential for changes regarding public transport. Future uses could develop in the direction of smaller shuttles that may move in a certain defined area of a city. This could, for example, be from a large metro station to a smaller neighbourhood.

In the area of manufacturing, the increasing integration of AI-based software tools into robotic hardware does not only lead to new generations of robotic systems, but also to **new business models**. The model **robot-as-a-service (RaaS)**, for example, foresees leasing a robot instead of purchasing it. Maintenance, upgrades and services are performed remotely by the supplier. Data from different robots from different customer sites can be aggregated and analysed to optimise an individual process. Adjustments in the robot's programme can automatically be uploaded to one or all of the robots operating in the production line. Advantages are especially seen for small and medium-sized enterprises (SMEs), as no initial investment and lower costs for system integration are promised. The obtained systems are continuously updated in relation to production requirements (IFR, 2018; 'Robots and the Workplace of the Future'; IFR, 2020; 'How Connected Robots are Transforming Manufacturing'). This flexibility, though, may hold some challenges and risks, especially regarding OSH, and shall therefore be explored in more detail.

4.2.2 Sectoral distribution

The analysis of automated physical tasks among sectors reveals a high number of automated or supported tasks in the sector **human health and social work activities.** Here, the majority of tasks can be found in **hospital activities**. Secondly, the **manufacturing** sector is strongly influenced. This cannot only be found in scientific literature, but is emphasized by the experts as well as the FOP consultation. The experts agree that the manufacturing sector is predominant regarding the deployment of advanced robotics and that outside this sector, deployment is lower. Within the manufacturing sector, the **automotive industry** is named as the main one. However, the human health and social work activities sector is represented slightly more in scientific literature, which might be due to a publication bias though. The **transportation and storage** sector is also addressed quite frequently in scientific literature and also mentioned by the experts. Less frequently observed in scientific literature, but emphasized by the experts, are the sectors of **construction** and **agriculture, forestry and fishing**. Especially regarding construction, Japan is leading in deployment. According to the experts, deployment in the construction sector is more difficult because a construction site is less structured (than, for example, a warehouse) and less easy to move around in. However, robotic applications are especially useful to take over or support workers with tasks that involve handling heavy loads, for example, automated cranes or, a relatively new development, the **exoskeleton**. The **agriculture, forestry and fishing** sector is quite developed regarding automated systems, and innovation of these technologies in the sector is rapidly increasing (EU-OSHA, 2020). The experts consider development of technologies in this sector very important to Europe. As the population is ageing and the attractiveness of working in this field might be low for young people, automation technologies can be useful. Figure 6 summarises the sectoral distribution of AI-based systems for the automation of physical tasks according to the analysed scientific literature.

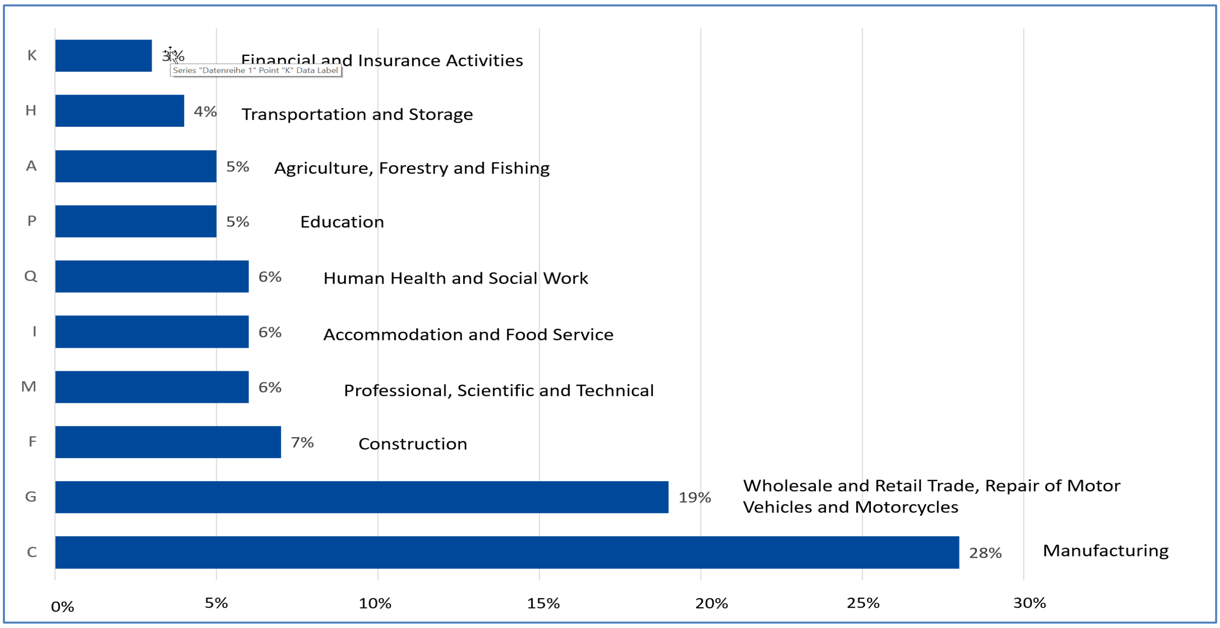
Figure 6: Automation of physical tasks – NACE sector distribution according to scientific literature



Source: Author

In Europe, the sectoral distribution of robotic systems capable of directly interacting with humans can also be derived from the ESENER-3 survey. Here, the data from the third wave indicates a strong pervasiveness of robotic systems again in the manufacturing sector (28 %), followed by the wholesale and retail trade; repair of motor vehicles and motorcycles (19 %). Within the interviewed sample, 6 % of the enterprises from the human health and social work sector report using HRI. In this wave, the lowest numbers of HRI applications are found in the sector of electricity, gas, steam and air conditioning supply (0.2 %) (Wischniewski et al., 2021). Figure 7 shows the top 10 NACE sectors in Europe reporting the use of HRI.

Figure 7: NACE (v. 2) code of enterprises with HRI according to ESENER-3



Source: Author

4.2.3 Impacted tasks (and jobs)

For the impacted tasks and jobs, a similar rationale applies as to cognitive tasks. As the nature of physical tasks implies, most physical tasks impacted by the automation of AI-based systems are object- related. However, there are also some physical tasks affected by the automation that are person-related. A task, which occurs in different areas (medicine, manufacturing and construction) but is automated or supported likewise by different types of robotic systems, is **lifting** objects or even people. This is a good example of how the same task is automated in different areas and their associated jobs. In the medical field, apart from lifting, a number of systems provide other **movement support**, like walking. Other physical tasks that are highly affected by robotic systems are **cleaning** or **transporting**. As described by most experts, tasks more likely to be automated are **repetitive** and **routine tasks**. These tasks can be programmed and coded, and a system can be built that learns from this data using AI-methods or techniques. Therefore, easy physical tasks are more likely to be replaced. The experts see a potential of job destruction, especially among **low-skilled jobs** with high levels of repetitiveness and routine characteristics. In a slightly contrasting view, it is noted that many routine physical tasks already have been automated through mechanisation, and that there may be fewer tasks left to automate.

In the opinion of some experts, the use of collaborative robots even has the potential to create more jobs. As new technologies enter the market, new types of jobs tend to emerge, specifically addressing opportunities and needs created by the technology. Examples of this could be educational jobs specified for working with such systems, or increased demand for specialists, like software developers for AI-based systems. These systems have the potential to combine the strengths of humans with those of machines. AI can help to coordinate the allocation of work. Teaming humans with robots can increase productivity, thus benefitting the organisation, which in turn is able to invest more and create new jobs. An example can be seen in cleaning activities. It is assumed that cleaning robots will change the work pace, the ability to decide on a specific task order and maintenance tasks. With such systems, cleaning staff will not wipe floors themselves, but will decide where and when to clean. This is probably the most typical impact of this kind of automation. However, at the same time, these systems can perform the work task of more than one human worker at a time. Consequently, we will be observing a change towards a situation where one human orchestrates multiple robotic systems.

4.3 Task impact – Evaluation and preliminary OSH implications

Regarding the pervasiveness of systems and their use, a slight publication bias is observable in scientific literature. Medicine and education science are both disciplines with eager publication ambitions and are therefore slightly overrepresented in scientific literature. This is especially noticeable for advanced robotics. As pointed out by the experts and the FOP consultation, but mainly indicated by the ESENER-3 data, most human-robot interaction applications are found in manufacturing (28 %) followed by the wholesale and retail trade including repair of motor vehicles and motorcycles (19 %). The other sources indicate that, apart from the manufacturing sector, most technology applications are deployed in the sector of human health and social work with a very strong focus on healthcare.

According to the presented taxonomy (see figure 4), the task characterisation regarding routine and non-routine is a crucial element in terms of automation potential. This is the case for physical as well as cognitive tasks. The expert interviews as well as the results from the FOP consultation support a view commonly found in scientific literature. Physical and cognitive tasks that are easily codified (that is, routine) are the most affected ones. Tasks or jobs with more codifiable tasks will be more rapidly displaced. Mid-skilled jobs hold high numbers of routine tasks. Therefore, according to this perspective, the number of mid-skilled jobs will most likely be reduced due to the use of AI-based systems, simultaneously increasing the number of high-skilled and low-skilled jobs. The mid-skilled job group is more likely to experience a heightened fear of job loss and insecurity regarding their employment. One way to address this fear is to include workers early on in the process when introducing the technology, as well as to offer educational programmes for the workers to develop new skillsets.

Regarding the development of skills, the experts describe different requirements depending on the system interaction role. For someone using the technology as an assistive system, it would be training like for any new technology, including some form of introduction phase. The rest is done through learning by doing, which is by definition in these kinds of contexts, learning on the job. For people maintaining the systems or further developing them, the question is whether less formalised on-the-job training is sufficient or if they may require further skills training. These skill-related changes in job and task structure pose the opportunity of reskilling and upskilling workers during the introduction of a system. It is a vital step to mitigate the risk of deskilling the workforce. Furthermore, placing adequate focus on providing workers with not only the needed knowledge to operate the technology, but to understand its functioning, can increase their feeling of control. When designing and developing new systems, not only the skills of direct users need to be considered but also skills of different stakeholders. For example, when deploying technology for smart robotics, it is not only important for those directly working with the robot to understand the system, but also for parties like trade unions, work councils and shop stewards, to function in their positions to their best extent. However, addressing this skill level of indirect stakeholder can be quite advanced.

Further, the experts describe a process of upskilling and deskilling in the future. There might be a risk of deskilling when AI-based systems are used for performing some tasks. For instance, for routine tasks such as cleaning, there will be the risk of people losing the skill of this specific task. The experts argue that deskilling rather appears at workforce level, but not at a personal level. For instance, in the car industry the workers are semi-skilled; but the more manufacturers use machines, the less they will need these workers. One can argue that this will liberate humans to do more creative work or engage in more complex tasks. Creative work can be represented in such abstract ways as problem solving or in a more literal way of artistic creativity, if the job contains such tasks. But these decisions are political or based on individual career choices, since technology outside of the social relation, per se is neutral.

In addition to the literature review, the expert interviews revealed further opportunities and challenges for OSH associated with the use of AI-based systems and advanced robotics for the automation of tasks. According to the experts, new technologies can have a positive impact on OSH for workers according to most stakeholders, especially regarding the so-called 3D jobs (dirty, dull and dangerous).

More specifically related to physical tasks (object- and person-related) supported by advanced robotics, the interviewed experts mainly address issues regarding the **physical OSH dimension**. For instance, the **reduction of physical risks** is often mentioned by the experts. Especially using robotic systems for physically strenuous tasks can be beneficial and has the potential for long-term improvements. Exoskeletons, for example, are able to support **heavy lifting tasks.** However, it has to be noted that long-term effects associated with the use of exoskeletons might not only be beneficial as indicated by some very first studies. Yet, reliable evidence on this matter is still missing. Physical ergonomics can be improved by **reducing awkward and unhealthy postures** in different environments. In the health sector, for example, nurses experience a rather high rate of injury, mainly caused by the need to lift patients, which could be alleviated with assisting cobots or exoskeletons. An improved handling of heavy workloads and increasing efficiency might **reduce perceived stress**. A more in-depth assessment of the automation of physical tasks can be found in the Task 3 report ‘Assessment of the OSH challenges and opportunities associated with the state of knowledge on intelligent cobots.’ At first glance, smart ICT seems to be more related to the psychosocial OSH dimension, but the **psychosocial OSH dimension** is also very relevant when deploying advanced robotics for the (semi-)automation of physical object- and person-related tasks or cognitive information-related tasks.

AI-based systems can also help to get rid of **unfavourable and repetitive cognitive routine tasks**, leading to work becoming more interesting for workers. Smart ICT might have the potential to **reduce stress** by improving workforce planning within and across teams and by improving the workflow. Close cooperation with AI-based systems further holds the potential for humans to **optimise supportive functions** in a desired way. Dynamic systems where the algorithms may advance their functionalities through AI-based techniques allow a worker-centred optimisation of the system. The physical OSH dimension in relation to the (semi-)automation of cognitive tasks is not mentioned by experts. The aspect of prolonged sitting could be identified in this category, albeit this is not specific to AI-based systems. The literature, too, focuses noticeably on the mental impact of this type of automation. EU-OSHA’s forthcoming report “Artificial Intelligence and automation of cognitive tasks: Implications for occupational safety and health” provides a more in-depth view on this topic.

For both, the (semi-)automation of cognitive tasks and physical tasks, high degrees of autonomy also raise a number of risks. In relation to impacts on workers’ psychological wellbeing, the experts mentioned the risk that an AI-based system might be highly automated or even autonomous to a degree where it **dictates a certain course of actions** to the worker. In this case, there is the risk that workers will negatively **experience a loss of control** over their own work. Dynamic learning and adaptive systems further hold the risk of output not being completely predictable since the machine changes its behaviour depending on the processing of information. **Unpredictability** of systems can **reduce trust and impair user acceptance**.

More in relation to OSH management, the experts see the risk that when AI-based systems **change the nature of a workers' task**, the newly arising health and safety risks (of the changed task) may not have been adequately assessed. Experts agree that awareness among workers and line managers is crucial, as well as in-depth training of workers on how to handle AI-based systems. The role and the position of line managers and supervisors is crucial and should be taken into account more when developing regulation or OSH management approaches. One expert mentioned that workers should participate during the design phase of an AI-based system so that it could take into account the workers' actual use. Especially in terms of robotics, developing and controlling flawless detection, safety and protection systems and software becomes key in eliminating health and safety risks.

The effects on OSH-related challenges and opportunities have to be elaborated and made visible. They are addressed briefly in this report and are further investigated in EU-OSHA's forthcoming reports, "Artificial Intelligence and automation of cognitive tasks: Implications for occupational safety and health" and "Robots, cobots and Artificial Intelligence for the automation of physical tasks: Implications for occupational safety and health".

5 Overview of policies and strategies

Following the mapping of current and potential uses, this chapter will address legally binding regulation on a European and national level as well as not legally binding initiatives and programmes on AI-based systems, advanced robotics and OSH. Information at the level of the EU countries was collected primarily through the FOP consultation.

5.1 European level

This section will present legally binding regulation relevant to AI-based systems and advanced robotics used for the automation of tasks and OSH on a European level. Further, relevant European strategies, programmes and initiatives promoted by major stakeholder and contributors will be outlined. Finally, gaps and needs for regulation and further activities will be summarised.

It is noteworthy that all major European OSH relevant stakeholders present some strategy or initiative in relation to artificial intelligence and the potential impact on workplaces. Most stakeholders present some form of requirements or demand principles for AI-based systems, which show similarities and shared values. The principle that finds the highest agreement is **system transparency**, which is addressed in nearly every initiative and also in EU-OSHA's foresight study[7], their Healthy Workplaces Campaign[8] and publication on the future of work regarding AI-based tools[9] . In addition to that, explainability is highlighted[10]. Furthermore, the EU[10] Commission and OECD[11] both demand **technical robustness** as well as the **respect of human rights**, **diversity** and **non-discrimination** for AI-based systems. **Fairness** is also explicitly mentioned in the social partners' shared framework agreement[12]. Here, within the EU Commission principles and the European Trade Union Institute (ETUI)[13] initiative, the aspect of **data privacy** and **data governance** are also pointed out. The aspect of **accountability** is explicitly mentioned by ETUI and the EU Commission. A high-level Expert group on AI of the European Commission also presents ethic guidelines with a set of seven key requirements that these systems should meet to be trustworthy[14]. The EU Commission also strongly supports a human-centred approach[10] and participation[10] of workers in the process. However, all initiatives, strategies and programmes address AI-based systems on a more general level. The more specific focus on the automation of tasks and OSH is addressed rather indirectly.

[7] https://osha.europa.eu/en/publications/foresight-new-and-emerging-occupational-safety-and-health-risks-associated
[8] https://healthy-workplaces.eu/
[9] https://osha.europa.eu/en/publications/osh-and-future-work-benefits-and-risks-artificial-intelligence-tools-workplaces/view
[10] https://ec.europa.eu/info/publications/white-paper-artificial-intelligence-european-approach-excellence-and-trust
[11] https://oecd.ai/
[12] https://www.etuc.org/system/files/document/file2020-06/Final%2022%2006%2020_Agreement%20on%20Digitalisation%202020.pdf; https://www.businesseurope.eu/publications/european-social-partners-framework-agreement-digitalisation;
[13] https://www.etui.org/publications/foresight-briefs/labour-in-the-age-of-ai-why-regulation-is-needed-to-protect-workers
[14] https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

5.1.1 Regulation

Within Europe there are currently two main pieces of legislation that apply to technology and workplaces and therefore also build the legislative basis for AI-based systems and advanced robotics for the automation of tasks. One of the main legislations governing the harmonisation of essential health and safety requirements for machinery at EU level is the **Machinery Directive 2006/42/EC**[15]. It applies to products that are to be placed on the EU market for the first time. The evaluation of this directive in 2018 revealed a general fit of the directive for digital innovation. However, some concerns were raised that AI-based systems might challenge the suitability of the directive in the future (EU Commission, 2018). Consequently, the Machinery Directive is under revision to cover new hazards and risks in relation to workplace equipment.

The second important directive to be named is the **OSH Framework Directive 89/391/EEC**[16]. This directive is of fundamental importance as it is the basic safety and health legal act which lays down general principles concerning the prevention and protection of workers' safety and health. It lists the general principles of prevention (e.g., avoiding risks, risk evaluation, consulting workers, training, etc.) and states employers' and workers' obligations. While not specifically written for only AI-based systems and advanced robotics, given its broad coverage it can be applied to the risks AI-based systems pose, too.

In 2021, however, as artificial intelligence is an area of strategic importance, the EU Commission launched an additional legislative horizontal regulatory proposal: a proposal for the **Artificial Intelligence Act**[17]. Some points relevant to this project are highlighted briefly in the next paragraph. At the time of the writing of this report, the EU Commission is in favour of a horizontal EU legislative instrument for high-risk AI systems only and the possibility to follow a code of conduct for providers of non-high risk AI-based systems. The proposal includes a section on **prohibited artificial intelligence practices** (Article 5) such as:

> the placing on the market, putting into service or use of an AI system that deploys subliminal techniques beyond a person's consciousness in order to materially distort a person's behaviour in a manner that causes or is likely to cause that person or another person physical or psychological harm. (p. 43, Regulation on a European Approach for Artificial Intelligence)

It also includes a **classification of AI-based systems as high-risk**. Among others the according Annex of the section lists the following systems, also in a section especially dedicated to the working context, the category **employment, workers management and access to self-employment**:

> AI systems intended to be used for recruitment or selection of natural persons, notably for advertising vacancies, screening or filtering applications, evaluating candidates in the course of interviews or tests; AI intended to be used for making decisions on promotion and termination of work-related contractual relationships, for task allocation and for monitoring and evaluating performance and behaviour of persons in such relationships. (p. 4, Annex III)

The proposal further includes a chapter on **requirements for high-risk AI-based systems**, which among others holds **Article 13 Transparency and provision of information to users** and **Article 14 Human oversight**. Article 13 demands an appropriate type and degree of transparency and article 14 appropriate human-machine interface tools, that they can effectively been overseen by natural persons while the system is in use as well as preventing or minimising the risks to health, safety or fundamental rights that may emerge by the use of AI based systems.

5.1.2 Strategies, programmes, initiatives and campaigns

A number of OSH relevant international and European stakeholders have published strategies, guidelines or position papers in the context of AI-based systems and advanced robotics. These stakeholders include research institutions, unions, employers, representatives of the industry and governmental institutions. The content of the different proposals will be presented briefly in this chapter.

In 2020, the international **Organisation for Economic Co-operation and Development (OECD)** launched the platform 'AI Observatory' providing a database of AI policies from around the world. As stated on the website, the AI policy observatory 'combines resources from across the OECD, its partners and stakeholder

[15] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32006L0042

[16] https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=celex%3A31989L0391

[17] https://digital-strategy.ec.europa.eu/en/library/proposal-regulation-laying-down-harmonised-rules-artificial-intelligence

groups.' Further, it facilitates 'dialogue between stakeholders and evidence-based policy analysis in the areas where AI has the most impact.' The platform provides dashboards with information on AI policy areas, explores over 600 AI policy initiatives from over 60 countries and presents latest trends and data on AI developments. Further, the OECD presents five complementary value-based principles for trustworthy AI on the platform (OECD.AI, 2021). The human-centred AI principles were adopted by G20, as stated in the G20 ministerial statement on trade and digital economy. The five principles are listed below, according to the OECD observatory website:

- AI should benefit people and the planet by driving inclusive growth, sustainable development and well-being.
- AI systems should be designed in a way that respects the rule of law, human rights, democratic values and diversity, and they should include appropriate safeguards.
- There should be transparency and responsible disclosure around AI systems to ensure that people understand AI-based outcomes and can challenge them.
- AI systems must function in a robust, secure and safe way throughout their life cycles and potential risks should be continually assessed and managed.
- Organisations and individuals developing, deploying or operating AI systems should be held accountable for their proper functioning in line with the above principles.

As an industrial representative, the **International Federation of Robotics (IFR)** issues the report on 'World Robotics R&D Programs' on worldwide advanced robotics on a regular basis (IFR, 2020; IFR 2021). The aim of this report is to give an overview of governmental focus and investments in the main global robotics markets. In this publication, worldwide initiatives and programs regarding advanced robotics have been collected and summarised. Their extensive analysis comprises three global regions (Asia, Europe and America) and according countries. The report presents the robotics **research and development programmes of each country and region in detail** including background, funding budget or issuing authority. Among the highlighted programmes are, for example: the 'Strategic Innovation Promotion Program' (SIP) by the Japanese government, which has prioritised manufacturing, service sectors and infrastructure and construction for the development of robot applications; and the Korean government's '3rd Basic Plan for Intelligent Robots,' which runs from 2019 to 2023. In addition to agriculture, healthcare and disaster response, it focuses on service robotics, wearable devices, logistics, underwater exploration and defence.

The **European Commission** has published a white paper 'On Artificial Intelligence – a European approach to excellence and trust' (2020). In this paper, the Commission expresses its support of a regulatory and investment-oriented approach to promote both the increased uptake of AI and to address the risks associated with this technology. The aim of the paper is to set out policy options and how to achieve them. It further describes the setting up of the High-Level Expert Group by the Commission, which published 'Ethics guidelines for trustworthy AI' in 2019. Within the guidelines, seven key requirements to build a regulatory framework for trustworthy AI were identified. According to the EU Commission website, the ethics guidelines for trustworthy AI are (EU Commission, 2021):

- **Human agency and oversight:** AI systems should empower human beings, allowing them to make informed decisions and fostering their fundamental rights. At the same time, proper oversight mechanisms need to be ensured, which can be achieved through human-in-the-loop, human-on-the-loop, and human-in-command approaches.
- **Technical robustness and safety:** AI systems need to be resilient and secure. They need to be safe, ensuring a fall back plan in case something goes wrong, as well as being accurate, reliable and reproducible
- **Privacy and data governance:** Besides ensuring full respect for privacy and data protection, adequate data governance mechanisms must also be ensured, taking into account the quality and integrity of the data, and ensuring legitimised access to data.
- **Transparency:** The data, system and AI business models should be transparent. Traceability mechanisms can help achieving this. Moreover, AI systems and their decisions should be explained in a manner adapted to the stakeholder concerned. Humans need to be aware that they are interacting with an AI system, and must be informed of the system's capabilities and limitations.

- **Diversity, non-discrimination and fairness:** Unfair bias must be avoided, as it could have multiple negative implications, from the marginalization of vulnerable groups, to the exacerbation of prejudice and discrimination. Fostering diversity, AI systems should be accessible to all, regardless of any disability, and involve relevant stakeholders throughout their entire life circle.
- **Societal and environmental wellbeing:** AI systems should benefit all human beings, including future generations. It must hence be ensured that they are sustainable and environmentally friendly. Moreover, they should take into account the environment, including other living beings, and their social and societal impact should be carefully considered.
- **Accountability:** Mechanisms should be put in place to ensure responsibility and accountability for AI systems and their outcomes. Auditability, which enables the assessment of algorithms, data and design processes plays a key role therein, especially in critical applications. Moreover, adequate an accessible redress should be ensured.

In 2020, the **European Trade Union Confederation (ETUC)** published their 'Resolution on the European strategies on artificial intelligence and data,' a resolution paper targeted towards artificial intelligence on a European level (ETUC, 2020). According to their key messages as presented in the publication, ETUC demands that European AI and data strategies should 'provide a legal and empowering European framework based on human rights, and therefore including labour and trade union rights and ethical rules.' This postulation is in line with the second OECD principle. ETUC further claims to 'prohibit discriminatory treatments on the basis of biased algorithms' and stresses the importance of data protection and privacy. Furthermore, the resolution proposes that 'the principle of "human remains in control" should apply to workers and managers.'

The **European Trade Union Institute (ETUI)** published a foresight brief on 'A law on robotics and artificial intelligence in the EU?*'* targeting both AI and robotic regulation on European level. It examines the regulatory aspects of existing and future technologies, drawing attention to several key issues, such as the visibility, accountability and liability of all stakeholders (ETUI, 2020). They stress that legislation 'should consider fundamental questions related to responsibility and liability' as a 'tendency to delegate responsibilities to artificially intelligent systems will become a serious problem for our society and for our legal systems globally.' According to ETUI, the EU needs to implement requirements to exercise the 'right to explanation' of models and decisions made by automated or artificially intelligent algorithmic systems. In a second position paper, named 'Labour in the age of AI: Why regulation is needed to protect workers,' ETUI suggests that the EU needs to put in place an adequate ethical and legal framework for working with AI. This foresight brief argues that such a framework must be solidly founded on regulation which can be achieved by updating existing legislation and that it must pay specific attention to the protection of workers. The claimed seven key dimensions that future AI regulation should address:

- safeguarding worker privacy and data protection;
- addressing surveillance, tracking and monitoring;
- making the purpose of AI algorithms transparent;
- ensuring the exercise of the 'right to explanation' for decisions made by algorithms or machine learning models;
- preserving the security and safety of workers in human–machine interactions;
- boosting workers' autonomy in human–machine interactions; and
- enabling workers to become 'AI literate'.

While ETUC and ETUI address specific requirements towards potential future legislation and regulation, this point of view is contrasted by **BusinessEurope**'s strategy paper on 'Robotics and automation - BusinessEurope strategy paper.' (BusinessEurope, 2018). They focus on advanced robotics in Europe and claim a critical assessment of existing regulation to determine whether all frameworks in place are suitable to enable responsible robotics use and development. To do so, they encourage in-depth analysis through use cases. Gaps and needs should then be addressed on sectoral level.

In 2020, the **European Social Partners Framework Agreement on Digitalisation** was launched by the European cross-sectoral social partners BusinessEurope, SMEunited, European Centre of Employers and Enterprises providing Public Services (CEEP) and ETUC (and the liaison committee EUROCADERS/CEC).

This agreement is a shared commitment of the contributing partners 'to optimise the benefits and deal with the challenges of digitalisation in the world of work' (ETUC, 2020). The framework agreement includes a chapter especially dedicated to 'Artificial Intelligence (AI) and guaranteeing the human in control principle.' The agreement demands the guaranteed control of humans over machines and AI in the workplace. Further, it points out that 'potential tensions between respect for human autonomy, prevention of harm, fairness and explicability of decision making should be acknowledged and addressed.' For that purpose, it also includes a number of measures to be considered. Among them are the following related to the deployment of AI systems (ETUC, 2020):

- AI systems should follow the human in control principle,
- AI systems should be safe, i.e. should prevent harm,
- AI systems should follow the principles of fairness,
- AI systems need to be transparent and explicable with effective oversight.

Furthermore, the agreement demands that if AI systems are used in human-resources procedures transparency needs to be safeguarded through the provision of information. In addition, an affected worker can make a request for human intervention and/or contest the decision along with testing of the AI outcomes. Finally, AI systems should be designed and operated to comply with existing law, including the General Data Protection Regulation (GDPR), and guarantee privacy and dignity of the worker.

In the EU, robotics funding has been directed through the seven-year research framework program, **Horizon 2020**, which ran from 2014 to 2020 and covered a wide range of research and innovation topics including manufacturing, consumer, healthcare, transportation, and agri-food robotics. The final work program of Horizon 2020 ran for three years from 2018 to 2020 with a budget of 158 EUR million. It focused on digitalisation of industry through robotics, robotics applications in promising new areas, and robotics core technologies such as AI and cognition, cognitive mechatronics, socially cooperative human-robot interaction, and model-based design and configuration tools. According to the latest version of the report from 2021, the EU Commission is expected to provide a total funding of EUR 198.7 million for the robotics related work program in Cluster 4 within the new programme, **Horizon Europe.**

On the governmental side, the **European Council** included some AI-based systems related content in their new strategic agenda for EU 2019-2024 (European Council, 2019). This includes working on all aspects of the digital revolution and artificial intelligence: infrastructure, connectivity, services, data, regulation and investment. They also published the 'Coordinated plan on the development and use of artificial intelligence made in Europe.' Within this plan, the Council underlines the importance of fostering the development and use of artificial intelligence in Europe. This is to be done by increasing investment, reinforcing excellence in artificial intelligence technologies and applications, and strengthening research and innovation collaboration between industry and academia in this field. Furthermore, the European Parliament hast established the **Special Committee on Artificial Intelligence in a Digital Age (AIDA)** with the goal of setting out a long-term EU roadmap on AI. According to its mandate, AIDA will study the impact and challenges of rolling out AI, identify common EU-wide objectives, and propose recommendations on the best ways forward[18]. Another relevant activity by the European Parliament is the Panel for the Future of Science and Technology (STOA). This panel forms an integral part of the structure of the European Parliament. It is composed of 27 Members of the European Parliament (MEPs) and carries the political responsibility for STOA's work. Among the STOA priority areas, 'artificial intelligence and other disruptive technologies' is number one in the thematic priorities[19].

To gain a better understanding of how digitalisation could influence workers' safety and health in the European Union and to develop adequate strategies to meet these changes to work an OSH, **EU-OSHA** has conducted an extensive **foresight study on digitalisation** (including ICT-enabled technologies, AI and robotics). It analyses major impacts on the nature and location of work. The results are presented in the European risk observatory report 'Foresight on new and emerging occupational safety and health risks associated with digitalisation by 2025' (EU-OSHA, 2018). The foresight study uses experts' knowledge and the development of different scenarios to assess trends and drivers of changes related to workplaces and new and emerging OSH risks associated with digitalisation in 2025. As one result, the foresight study

[18] Available at: https://www.europarl.europa.eu/committees/en/aida/about
[19] Available at: https://www.europarl.europa.eu/stoa/en/about/history-and-mission

identifies a number of OSH challenges. Among the main findings are, for example, new risks by automation technologies particularly influenced by system transparency and underlying algorithms or the design of human-machine interfaces. Risks are also seen in relation to new and changing human-machine interfaces in particular related to ergonomics and cognitive load. The increasing importance of psychosocial and organisational factors is also mentioned as a key finding. EU-OSHA also presents an OSH overview on emerging risks and has an upcoming 'Healthy Workplaces Campaign' to be launched in 2023, dedicated to digitalisation and OSH.

5.1.3 Gaps and needs

In general terms, the responses collected through the FOPs do not highlight any particular needs or gaps regarding regulation on a European level in terms of worker protection. Especially the OSH framework directive is labelled positively. All new hazards and risks are properly covered in the Machinery Directive 2006/42/EC in relation to workplace equipment. There is an obvious evolution in the technology, for instance, automation in the sectors of construction or agriculture (the inclusion of software into the design of the machines) that have an impact on the workers' tasks. This may cause certain issues but those are already covered by the Directive.

However, some of the experts do describe the lack of a more global perspective which takes into account the deployment of AI-based systems in industry sectors. According to them, these issues should not be addressed in individual directives such as the Machinery Directive. A more favourable approach would be a separate directive addressing this – a horizontal approach for safeguarding systems (for all AI-related issues). Broadening the regulative body in this way has the advantage of a longer validity and fewer updates would be necessary. Furthermore, by this, the technology neutral quality of the Machinery Directive would be kept.

What is seen as a greater issue is the lack of proper implementation and enforcement of the Machinery Directive. Legislation can only be effective when applied properly. Some see evidence that market surveillance is not working. The same happens with labour inspections. Although the majority of labour inspectors have general OSH knowledge, some Member States face the challenge of lacking specialisation towards AI-based systems. Without control and enforcement, simply having legislation addressing AI-based systems is not sufficient to prevent or solve OSH-related problems. Consequently, it is more the challenge of lacking expertise from labour inspections and accident insurance bodies rather than missing regulation. This issue further raises the question of how and whether, for example, labour inspections tasks could be supported by AI-based systems. An example of this already happening in the field is set by the Distributed Wind Energy Association (DWEA). They utilise an AI-based system in the process of inspection planning, where collected output from a performed inspection is used to train the algorithm for choosing future inspection objects. EU-OSHA also published a discussion paper on big data in the context of safety inspection efficiency, concluding that human-made decisions that are risk-informed on the basis of algorithmic output are preferable (EU-OSHA, 2019c). These are two examples of possible application of the technology, illustrating that it is possible, but that on a higher level the questions of how to implement it in inspection tasks and whether it makes sense in specific cases is still open. Another standing question is how OSH management systems are influenced and could benefit through AI-based systems.

Before enacting new rules, existing rules should be checked and verified. It is not possible to regulate on issues that do not exist at present. Directives must remain of general application because they need to be adapted to the new circumstances. Standards are then to be developed and they will be applied by manufacturers. A system of harmonised standards, requirements and guidance is seen as a suitable system. EU-OSHA's forthcoming reports, "Artificial Intelligence and automation of cognitive tasks: Implications for occupational safety and health" and "Robots, cobots and Artificial Intelligence for the automation of physical tasks: Implications for occupational safety and health" present relevant standards regarding robotic systems.

5.2 National level

In line with section 5.1, this section aims to provide an overview of national legally binding regulation as well as strategies, programmes, initiatives and campaigns within the European Member States. This section is mainly based on the answers from the FOP consultation.

5.2.1 Regulation

Within the FOP consultation, only a few countries report specific initiatives in the field of national legally binding regulation regarding **AI-based systems such as advanced robotics or smart ICT** and **OSH**. **Austria** reports specific discussion regarding advanced robotics that could result in a national legally binding (international) standard. **The Netherlands** reports that in terms of smart robotics there are many (mandatory) discussion platforms deriving from the Machinery Directive for inspectors, for industry partners, for standardization bureaus, etc. **Finland** reports that data handling in relation to smart ICT is being included in preparation for many legislative updates, but on a more general level.

According to the replies that we received to the questions, currently nothing specific is being prepared in terms of legislation on AI-based systems and OSH, though expert level discussions with business representatives are ongoing. Standards are being discussed on AI and biometrics, in co-operation with other European standardization experts. Much of the present legislation covering OSH is at some level applicable when using AI-based systems and advanced robotics. The answers from the FOPs do not directly indicate whether there are any challenges or difficulties in applying relevant regulation on a national level. However, as some replies from the experts and the FOPs indicate, there isn't always a very clear picture of how to comply with relevant legislation on all levels. At this point, it remains unclear if and how instruments (like risk assessments or the participation of worker representatives) are involved systematically in consultation, assessment or design processes. More insights on this topic will possibly be gained in Work Package 2 when addressing the company level in more detail.

5.2.2 Strategies, programmes, initiatives and campaigns

In terms of not legally binding initiatives, programmes or campaigns, most countries report activities. For example Austria, Croatia and the Netherlands report awareness raising campaigns in relation to AI-based systems such as advanced robotics or smart ICT and the impact on OSH. **Croatia** names the formal submission of the Croatian Artificial Intelligence Association's (CroAi) opinion[20] on the EU's White Paper 'On Artificial Intelligence (AI)' aiming at creating more spaces for start-ups. CroAi sees itself as a link between business, politics, academia and the general public. Further, Croatia names a report on the potential of AI for Croatia by the Croatian Employers Association[21]. The report outlines recommendations and guidance regarding expectations in the use of AI-based applications. In **the Netherlands**, a running campaign addresses privacy in relation to data systems and government funded research documentation is focusing on developments in the labour market where ICT systems play an important role. Furthermore, a specialist group in the Dutch National Safety Expert Federation, which involves the social partners, is active in the field of advanced robotics. **Ireland** reports discussions in this field by the National AI Strategy Group to look at developments for industry and regulation. A national AI strategy for Ireland with the working title 'AI – Here for Good' is being developed. It aims at ensuring that Ireland's use of artificial intelligence will benefit society. This shall be done in line with EU's and OECD's principles on trustworthy AI. 'The National Strategy for Artificial Intelligence' (2020) published by the **Norwegian** Ministry of Local Government and Modernisation offers an overview of the many AI-related policy goals held by the government. The primary point of concern raised in Norway's national strategy is that future labour markets will undergo a dramatic transformation, as the spread of AI will increase the likelihood of employees changing jobs and updating their skills more often. Hence, Norway's AI strategy identifies major investments in education as necessary to combat job redundancy and displacement.

Sweden's Ministry of Enterprise and Innovation outlined a set of conditions that should shape the development of national policies around AI in their 2019 report on 'National Approach to Artificial Intelligence.' The first condition promotes education and training towards AI-based systems. The second condition identifies the necessity for more research into AI and its varied applications. The third condition outlined is the need for greater governmental support for incubating AI innovation and implementation. However, the impact of AI on workers is not directly considered in Sweden's report, beyond the recognition that some tasks will be automated.

[20] https://croai.org
[21] https://www.hup.hr/EasyEdit/UserFiles/Ivana%20Zlatari%C4%87/hup-ict-de-ai-potencijal-umjetna-inteligencija-za-hrvatsku.pdf

Sectoral social partner's initiatives and especially **guidelines** are also named by most countries. **Austria** for example mentions 20 brochures on different topics of digitalisation within the programme 'Work New 4.0'[22]. The initiative was founded by the Federal Ministry Republic of Austria Climate Action, Environment, Energy, Mobility, Innovation and Technology as well as employers' and employees' associations. In their publication 'Work New 4.0,' the initiative has collected extended abstracts from different experts addressing topics in relation to 'humans in the digital factory' like human-machine interaction (e.g, head-mounted displays and ergonomics, human-centred AI) or work quality and organisation (e.g., leadership in a digitalised world of work). **Finland**, for example, names the 'AI Ethics Challenge' initiative – a challenge for companies to take part in discussing what the ethical rules for using AI are, aiming at collecting ethical guidelines. Further, Finland mentions the national artificial intelligence programme 'AuroraAI' (2019-2022) to improve public administration, including OSH administration; and the 'Well-being and Health Sector's Artificial Intelligence and Robotics Programme (Hyteairo)' to speed up the use of artificial intelligence and robotics in the sector's services and operating processes, determining and eliminating obstacles. The Finnish 'VUOKKO' occupational safety initiative programme aims to develop data collection and handle digital programmes for labour inspections. However, the program is just being set up. **France** reports a prevention guide for manufacturers and users for the implementation of collaborative robot applications[23]. The objective of this prevention guide is firstly to present the general context of the implementation of a collaborative robot application, in such a way as to demonstrate its main operational and safety characteristics. Secondly, it aims to address more specifically the risk prevention approach of a collaborative robot application using a concrete example of industrial production. To undertake this activity, a working group including experts from industry (robot manufacturers, integrators, technical centres, professional organisations), user companies, inspection, standardisation bodies and INRS (France's institute for research and safety) was set up under the aegis of the Direction Générale du Travail (DGT, General Directorate for Labour). **Greece** named the report 'Greece: With AI to the future'[24] as well as the 'Digital Transformation Bible 2020-2025'[25] which is currently in public consultation. Among others, it mentions the development of a program called 'Artificial Intelligence for Justice,' to process legal files and support legal decisions. **Germany** reports campaigns on advanced robotics and smart ICT and their use in the workplace as part of their AI strategy[26] as well as the 'HighTech Strategy 2025'[27] of the German Government. Furthermore, the 'German Standardization Strategy on AI' is reported[28]. The German Federal Institute of Occupational Safety and Health has launched the programme 'Occupational Safety & Health in the Digital World of Work' focusing among others on how OSH management systems are influenced and could benefit through AI-based systems. Germany has two relevant initiatives worth mentioning. The platform 'Lernende Systeme – Germany's Platform for Artificial Intelligence'[29] was launched by the Federal Ministry of Education and Research. Its aim is to bring together expertise from science, industry and society, consolidating the current state of knowledge on self-learning systems and AI. The steering committee, whose members have been appointed by the ministry, decides on the strategic and content-related focus of initiative. Within seven working groups comprised of experts from science, companies, government and civil society, developments and the introduction of self-learning systems are discussed, actions areas are identified and practical recommendations are given. Among the seven working groups for example are 'Future of Work and Human-Machine Interaction,' 'Mobility and Intelligent Transport Systems' and 'Health Care, Medical Technology Care.' The other initiative 'Platform Industrie 4.0'[30] is more specifically directed towards the manufacturing sector. It was also launched by the Federal Ministry of Education and Research as well as the Federal Ministry for Economic Affairs and Energy. Within this platform, there are also six working groups that consist of experts from businesses, associations, work councils and academia. They develop concepts, solutions and recommendations on key topics of 'Platform Industrie 4.0' among the working groups. The initiative further provides a transfer network for small and medium-sized

[22] https://plattformindustrie40.at/wp-content/uploads/2020/11/Industrie4.0_LoseBlattsammlung_Okt2020.pdf
[23] https://travail-emploi.gouv.fr/IMG/pdf/guide_de_prevention_25_aout_2017.pdf
[24] https://www.accenture.com/_acnmedia/Accenture/Redesign-Assets/DotCom/Documents/Local/1/Accenture-With-AI-to-the-Future-2019.pdf#zoom=50
[25] http://digitalstrategy.gov.gr
[26] https://www.ki-strategie-deutschland.de/home.html
[27] https://www.bmbf.de/en/high-tech-strategy-2025.html
[28] https://www.din.de/resource/blob/772438/6b5ac6680543eff9fe372603514be3e6/normungsroadmap-ki-data.pdf
[29] https://www.plattform-lernende-systeme.de/home-en.html
[30] https://www.plattform-i40.de/PI40/Navigation/EN/Home/home.html

enterprises (SMEs) as well as a network for international cooperation. **Ireland's** National Standards Authority (NSAI) is working on ISO/TC299 Developing Safety Standards for Robotics. **Portugal** reports the national government program 'Digital Transition Action Plan'[31] and the following publication, 'Human-Centred Approach for the Design of a Collaborative Robotics Workstation'[32].

Most European countries also report **recommendations** given by major stakeholders (e.g., ministries, research organisations, worker unions, employer organisations or manufacturers) on a national level, directly addressing the (semi-/full) automation of physical and/or cognitive tasks through AI-based systems such as advanced robotics or smart ICT and the impact on OSH. Recommendations given by the state for example are named by **Austria** with the mission 'AIM AT 2030 – Artificial Intelligence Mission Austria 2030' by the Federal Ministry for Digital and Economic Affairs[33]. **Finland** names ministries, such as the Ministry of Social Affairs and Health, the Ministry of Economic Affairs and Employment and the Ministry of Finance as sources for specific recommendations. **The Netherlands** name state recommendations on smart ICT and privacy given by the Ministry of Social Affairs and Employment (SZW) through worker protection legislation and the Ministry of Economic Affairs and Climate Policy (EZ) through subsidies of robot/AI development programmes. Recommendations given by worker unions are also mentioned by a couple of countries such as **Austria** and **Finland**. Also, **Germany** names the concept paper on 'AI for Good Work' by the German Trade Union Confederation[34]. Furthermore, some countries indicate the availability of recommendations by employer organisations or manufacturers, for example, Austria, Croatia, Finland and Germany, who address the paper on AI by the Federation of German Employers' Associations[35]. Apart from that, other issuing authorities are also named by some countries. **Finland**, for example, states that all social partners and research/expert organisations are involved in general level national discussion on what the future of digitalisation of work life is and what national or sector specific strategies are needed to prepare for the future. For example, the current COVID-19 situation has sped up the discussion on what the future of work will be like and what is needed in work life. The discussion is done in various groups and levels. **Germany** states that when implementing HRI into workplaces, recommendations are given by the German Institute for Occupational Safety and Health of the German Social Accident Insurance. Some countries also report additional activities on a more regional or sectoral level or issued by a specific company in the form of a code of practices. These range from local projects, for example in Finland, over sectoral exhibitions and working groups, for example in France, to industry specific seminars, for example in Portugal.

With regards to national public research funding directly related to AI-based systems and advanced robotics and the impact on OSH within the next five years, different funding programmes are mentioned by some countries. For example, Austria mentions a programme to support the safe and responsible handling of AI in companies in Austria, under which guidelines for trustworthy AI are tested for their practicability, checked for regulatory compatibility, further developed if necessary and disseminated to future sectors. The aim is to anchor the prelude for the responsible use of AI as an integral part of every AI project in the economy[36]. Another example is given by Germany, which mentions two programmes: the funding programme 'Innovation Spaces' by the German Federal Ministry of Labour and Social Affairs, and 'Innovations for the production, service and work of tomorrow' by the German Federal Ministry of Education and Research.

5.2.3 Gaps and needs

Regarding gaps and needs on a national level, the answers from the FOP consultation indicate that many countries seem to be missing national activities on a more tangible level. A number of countries seem to be missing national legally binding regulation regarding the automation of physical and/or cognitive tasks through AI-based systems such as advanced robotics or smart ICT and the impact on OSH. At the same time, the expert interviews and FOP consultation indicate that on a European level there are in general no gaps regarding binding regulation, which also implies a sufficient enforcement of European legislation on a national level. This contradictive picture might be caused by different stakeholders' views or indicate a mismatch between existing regulation and their practical application and awareness. Especially with new technologies, there are ongoing legislative processes and it is the companies' obligation to continuously

[31] https://dre.pt/application/conteudo/132133788
[32] https://link.springer.com/chapter/10.1007/978-3-030-41486-3_41
[33] https://www.bmk.gv.at/dam/jcr:8acef058-7167-4335-880e-9fa341b723c8/aimat_ua.pdf
[34] https://www.dgb.de/themen/++co++90915258-9f34-11ea-9825-5254008f5c8c
[35] https://arbeitgeber.de/wp-content/uploads/2020/12/bda-arbeitgeber-broschuere-kuenstliche_intelligenz.pdf
[36] https://www.aws.at/fileadmin/user_upload/Downloads/Programmdokument/aws_Digitalisierung_Kuenstliche-Intelligenz_PD.pdf

inform themselves on these developments, which can be difficult given the complexity of the topic. Labour inspectors also need specialised training on AI-based systems, and the legislative landscape surrounding them, to be able to sufficiently and correctly act on them. Furthermore, it could also indicate experienced insecurity of different stakeholders as how to apply legally binding regulation on a national level, rather than real seen gaps.

The gap between existing regulation and an adequate application is also supported by some answers of the FOPs, stating that clear guidelines for different industries are poorly developed and that most research is technology-fixed and does not consider OSH. Although there are some good examples of relevant national activities in relation to AI-based systems and advanced robotics in some countries, there are also a number of countries that report to be missing recommendations by major stakeholders, national public research, initiatives, programmes and guidelines. Portugal also adds that statistical information about implemented AI-based systems is missing. From Austria's point of view, safety in the workplace is generally little promoted and research institutes do little research in the field of prevention and worker protection. Finland describes that ethical guidelines on national level are needed, for example, guaranteeing basic human rights and privacy of personal data handling. As stated by the Netherlands, OSH is not debated much in the context of new emerging technologies, but the topic's revenue and employment rather prevail. However, where it is debated, it is mostly related to (mental) wellbeing and stress.

6 Summary and Conclusion

This report aimed at explaining types and definitions of AI-based systems and advanced robotics for the automation of tasks, mapping current and potential uses and providing an overview of policies, strategies and programmes in relation to these systems for the automation of tasks and OSH.

AI-based systems and advanced robotics are not entirely new, however, the extraordinary increase in computational power within the last years has fostered a tremendous increase in the availability and performance of AI-based applications. The effects of technological changes on opportunities and challenges for OSH have always accompanied technology evolution. Yet, AI-based systems and advanced robotics used for the automation of tasks hold the potential for a qualitative shift in opportunities and challenges for OSH or even the creation of entirely new benefits and risks. Regarding the definitions of such systems, it has to be noted that the picture is quite heterogeneous. There is no unified and conclusive definition of AI-based systems for the automation of tasks. Consequently, we have developed a taxonomy taking into account a task approach, high-level definitions of AI-based systems and technology characteristics. It includes a differentiation of system capabilities in relation to analysing their environments and performing actions. Further, it takes task characteristics into account and the aspects of (semi-) automation of these tasks. Finally, the taxonomy includes a categorisation of OSH dimensions. This overall taxonomy serves as a basis and framework for the further structuring of results and project objectives. OSH challenges and opportunities will be analysed throughout EU-OSHA's forthcoming reports, "Artificial Intelligence and automation of cognitive tasks: Implications for occupational safety and health" and "Robots, cobots and Artificial Intelligence for the automation of physical tasks: Implications for occupational safety and health".

Regarding the automation of **cognitive tasks**, the analysis of scientific literature as well as the in-depth expert interviews reveal that elaborate software systems in the field of decision support systems and pattern recognition, especially in **speech and language based tasks**, dominate the field. AI-based systems for the automation of cognitive tasks are most frequently found in the sector of **human health and social work activities**, especially in the field of **medicine**. There are strong digitalisation movements in this sector, however, a slight overrepresentation due to a publication bias in scientific medical literature should not be neglected. One reason for this publication bias might result from the fact that this sector does hold some fields which have been less prone to digitalisation in the past. This kind of overrepresentation of a specific sector might overshadow contributions of other industries with a less prominent focus on scientific publications as they sometimes are further away from the scientific community or less inclined to publicising their working methods, possibly due to industry secrecy. Hence, it is important to not uncritically inflate the quantity of publications, the impact and involvement a technology is having in a specific sector. With relation to special tasks, it becomes clear that especially **information-based tasks** show high potential for the use of AI-based systems. Very frequently the task of **providing a medical diagnosis** is supported. Additionally, a variety of **communication tasks** are supported or substituted by AI-based systems. This can range from a short dialogue in order to give information on a pre-defined setting to more complex translation tasks. AI-based systems show high performance in the processing and output generation of any kind of speech and language data. Therefore, the use of natural language processing and conversational agents are frequently found. Furthermore, the use of **robotic systems for the automation of cognitive** tasks, information- and person-related is striking. These systems can be found supporting **learning**, **services tasks** and **therapeutic actions** like supporting therapy commitment.

Regarding the automation of **physical tasks**, a variety of robotic applications can be found. Especially within the **manufacturing** sector, there has been a long history with the applications of robotic systems for a number of object-related tasks like **lifting**, **assembling**, **welding** or **painting**. This is also clearly pointed out by the ESENER-3 data and followed by the sectors **wholesale and retail trade; repair of motor vehicles and motorcycles**. The ESENER-3 data does not provide any deeper insights into what types of robotic systems are used in the different enterprises. However, as this sector includes warehousing tasks, in the area of wholesale, the answers could refer to **mobile robots** or **autonomous vehicles** used for **transportation** tasks. Within scientific literature, this sector is closely linked to **transportation and storage** as some studies differentiate less between sectors and focus more on the specific system.

Furthermore, scientific literature as well as the experts' consultation both reveal a broad application of robotic systems also in the sector of **human health and social work activities**, although this sector is not very strongly represented in the ESENER-3 data. Within this sector, but not exclusively, the tasks of **lifting**, or more general **movement support** in any way, **transportation** or **cleaning** are mostly supported or substituted by advanced robotics or exoskeletons. Regardless of the specific sector, the results indicate that **routine tasks** are the most affected by AI-based systems and advanced robotics. However, the more complex AI-methods are integrated into a specific system, the more it is capable of dealing with unstructured physical or digital environments, meaning the less the aspect of codifiable tasks is an issue.

On a European level, most strategies, campaigns or initiatives mainly address broad requirements that AI in general should meet and present principles that potential AI frameworks or regulation should be based on. Yet, they differ slightly in their objectives. Most initiatives explicitly direct a plea, for example, towards policy-makers or system designers. This is the case for the five OECD principles or the seven EU Commission key requirements for trustworthy AI, as well as for the key dimension brought forward by ETUI and the European Social Partners Framework Agreement on Digitalisation. The OECD AI-observatory further provides a platform for different AI-related activities and evidence-based analysis in a dashboard format. Initiatives on the topic of AI-based systems by the unions as well as the EU commission explicitly address the issue of regulation. The contrasting view is brought forward by the employer side, which states for example that less regulation holds greater potential for successful adaptation of advanced robotics. However, what becomes obvious, when analysing the different activities on a European level are a number of shared values which can be found among them. **Data privacy**, **fairness**, and **accountability** are commonly addressed by different stakeholders. The principle of **transparency** and the principle of the **human being in control or preserving workers' autonomy** are the most striking aspects named by the different stakeholders. The latter (human in control / preserving autonomy) is addressed within the principles presented by the EU Commission, ETUC, ETUI as well as in the European Social Partners Framework Agreement on Digitalisation. These values and principles are to some extent related to OSH, especially to psychosocial risks and will therefore be investigated with priority in further actions of this project. The ongoing discourse has resulted in the very recently launched proposal for the Artificial Intelligence Act: the proposal for a horizontal regulation on European level is now under discussion.

On a national level, nearly every country reports some form of not legally binding activity related to AI-based systems and advanced robotics. Within the European countries, a vast number of sectoral programmes, social partner's guidelines or recommendations given by major stakeholders or the state can be found. Nevertheless, most countries also report to be missing activities regarding the application of legally binding activities. This can be seen as a striking result, as it strongly indicates moving in the direction of what is often referred to as a 'knowing-doing gap' or as a gap between the provision of relevant knowledge through initiatives, programmes or recommendations and their actual practical use and application. An important measure towards increasing the enforcement of legally binding activities is the inclusion of labour inspectors who have the necessary specialised knowledge on AI-based systems and the legal landscape around them. On a more global level, there are large numbers of campaigns, actions, strategies and visions. As the issue becomes more specific, related to specific industries, jobs or tasks, the picture becomes blurry, for example, with regards to specific system or workplace design recommendations. However, some activities can be considered as good examples linking relevant stakeholders and knowledge. This has also been pointed out by the experts. They further consider that raising awareness is particularly important, and policy-makers can have an important role in bringing this to attention. Information should be provided about psychosocial, physical and organisational risks. Equipping employers and managers with adequate information about the implications on OSH regarding the use of advanced robotics and AI-based systems for the automation of tasks as well as with tools to avoid potential risks is important.

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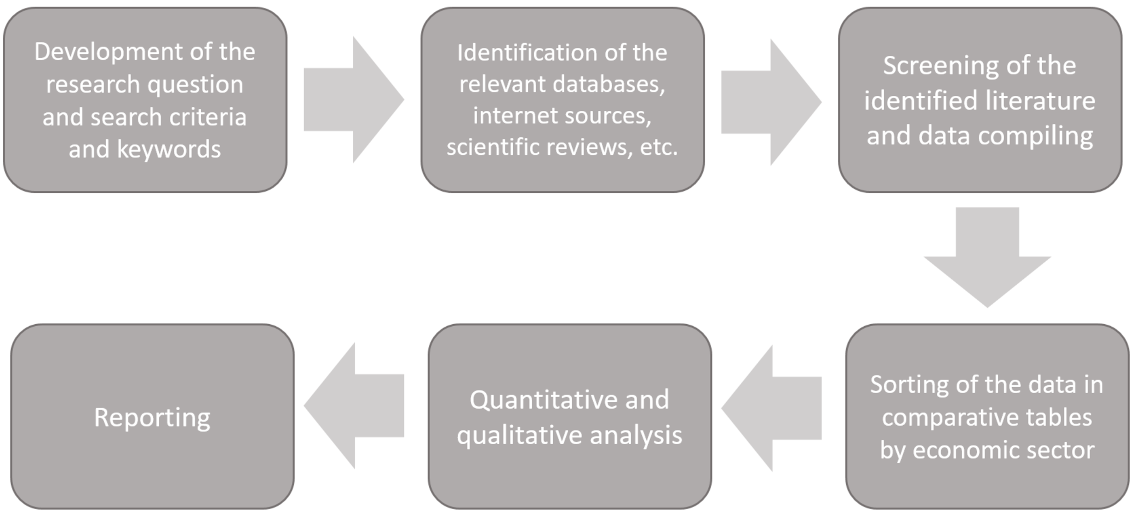
8 ANNEX

8.1 Detailed methodology systematic literature reviews

While grey literature was mainly used for the analysis of policies, strategies, programmes and initiatives as well as to derive theoretical definitions of AI-based systems leading to a project specific framework, the current state of research is based on three systematic literature reviews. To identify the current state of research regarding AI-based systems for the automation of tasks, we conducted three separate systematic literature searches. The first addressed AI-based systems, the second addressed advanced robotics, and more precisely human-robot interaction, and the third addressed the automation of tasks. The methodological approach was identical for all three searches and will be described in the following section. All three searches focused on high quality scientific publications (such as systematic literature reviews and meta-analyses) and were identified by a structured search process in selected established databases.

Based on previous work experience, the goal was not to apply a too complex search string to begin with, but rather to yield a broad range of studies with a more generic search string. Therefore, we decided to first search for the general topic and screen for OSH-related content manually. Furthermore, some papers include OSH topics but do not feature them as a main keyword. Therefore, a more generalised search string allowed us to capture more results. Non-applicable results were removed in the following steps of the review process. Figure 8 presents the overall procedure for all three systematic literature searches.

Figure 8: Procedure for the systematic literature searches



Source: Author

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").

For advanced robotics, the following search string was applied in the databases:

("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").

For automation of tasks (AOT), the following search string was applied in the databases:

("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").

It has to be noted that for more distinct results the additive phrase *"systematic literature review" / "meta-analysis"* was split, so that effectively two separate searches per topic were conducted. The results are depicted separately below.

All publications were screened on title, keyword and abstract basis. Included references were then analysed on full-text level. For the screening process as well as for the full-text analysis, the inclusion and exclusion criteria presented in Table 1 were used to determine the final sample to be included in the analysis.

Table 1: Inclusion and exclusion criteria for the literature searches

Primary content criteria	To be included into the continuous analysis, the abstract or full-text needed to address the topics of interest (HRI or AI) in the context of human involvement or impact. This means that a human had to be directly or indirectly impacted by the system. At this stage, there is no strict focus on work-related context yet. All publications meeting this criterion were included in the identification of the remaining four areas of interest.
OSH implications	Each paper that was eligible was then screened for any direct or indirect OSH implications. This differentiation is important, since only a few papers directly assess these impacts, but there are valuable insights to be gained by extracting information from indirect implications. To give an example to further understand this criterion, a paper assessing factors affecting trust in a system does not contain any direct implications regarding OSH. However, as literature shows, trust is a vital factor when it comes to using technology correctly and experiencing the benefits (such as improved cognitive workload, less stress, etc.) from it.
Language	The literature review focused on articles published in English.
Quality of publication	Papers had to be a published systematic review or meta-analysis of substantial quality (e.g., peer reviewed).

On full-text level, the publications were analysed regarding the *description of tasks*, the description of the *specific working context*, the *addressed sector*, the *type of technology* and *OSH implications* and coded. Studies were also included if a specific job (associated with a specific task) was affected by the technology in a secondary way. While, for example, a teacher does not primarily use artificial intelligence applications for students' vocabulary training, their job/task is impacted by the technology. Often mobility assistive robots in elderly care are explored from the users' perspective. However, the caregiver's job is also directly affected. While these kind of papers often do not yield any direct implications for OSH, they are vital to assess the accurate range of our four areas of interest *technology*, *job affected by the technology*, *task* or *sector.* This allowed us to more accurately describe the nuanced research landscape.

The analysis of existing use cases or planned use cases, especially for intelligent robots, will provide a mapping of current and potential future uses of these systems. Several sectors emerged based on the search results, indicating areas of interest as well as acute research gaps.

8.2 Detailed review results

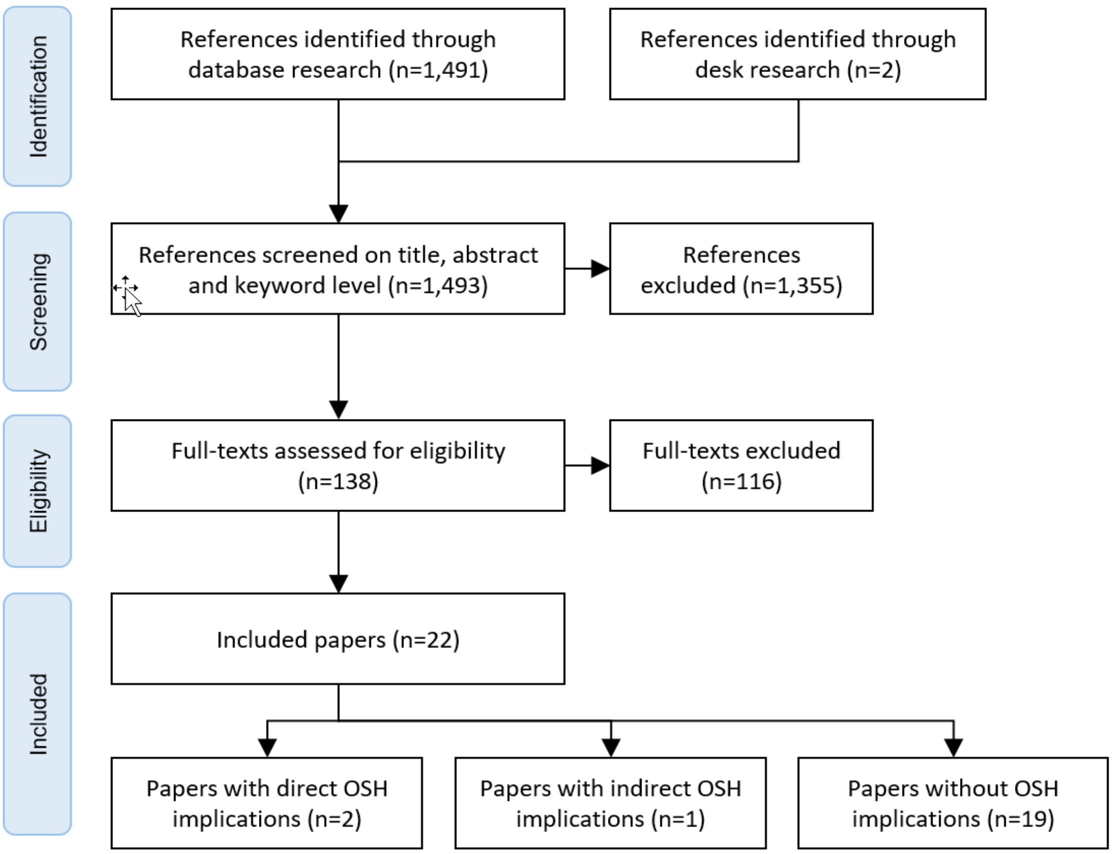
In the following sections, further details of the systematic literature search are provided. This includes systematic review and meta-analyses results for artificial intelligence, human-robot interaction and automation of tasks.

For each paper, available information on the type of technology, the sector based on the 21 main categories of the NACE Rev. 2.0 (Nomenclature of Economic Activities) code to which the use-cases can be assigned, as well as the task and the job affected by the technology were extracted and mapped. It has to be noted that not every study provided detailed information on each area of interest, as it is in the nature of reviews and meta-analyses to combine data from a great variety of sources. In a final step, possible direct or indirect OSH implications were extracted and coded for use in EU-OSHA's forthcoming reports, "Artificial Intelligence and automation of cognitive tasks: Implications for occupational safety and health" and "Robots, cobots and Artificial Intelligence for the automation of physical tasks: Implications for occupational safety and health".

8.2.1 AI-based systems

Regarding artificial intelligence, a total of 33 studies were screened for the interest areas (22 systematic literature reviews, 11 meta-analyses). There were 4 papers that included direct or indirect implications regarding OSH (3 systematic literature reviews, 1 meta-analysis). The included systematic reviews and meta-analyses are listed in section 8.3. 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. It has to be noted that some of the same primary papers might be included in several systematic reviews and/or meta-analyses. The original search string yielded 1,493 systematic literature reviews that were screened and analysed as shown in Figure 9.

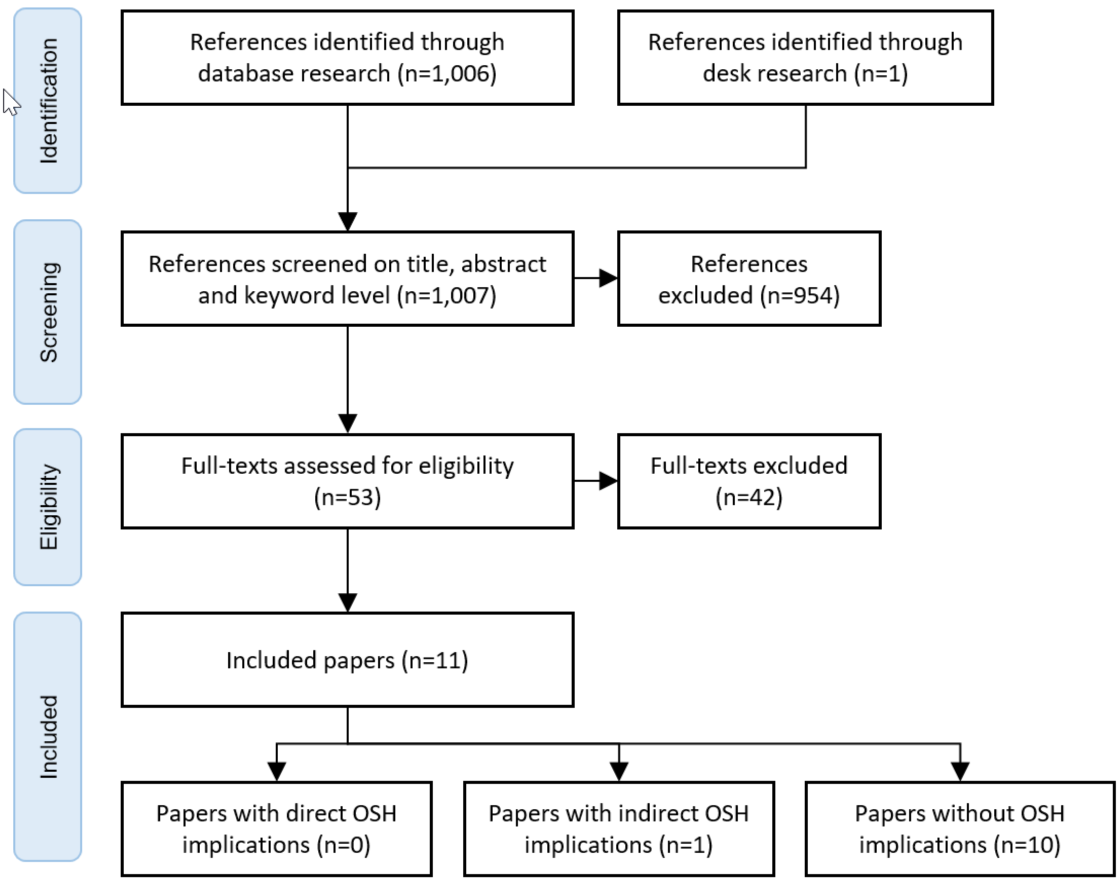
Figure 9: Overview of selection process for systematic reviews on AI-based systems



Source: Author

The original search string further yielded 1,007 meta-analyses that were then screened and analysed too (see figure 10).

Figure 10: Overview of selection process for meta-analyses on AI-based systems

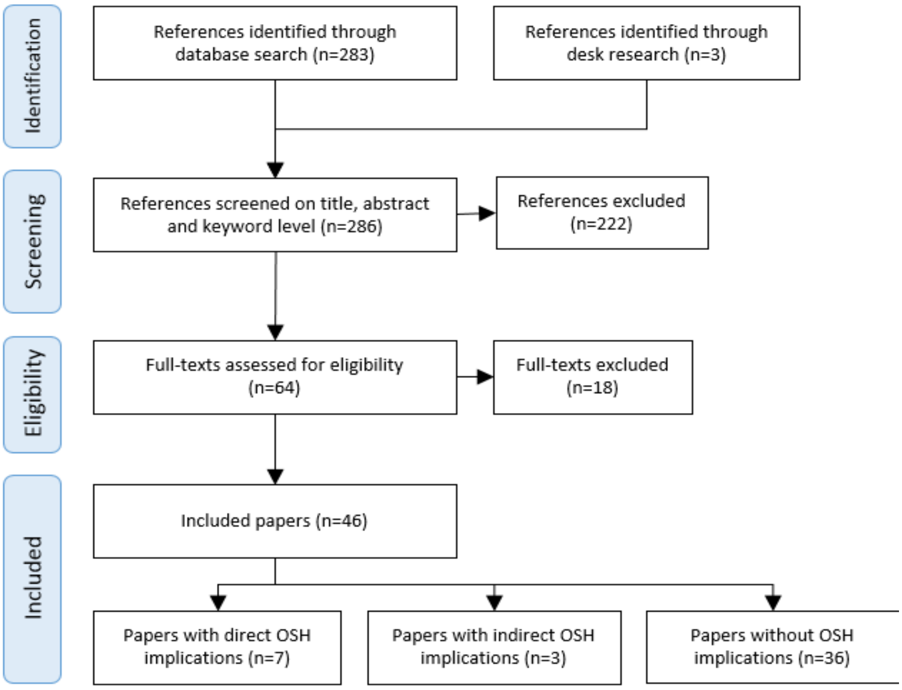


Source: Author

8.2.2 Human-robot interaction

Regarding advanced robotics literature, a total of 57 studies were screened for their areas of interest (46 systematic literature reviews and 11 meta-analyses). There were 16 papers that included direct or indirect implications regarding OSH (10 systematic reviews and 6 meta-analyses). The included systematic reviews and meta-analyses are listed in section 8.3. While the systematic reviews covered around 1,844 primary publications, the meta-analysis covered 343. It has to be noted that some of the same primary papers might be included in several systematic reviews and/or meta-analyses. The original search string yielded 286 systematic literature reviews that were screened and analysed as shown in figure 11.

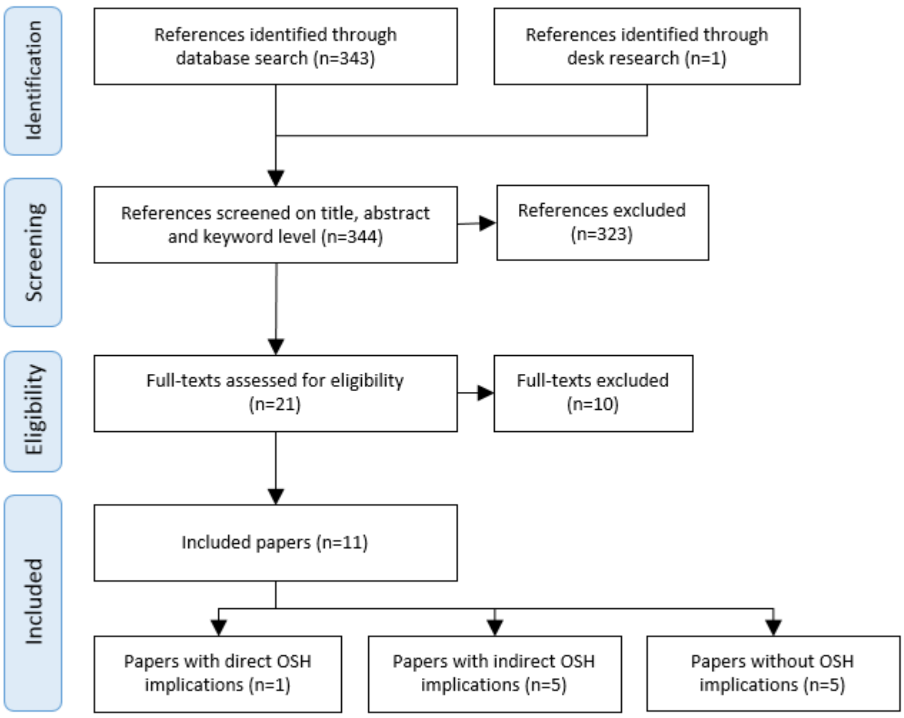
Figure 11: Overview of selection process for systematic reviews on HRI



Source: Author

The original search string further yielded 344 meta-analyses that were then screened and analysed too (see figure 12).

Figure 12: Overview of selection process for meta-analyses on HRI

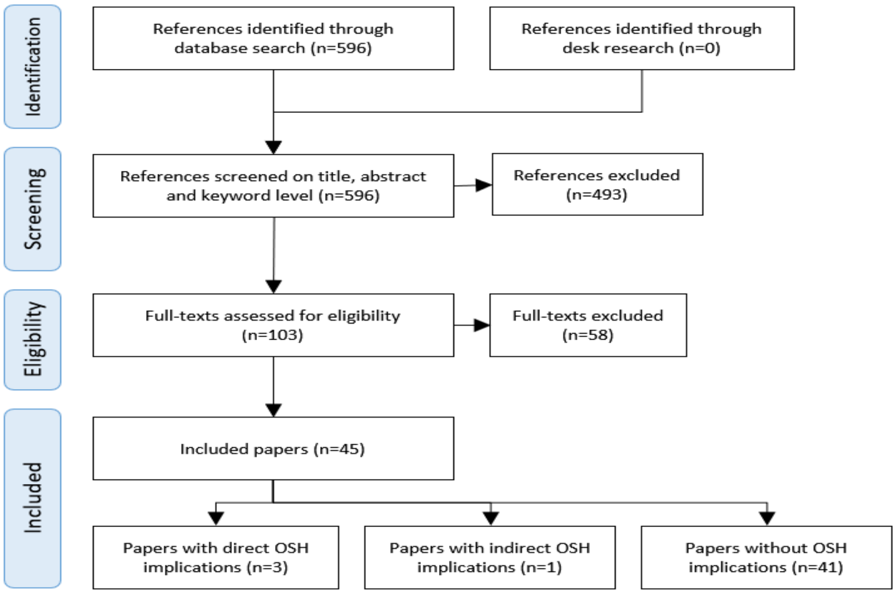


Source: Author

8.2.3 Automation of tasks (AOT)

While the selection criteria stayed largely consistent with the other two reviews, some key changes were made to improve the final result. As automation of tasks is a much more diverse field of research compared to a specific technology, an interaction between human and system could not be used as a selection criteria. Secondly, to increase the focus on OSH, and the impact of task automation in that context, the automation had be impactful/meaningful to the result and not only a method used in the paper. All papers needed to contain a tangible task, performed by a described technology in a work-related or relatable context. The original search string yielded 596 systematic literature reviews that were screened and analysed as shown in figure 13.

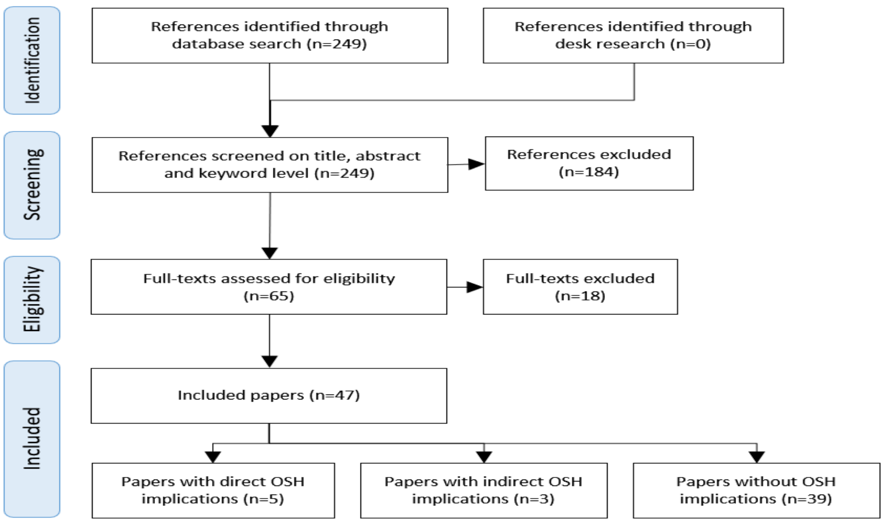
Figure 13: Overview of selection process for systematic reviews on AOT



Source: Author

The original search string further yielded 249 meta-analyses that were screened and analysed as shown in figure 14.

Figure 14: Overview of selection process for meta-analyses on AOT



Source: Author

8.3 Overview of analysed studies

Included systematic reviews for artificial intelligence

Author	Year	Title	Number of base studies	Type of AI	Job affected by the system	Task	NACE sector	OSH implications
de Almeida et al.	2015	A systematic literature review of multicriteria and multi-objective models applied in risk management	263	DSS	n/s	Risk Assessment	Information and Communication	No
Anjomshoae et al.	2019	Explainable Agents and Robots: Results from a Systematic Literature Review	62	XAI	n/s	n/s	n/s	No
Aslam et al.	2017	Decision Support System for Risk Assessment and Management Strategies in Distributed Software Development	80	DSS	Team Lead (IT)	Decision Support in Group Dynamics	Information and Communication	Yes
Bavaresco et al.	2020	Conversational agents in business: A systematic literature review and future research directions	n/s	Chatbot	Customer Support	Communication	Information and Communication	No
Choudhury et al.	2020	Role of Artificial Intelligence in Patient Safety Outcomes: Systematic Literature Review	53	DSS	Medical Health Professionals	Decision Support in Medical Fields	Human Health and Social Work Activities	No
Cioffi et al.	2020	Artificial Intelligence and Machine Learning Applications in Smart Production: Progress, Trends, and Directions	82	MLA	Industrial Workers	n/s	Manufacturing	No
de Cock et al.	2020	Effectiveness of Conversational Agents (Virtual Assistants) in Health Care: Protocol for a Systematic Review	n/s	Chatbot	Medical Health Professionals	Communication	Human Health and Social Work Activities	No

Author	Year	Title	Number of base studies	Type of AI	Job affected by the system	Task	NACE sector	OSH implications
Cresswell et al.	2020	Investigating the use of data-driven artificial intelligence in computerised decision support systems for health and social care: A systematic review	5	DSS	Medical Health Professionals	Decision Support in Medical Fields	Human Health and Social Work Activities	No
Davidson et al.	2020	Enabling pregnant women and their physicians to make informed medication decisions using artificial intelligence	31	DSS	Medical Health Professionals	Decision Support in Medical Fields	Human Health and Social Work Activities	No
Federici et al.	2020	Inside pandora's box: a systematic review of the assessment of the perceived quality of chatbots for people with disabilities or special needs	15	Chatbot	Caretakers, Medical Health Professionals	Skill Training	Human Health and Social Work Activities	No
El Kamali et al.	2020	Virtual Coaches for Older Adults' Wellbeing: A Systematic Review	56	E-Coach	Coaches, Mental Health Professionals, Medical Health Professionals	n/s	Human Health and Social Work Activities	No
Papadopoulos et al.	2020	A systematic review of the literature regarding socially assistive robots in pre-tertiary education	21	MLA (in robots)	Teachers	Learning Support	Education	No
Pombo et al.	2014	Knowledge discovery in clinical decision support systems for pain management: A systematic review	32	DSS	Medical Health Professionals	Decision Support in Medical Fields	Human Health and Social Work Activities	No
Rheu et al.	2020	Systematic review: Trust-building factors and implications for conversational agent design	29	Chatbot	n/s	Communication	Information and Communication	Yes
dos Santos Brito et al.	2020	Evolution of the Web of Social Machines: A Systematic Review and Research Challenges	56	Social Machines	n/s	Administrative Tasks	Administrative and Support Service Activities	No

Author	Year	Title	Number of base studies	Type of AI	Job affected by the system	Task	NACE sector	OSH implications
Schroeder & Adesope	2014	A Systematic Review of Pedagogical Agents' Persona, Motivation, and Cognitive Load Implications for Learners	n/s	Pedagogical Agents	Teachers	Learning Support	Education	No
Shanmathi et al.	2018	Computerised Decision Support System for Remote Health Monitoring: A Systematic Review	52	DSS	Medical Health Professionals	Decision Support in Medical Fields	Human Health and Social Work Activities	No
Sarkar et al.	2020	Machine learning in occupational accident analysis: A review using science mapping approach with citation network analysis	232	MLA	n/s	Risk Assessment	n/s	Yes
Triantafyllidis et al.	2020	Computerized decision support and machine learning applications for the prevention and treatment of childhood obesity: A systematic review of the literature	8	DSS	Medical Health Professionals, Dietician	Dietary Decision Support	Human Health and Social Work Activities	No
Vaca-Cardenas et al.	2020	Trends and Challenges of HCI in the New Paradigm of Cognitive Cities	51	n/s	City Planner, Administrative Positions	n/s	Administrative and Support Service Activities	No
Xie et al.	2020	Artificial Intelligence for Caregivers of Persons with Alzheimer's Disease and Related Dementias: A Systematic Literature Review	30	n/a	Caretakers, Medical Health Professionals	Living Assistance	Human Health and Social Work Activities	No
Yang et al.	2019	Artificial Intelligence in Intelligent Tutoring Robots: A Systematic Review and Design Guidelines	n/s	ITR	Teachers	Learning Support	Education	No

Included meta-analyses for artificial intelligence

Author	Year	Title	Number of base studies	Type of AI	Job affected by the system	Task	NACE sector	OSH implications
du Boulay	2016	Artificial Intelligence as an Effective Classroom Assistant	264	AIEDS (ITS)	Teachers	Learning Support	Education	No
Davis	2018	The impact of pedagogical agent gesturing in multimedia learning environments: A meta-analysis	20	Pedagogical Agents	Teachers	Learning Support	Education	No
Gholamian et al.	2007	Meta knowledge of intelligent manufacturing: An overview of state-of-the-art	n/s	n/a	Industrial workers	n/s	Manufacturing	No
Israelsen et al.	2020	Machine Self-confidence in Autonomous Systems via Meta-analysis of Decision Processes	n/s	n/a	n/s	Performance Evaluation	n/s	No
Moja et al.	2019	Effectiveness of computerized decision support systems linked to electronic health records: A systematic review and meta-analysis	28	DSS	Medical Health Professionals	Decision Support in Medical Fields	Human Health and Social Work Activities	No
Nesbit et al.	2014	How Effective are Intelligent Tutoring Systems in Computer Science Education?	50	ITS	Teachers	Learning Support	Education	No
Schroeder et al.	2013	How Effective are Pedagogical Agents for Learning? A Meta-Analytic Review	43	Pedagogical Agents	Teachers	Learning Support	Education	No
Sottilare et al.	2018	Designing Adaptive Instruction for Teams: a Meta-Analysis	300	ITS	Teacher, Coaches	Learning Support	Education	Yes
Valle-Cruz et al.	2018	Towards an Understanding of Artificial Intelligence in Government	69	n/a	Administrative Positions	Decision Support in Planning	Public Administration and Defence	No

Author	Year	Title	Number of base studies	Type of AI	Job affected by the system	Task	NACE sector	OSH implications
Vogel et al.	2017	Socio-cognitive scaffolding with Computer-Supported Collaboration Scripts: A meta-analysis	22	CSCL	Teacher	Learning Support	Education	No
Xu et al.	2014	The effectiveness of intelligent tutoring systems on K-12 students' reading comprehension: A meta-analysis	19	ITS	Teacher	Learning Support	Education	No

Included systematic reviews for human-robot interaction

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE aector	OSH implications
Ahmad et al.	2017	A systematic review of adaptivity in human-robot interaction.	37	Social Robots	n/s	Social Interaction	Human Health and Social Work Activities, Education	No
Anjomshoae et al.	2019	Explainable Agents and Robots: Results from a Systematic Literature Review Robotics Track	71	XAI-Robot Agents	n/s	n/s	Other	No
Anwar et al.	2019	A Systematic Review of Studies on Educational Robotics	147	Educational Robots	Teachers	Learning Support	Education	No
Basteris et al.	2014	Training modalities in robot-mediated upper limb rehabilitation in stroke: a framework for classification based on a systematic review	74	Medical Robots	Medical Health Professionals	Movement Support Lifting	Human Health and Social Work Activities	No
Begum et al.	2019	Are Robots Ready to Deliver Autism Interventions? A Comprehensive Review	20	n/s	Medical Health Professionals	n/s	Human Health and Social Work Activities	No
Bemelmans et al.	2012	Socially Assistive Robots in Elderly Care: A Systematic Review into Effects and Effectiveness	17	Social Bots	Caregivers	Social Interaction	Human Health and Social Work Activities	No

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE aector	OSH implications
Billings et al.	2012	Human-animal trust as an analog for human-robot trust: A review of current evidence	21	n/s	n/s	n/s	Other	No
Cai et al.	2019	Construction automation and robotics for high-rise buildings over the past decades: A comprehensive review	n/s	n/s	Construction Worker	n/s	Construction	No
Charisi et al.	2016	Evaluation methods for user-centered child-robot interaction	135	n/s	Teachers	Social Interaction	Other	No
Cheng et.al.	2018	The essential applications of educational robot: Requirement analysis from the perspectives of experts, researchers and instructors	n/s	n/s	Teacher	Learning Support	Education	No
Clabaugh & Mataric	2019	Escaping Oz: Autonomy in Socially Assistive Robotics	n/s	Social Bots	Medical Health Professionals, Mental Health Professionals, Teachers	Social Interaction	Human Health and-Social Work Activities	No
Dobra & Dhir	2020	Technology jump in the industry: human–robot cooperation in production	n/s	Industrial Robots	Industrial Workers	n/s	Manufacturing	No
Erich et.al.	2017	A Systematic Literature Review of Experiments in Socially Assistive Robotics using Humanoid Robots	16	NAO, etc.	n/s	Social Interaction	Other	No
Góngora et al.	2019	Social robots for people with aging and dementia: a systematic review of literature	38	Social Bots	Caregivers, Medical Health Professionals	Social Interaction	Human Health and Social Work Activities	No
Gualtieri et al.	2021	Emerging research fields in safety and ergonomics in industrial collaborative robotics: A systematic literature review	9	Industrial Robots	Industrial Workers	n/s	Manufacturing	No

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE aector	OSH implications
Hein & Nathan-Roberts	2018	Socially Interactive Robots Can Teach Young Students Language Skills; a Systematic Review	17	Educational Robots	Teachers	Learning Support	Education	No
Heineck et al.	2016	Model-Driven Development in Robotics Domain: A Systematic Literature Review	71	n/s	n/s	n/s	Other	No
Honig & Oron-Gilad	2019	Understanding and resolving failures in human-robot interaction: Literature review and model development	52	n/s	n/s	n/s	Other	Yes
Honig et al.	2018	Toward Socially Aware Person-Following Robots	107	Mobile Robots	n/s	Moving / Transport	Transportation and Storage	Yes
Kachoule et al.	2014	Socially Assistive Robots in Elderly Care: A Mixed-Method Systematic Literature Review	37	Social Bots	Caregivers	Social Interaction	Human Health and Social Work Activities	Yes
Kadir et al.	2019	Current research and future perspectives on human factors and ergonomics in Industry 4.0	n/s	Industrial Robots	Industrial Workers	n/s	Manufacturing	Yes
Lambert et al.	2020	A Systematic Review of Ten Years of Research on Human Interaction with Social Robots	86	Social Bots	n/s	Social Interaction	Other	Yes
Liu et al.	2020	Design and control of soft rehabilitation robots actuated by pneumatic muscles: State of the art	n/s	Medical Robots	Medical Health Professionals	Movement Support Lifting	Human Health and-Social Work Activities	No
Lopez et al.	2019	Walking Turn Prediction from Upper Body Kinematics: A Systematic Review with Implications for Human-Robot Interaction	24	Mobile Robots	n/s	n/s	Other	No
Lu et al.	2019	Service robots, customers and service employees: what can we learn from the academic literature and where are the gaps?	20	Service Robots	Service Workers	Service Work	Other Service Activities	Yes

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE aector	OSH implications
Mavridis	2015	A review of verbal and non-verbal human–robot interactive communication	n/s	n/s	n/s	Communication	Other	No
Mou et al.	2020	A Systematic Review of the Personality of Robot: Mapping Its Conceptualization, Operationalization, Contextualization and Effects	40	n/s	n/s	Social Interaction	Other	No
Naneva et al.	2020	A systematic review of attitudes, anxiety, acceptance, and trust towards social robots	97	n/s	n/s	n/s	Other	No
Nelles et al.	2019	Evaluation Metrics Regarding Human Well-Being and System Performance in Human-Robot Interaction - A Literature Review	25	n/s	n/s	n/s	Other	Yes
Ona et al.	2019	Robotics in Health Care: Perspectives of Robot-Aided Interventions in Clinical Practice for Rehabilitation of Upper Limbs	28	Medical Robots	Medical Health Professionals	Movement Support	Human Health and Social Work Activities	No
Panda & Saxena	2016	An insight to multi-tasking in cognitive robotics	25	Industrial Robots	n/s	Task Switching	Other	No
Papadopoulos et al.	2020	A systematic review of the literature regarding socially assistive robots in pre-tertiary education	21	Social Bots	Teacher	Learning Support	Education	No
Prewett et al.	2010	Managing workload in human–robot interaction: A review of empirical studies	113	n/s	Operator	n/s	Manufacturing	Yes
Prewett et al.	2010	Workload in Human-Robot Interaction: A Review of Manipulations and Outcomes	18	Single Robot Task	Teleoperators	n/s	Other	Yes
Rauch et al.	2020	Anthropocentric perspective of production before and within Industry 4.0	58	Industrial Robots	Industrial Workers	n/s	Manufacturing	Yes

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE aector	OSH implications
Robert	2018	Personality in the human robot interaction literature: A review and brief critique.	53	n/s	n/s	n/s	Other	No
Santamaria & Nathan-Roberts	2017	Personality Measurement and Design in Human-Robot Interaction: A Systematic and Critical Review	35	n/s	n/s	Social Interaction	Other	No
Schulz et al.	2019	Animation techniques in human-robot interaction user studies: a systematic literature review.	27	n/s	n/s	n/s	Other	No
Shishehgar et al.	2018	A systematic review of research into how robotic technology can help older people	58	n/s	Caregiver, Medical Health Professionals	n/s	Human Health and Social Work Activities	No
Tussyadiah	2020	A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism	n/s	n/s	Travel Agents	n/s	Other Service Activities	No
Vandemeulebroucke et al.	2018	How do older adults experience and perceive socially assistive robots in aged care: a systematic review of qualitative evidence	23	Social Bots	Caregivers	Social Interaction	Human Health and Social Work Activities	No
Vogan et al.	2020	Robots, AI, and Cognitive Training in an Era of Mass Age-Related Cognitive Decline: A Systematic Review	11	NAO, PARO	Caregivers	Social Interaction	Human Health and Social Work Activities	No
Werner et al.	2018	A systematic review of study results reported for the evaluation of robotic rollators from the perspective of users	17	Robotic Rollators	Caregivers, Medical Health Professionals	Movement Support Walking	Human Health and Social Work Activities	No
Werner et al.	2016	Evaluation Studies of Robotic Rollators by the User Perspective: A Systematic Review	28	Robotic Rollators	Caregivers, Medical Health Professionals	Movement Support Walking	Human Health and Social Work Activities	No
Zafrani et al.	2019	Towards a holistic approach to studying human–robot interaction in later life	80	n/s	Caregivers	Social Interaction	Human Health and Social Work Activities	No

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE aector	OSH implications
Zhong & Xia	2020	A Systematic Review on Exploring the Potential of Educational Robotics in Mathematics Education	20	LEGO Robots	Teachers	Learning Support	Education	No

Included meta-analyses for human-robot interaction

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE aector	OSH implications
Hancock et al.	2011	A Meta-Analysis of Factors Affecting Trust in Human-Robot Interaction	29	n/s	n/s	n/s	Other	Yes
Hancock et al.	2020	Evolving Trust in Robots: Specification Through Sequential and Comparative Meta-Analyses	48	n/s	n/s	n/s	Other	Yes
Leichtmann et al.	2020	How much distance do humans keep toward robots? Literature review, meta-analysis, and theoretical considerations on personal space in human-robot interaction	27	Mobile Robots	n/s	n/s	Other	No
Oleson et al.	2011	Antecedents of trust in human-robot collaborations	34	n/s	Public Defence Worker/ Military	n/s	Public Administration and Defence	No
Ötting et al.	2010	My workmate the robot: A meta-analysis on Human-Robot Interaction at the workplace	50	n/s	n/s	n/s	Other	Yes
Ötting et al.	2021	Let's Work Together: A Meta-Analysis on Robot Design Features That Enable Successful Human-Robot Interaction at Work	80	n/s	n/s	n/s	Other	Yes
Sanders et al.	2011	A Model of Human-Robot Trust: Theoretical Model Development	12	n/s	n/s	n/s	Other	Yes

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE aector	OSH implications
Schaefer et al.	2016	A meta-analysis of factors influencing the development of trust in automation: Implications for understanding autonomy in future systems	30	n/s	n/s	n/s	Other	Yes
Schiffeler et al.	2018	Fostering social construction of knowledge in hybrid teams by augmented reality	n/s	n/s	n/s	n/s	Other	No
Swangnetr et al.	2010	Meta-analysis of user age and service robot configuration effects on human-robot interaction in a healthcare application.	2	n/s	Medical Health Professionals	Medical Support	Human Health and Social Work Activities	No
Zheng et al.	2019	Robot-assisted therapy for balance function rehabilitation after stroke: A systematic review and meta-analysis	31	n/s	Medical Health Professionals	Movement Support	Human Health and Social Work Activities	No

Included systematic literature reviews for automation of tasks

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE sector	OSH implications
Abbe et al.	2016	Text mining applications in psychiatry: a systematic literature review	38	Artificial Intelligence: Text Mining	Mental Health Professionals	Text Mining	Human Health and Social Work Activities	No
Ali et al.	2020	Automatic Release Notes Generation: A Systematic Literature Review	9	Artificial Intelligence: Various Algorithms	Software Engineers	Generate Release Notes	Professional, Scientific and Technical Activities	No
Ali et al.	2020	A Systematic Review of the Application and Empirical Investigation of Search-Based Test Case Generation	68	Metaheuristic Search Techniques	Software Engineers	Automate the Process of Generating Test Cases	Professional, Scientific and Technical Activities	No

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE sector	OSH implications
Altaf et al.	2020	BIM Implication of Life Cycle Cost Analysis in Construction Project: A Systematic Review	24	Artificial Intelligence: Building Information Modelling	Administrators	Life Cycle Cost Analysis	Construction	No
Batouta et al.	2016	Automation in code generation: Tertiary and systematic mapping review	103	Automated Software: Automatic Code Generation Tool	Software Engineers	Code Generation	Professional, Scientific and Technical Activities	No
Beer et al.	2020	The Effects of Technological Developments on Work and Their Implications for Continuous Vocational Education and Training: A Systematic Review	21	Various	Mixed	Mixed	Mixed	Yes
Butler-Henderson & Crawford	2020	A systematic review of online examinations: A pedagogical innovation for scalable authentication and integrity	36	Automated Software: Online Examination Tools	Teachers	Online Examinations	Education	No
Clark et al.	2020	A full systematic review was completed in 2 weeks using automation tools: a case study	34	Automated Software: Systematic Review Automation Tools	Researchers	Data Extraction and Organisation	Professional, Scientific and Technical Activities	No
Deeva et al.	2021	A review of automated feedback systems for learners: Classification framework, challenges and opportunities	n/s (109 system outputs)	Automated Software: Feedback Systems	Teachers	Giving Feedback to Students	Education	No
Desgagne-Lebeuf et al.	2020	Scheduling tools for the construction industry: overview and decision support system for tool selection	38	Scheduling Tools (DSS)	Construction Managers	Scheduling	Construction	No
Dwivedi et al.	2019	Algorithms for Automatic Analysis and Classification of Heart Sounds–A Systematic Review	117	Artificial Intelligence: Wearable Cardiac Monitor	Medical Health Professionals	Medical Diagnosis/ Identification and Classification of the Heart Sounds	Human Health and Social Work Activities	No
Enríquez et al.	2020	Robotic Process Automation: A Scientific and Industrial Systematic Mapping Study	54	Robotic Systems	Manufacturers	Various	Manufacturing	No

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE sector	OSH implications
Dallora et al.	2019	Bone age assessment with various machine learning techniques: A systematic literature review and meta-analysis	26	Artificial Intelligence: Machine Learning Techniques	Medical Health Professionals	Medical Procedure/ Bone Marrow Analysis	Human Health and Social Work Activities	No
Garousi & Mantyla	2016	When and what to automate in software testing? A multi-vocal literature review	78	Automated Software: Software Testing Tools	Software Engineers	Software Testing	Professional, Scientific and Technical Activities	No
Galetsi et al.	2019	Values, challenges and future directions of big data analytics in healthcare: A systematic review	804	Decision Support Systems	Medical Health Professionals	Medical Decision Support	Human Health and Social Work Activities	No
Ghaouta et al.	2018	Big Data Analytics Adoption in Warehouse Management: A Systematic Review	64	Artificial Intelligence: Big Data Analysis	Other	Supply Chain Management	Administrative and Support Service Activities	No
Ghaleb et al.	2016	Automated analysis of flow cytometry data: a systematic review of recent methods	12	Artificial Intelligence: Clustering Algorithms	Researchers	Flow Cytometry (automated data analysis)	Professional, Scientific and Technical Activities	No
Goddard et al.	2012	Automation bias: a systematic review of frequency, effect mediators, and mitigators	74	Decision Support Systems	Medical Health Professionals	Medical Decision Support	Human Health and Social Work Activities	Yes
Golub et al.	2016	A Framework for Evaluating Automatic Indexing or Classification in the Context of Retrieval	15	Artificial Intelligence: Indexing Tools	Researchers	Automatic Classification/ Automatic Indexing	Professional, Scientific and Technical Activities	No
Govindan et al.	2010	Automated detection of harm in healthcare with information technology: a systematic review	43	Automated Software: Clinical Information Systems	Medical Health Professionals	Automated harm-detection methods	Human Health and Social Work Activities	No
Greenwood et al.	2018	Automated Language Environment Analysis: A Research Synthesis	53	Artificial Intelligence: Language Environment Analysis	Teachers	Automated Speech Analysis	Education	No

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE sector	OSH implications
Kong et al.	2019	Automated Testing of Android Apps: A Systematic Literature Review	103	Automated Software: Software Testing Tools	APP/Software Engineers	Automated Software Testing	Professional, Scientific and Technical Activities	No
Köpcke et al.	2014	Employing computers for the recruitment into clinical trials: a comprehensive systematic review	101	Clinical Trial Recruitment Support Systems (DSS)	Medical Health Professionals	Assessing Suitability for Medical Trials	Administrative and Support Service Activities	No
Lyell & Coiera	2017	Automation bias and verification complexity: a systematic review	40	Decision Support Systems	Medical Health Professionals	Medical Decision Support	Human Health and Social Work Activities	Yes
Marshall et al.	2016	Robot Reviewer: evaluation of a system for automatically assessing bias in clinical trials	n/s (12,808 trials)	Artificial Intelligence: Machine Learning Algorithms	(Clinical) Researchers	Bias Assessment	Professional, Scientific and Technical Activities, Human Health and Social Work Activities	Yes
Matwin et al.	2010	A new algorithm for reducing the workload of experts in performing systematic reviews	15	Artificial Intelligence: Fragmented Complement Naïve Bayes	(Pharmaceutical) Researchers	Literature Review	Professional, Scientific and Technical Activities	Yes
McDonald et al.	2019	Toward Computational Simulations of Behavior During Automated Driving Takeovers: A Review of the Empirical and Modeling Literatures	12	Artificial Intelligence: Automated Driving	Drivers	Driving Support	Transportation and Storage	Yes
McKechnie et al.	2018	Automated speech analysis tools for children's speech production: A systematic literature review	32	Automated Software: Speech Analysis Tools	Teachers	Automated Speech Analysis	Education	No
Milne-Ives et al.	2020	The Effectiveness of Artificial Intelligence Conversational Agents in Health Care: Systematic Review	31	Conversational Agents	Medical Health Professionals	Medical Support: Behaviour Change, Treatment Support, Health Monitoring, Training, Triage, and Screening Support	Human Health and Social Work Activities	No
Mohammed et al.	2020	The Perception System of Intelligent Ground Vehicles in All Weather Conditions: A Systematic Literature Review	n/s	Artificial Intelligence: Automated Driving	Others	Driving Support: Adaptive Cruise Control & Pedestrian Collision Avoidance	Transportation and Storage	No
Oña et al.	2018	A Review of Robotics in Neurorehabilitation: Towards an Automated Process for Upper Limb	30	Robotic Systems for Rehabilitation/ Exoskeletons	Medical Health Professionals	Movement Support	Human Health and Social Work Activities	No

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE sector	OSH implications
Papadimitriou et al.	2020	Transport safety and human factors in the era of automation: What can transport modes learn from each other?	74	Automated Transport Systems	Operators	Transport	Transportation and Storage	Yes
Patil & Agarkar	2019	Systematic Review of Data Mining based Recommendation Methods Reference to Business to Business (B2B) Recommendation	8	Recommender Systems (data mining)	Other	B2B Marketing	Other Service Activities	No
Rafi et al.	2012	Benefits and limitations of automated software testing: Systematic literature review and practitioner survey	25	Automated Software: Software Testing Tools	Software Engineers	Automated Software Testing	Professional, Scientific and Technical Activities	No
Sen et al.	2020	A Comprehensive Review of Work-Related Musculoskeletal Disorders in the Mining Sector and Scope for Ergonomics Design Interventions	98	Multiple	Mining Workers	Mixed	Mining and Quarrying	Yes
Shingleton & Palfai	2016	Technology-delivered adaptations of motivational interviewing for health-related behaviors: A systematic review of the current research	49	Multiple	Medical Health Professionals	Technology-delivered Motivational Interviewing Interventions	Human Health and Social Work Activities	No
Slovis et al.	2017	Asynchronous automated electronic laboratory result notifications: a systematic review	34	Automated Software: Electronic Notification Systems	Medical Health Professionals	Medical Support: Notifications of Laboratory Results	Human Health and Social Work Activities	No
Stanfill et al.	2010	A systematic literature review of automated clinical coding and classification systems	113	Artificial Intelligence: Clinical Coding Tools	Medical Health Professionals	Clinical Coding and Classification	Human Health and Social Work Activities	No
Syed et al.	2020	Robotic Process Automation: Contemporary themes and challenges	68	Robotic Systems	Other	Robotic Process Automation	Other	No
Thangiah & Basri	2016	A preliminary analysis of various testing techniques in Agile development - a systematic literature review	256	Automated Software: Software Testing Tools	Software Engineers	Automated Software Testing	Professional, Scientific and Technical Activities	No

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE sector	OSH implications
Vallury et al.	2015	Computerized Cognitive Behavior Therapy for Anxiety and Depression in Rural Areas: A Systematic Review	11	Automated Software: Medical Application	Mental Health Professionals	Computerized Cognitive Behaviour Therapy	Human Health and Social Work Activities	No
Verberk & de Leeuw	2012	Accuracy of oscillometric blood pressure monitors for the detection of atrial fibrillation: a systematic review	5	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Walker.	2008	Computer-Assisted Library Instruction and Face-to-Face Library Instruction Prove Equally Effective for Teaching Basic Library Skills in Academic Libraries	40	Automated Software: Educational tool	Librarians	Computer-assisted Instruction	Other Service Activities	No
Wäldchen & Mäder	2018	Plant Species Identification Using Computer Vision Techniques: A Systematic Literature Review	120	Artificial Intelligence: Image Processing	(Plant) Researcher	Plant Species Identification	Professional, Scientific and Technical Activities	No
Wulff et al.	2019	Clinical Decision-Support Systems for Detection of Systemic Inflammatory Response Syndrome, Sepsis, and Septic Shock in Critically Ill Patients: A Systematic Review	55	Decision Support Systems	Medical Health Professionals	Medical Decision Support	Human Health and Social Work Activities	No
Xiao et al.	2018	Opportunities and challenges in developing deep learning models using electronic health records data: a systematic review	98	Artificial Intelligence: Electronic Health Record	Medical Health Professionals	Medical Diagnosis: Disease Detection/ Classification, Sequential Prediction of Clinical Events, Concept Embedding, Data Augmentation	Human Health and Social Work Activities	No
Zafar et al.	2018	Business Process Models to Web Services Generation: A Systematic Literature Review	30	Business Process Modelling Tools	Other	Business Process Automation	Administrative and Support Service Activities	No

Included meta-analyses for automation of tasks

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE sector	OSH implications
Aardoom et al.	2020	Effectiveness of eHealth Interventions in Improving Treatment Adherence for Adults With Obstructive Sleep Apnea: Meta-Analytic Review	18	Automated Software: Information and Communication Technologies	Medical Health Professionals	Notifications	Administrative and Support Service Activities	No
Andreadis et al.	2019	Attended Versus Unattended Automated Office Blood Pressure: A Systematic Review and Meta-analysis	12	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Argolo et al.	2020	Lowering costs for large-scale screening in psychosis: a systematic review and meta-analysis of performance and value of information for speech-based psychiatric evaluation	28	Automated Software: Speech Analysis Programmes	Mental Health Professionals	Medical Diagnosis/ Automated Speech Evaluation	Human Health and Social Work Activities	No
Balas et al.	2004	Computerized knowledge management in diabetes care	40	Automated Software: Knowledge Management System	Medical Health Professionals	Medical Procedure/ Automated Information Interventions	Human Health and Social Work Activities	No
Borrelli et al.	2019	Sodium removal by peritoneal dialysis: a systematic review and meta-analysis	30	Automated Medical Device: Dialysis Machines	Medical Health Professionals	Medical Procedure/ Dialytic Sodium Removal	Human Health and Social Work Activities	No
Brogi et al.	2017	Clinical Performance and Safety of Closed-Loop Systems: A Systematic Review and Meta-analysis of Randomized Controlled Trials	36	Automated Medical Device: Closed-loop Systems Respiratory Support System	Medical Health Professionals	Medical Procedure/ Respiration Support	Human Health and Social Work Activities	No
Clark et al.	2019	Accuracy of automated blood pressure measurements in the presence of atrial fibrillation: systematic review and meta-analysis	13	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Denault et al.	2019	Automatic versus Manual Oxygen Titration in Patients Requiring Supplemental Oxygen in the Hospital: A	9	Automated Medical Device: Closed-loop Oxygen Titration Devices	Medical Health Professionals	Medical Procedure/ Automatic Oxygen Titration	Human Health and Social Work Activities	No

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE sector	OSH implications
		Systematic Review and Meta-Analysis						
Deng et al.	2019	Validation of a Semiautomated Natural Language Processing-Based Procedure for Meta-Analysis of Cancer Susceptibility Gene Penetrance	10	Artificial Intelligence: Natural Language Processing	Researchers	Semi-automated Natural Language Processing	Professional, Scientific and Technical Activities	Yes
Gurung et al.	2011	Computerized lung sound analysis as diagnostic aid for the detection of abnormal lung sounds: a systematic review and meta-analysis	8	Automated Software: Computerized Lung Sound Analysis	Medical Health Professionals	Medical Diagnosis/ Automated Classification of Recorded Lung Sounds	Human Health and Social Work Activities	No
Jegatheswaran et al.	2017	Are Automated Blood Pressure Monitors Comparable to Ambulatory Blood Pressure Monitors? A Systematic Review and Meta-analysis	19	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Kassavou & Sutton	2018	Automated telecommunication interventions to promote adherence to cardio-metabolic medications: meta-analysis of effectiveness and meta-regression of behaviour change techniques	17	Automated Software: Interactive Voice Response System	Medical Health Professionals	Automated Telecommunication Interventions	Human Health and Social Work Activities	No
Kim et al.	2019	Diagnostic utility of automated indirect immunofluorescence compared to manual indirect immunofluorescence for anti-nuclear antibodies in patients with systemic rheumatic diseases: A systematic review and meta-analysis	22	Automated Medical Device: Indirect Immunofluorescence	Medical Health Professionals	Medical Diagnosis/ Anti-nuclear Antibody Screening	Human Health and Social Work Activities	No
Kitano et al.	2019	Accuracy of Left Ventricular Volumes and Ejection Fraction Measurements by Contemporary Three-Dimensional Echocardiography with Semi- and Fully Automated Software: Systematic Review and Meta-Analysis of 1,881 Subjects	6	Automated Software: Transthoracic Three-Dimensional Echocardiography, Left Ventricular Quantification	Medical Health Professionals	Medical Diagnosis/ Three-Dimensional Echocardiography	Human Health and Social Work Activities	No

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE sector	OSH implications
Kollias et al.	2019	Unattended versus attended automated office blood pressure: Systematic review and meta-analysis of studies using the same methodology for both methods	10	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Lepida et al.	2019	Systematic review with meta-analysis: automated low-flow ascites pump therapy for refractory ascites	9	Automated Medical Device: Automated Ascites Pumps	Medical Health Professionals	Medical Procedure/ Automated low-flow Ascites Pump Therapy	Human Health and Social Work Activities	No
Liebow et al.	2012	Effectiveness of automated notification and customer service call centers for timely and accurate reporting of critical values: a laboratory medicine best practices systematic review and meta-analysis	9	Automated Software: Notification System	Medical Health Professionals	Notifications	Administrative and Support Service Activities	No
Loerup et al.	2019	Trends of blood pressure and heart rate in normal pregnancies: a systematic review and meta-analysis	39	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Mahomed et al.	2013	Validity of automated threshold audiometry: a systematic review and meta-analysis	29	Audiometry Measuring Devices	Medical Health Professionals	Medical Procedure/ Automated Audiometry	Human Health and Social Work Activities	No
Manolesou et al.	2021	Experimental Devices Versus Hand-Sewn Anastomosis of the Aorta: A Systematic Review and Meta-Analysis	22	Automated Medical Device: Proximal Anastomotic Devices	Medical Health Professionals	Medical Procedure/ Anastomotic Artery Attachment	Human Health and Social Work Activities	No
Mehrholz et al.	2013	Electromechanical-assisted training for walking after stroke	23	Robotic System	Medical Health Professionals	Movement Support	Human Health and Social Work Activities	No
Meng et al.	2015	Diagnostic performance of the automated breast volume scanner: a systematic review of interrater reliability/agreement and meta-analysis of diagnostic accuracy for differentiating benign and malignant breast lesions	13	Automated Medical Device: Automated Breast Volume Scanner	Medical Health Professionals	Medical Procedure/ Breast Volume Scanner	Human Health and Social Work Activities	No

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE sector	OSH implications
Micali et al.	2019	Clinical outcomes of automated anastomotic devices: A metanalysis	9	Automated Medical Device: Proximal Anastomotic Devices	Medical Health Professionals	Medical Procedure/ Anastomotic Artery Attachment	Human Health and Social Work Activities	No
Mitra et al.	2018	Automated versus manual control of inspired oxygen to target oxygen saturation in preterm infants: a systematic review and meta-analysis	10	Automated Medical Device: Respiratory Support System	Medical Health Professionals	Medical Procedure/ Automated Fraction of Inspired Oxygen	Human Health and Social Work Activities	No
Myers	2019	A meta-analysis that helps clarify the use of automated office blood pressure in clinical practice	10	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Onnasch et al.	2014	Human Performance Consequences of Stages and Levels of Automation An Integrated Meta-Analysis	18	Multiple	Mixed	Mixed	Mixed	Yes
Pappaccogli et al.	2019	Comparison of Automated Office Blood Pressure With Office and Out-Off-Office Measurement Techniques	26	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Park et al.	2020	Measurement reliability of automated oscillometric blood pressure monitor in the elderly with atrial fibrillation: a systematic review and meta-analysis	10	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Park et al.	2019	Predictive validity of automated oscillometric blood pressure monitors for screening atrial fibrillation: a systematic review and meta-analysis	13	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Park & Park	2019	Can an automatic oscillometric device replace a mercury sphygmomanometer on blood pressure measurement? a systematic review and meta-analysis	24	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Posadzki et al.	2016	Automated telephone communication systems for preventive	132	Automated Telephone Communication Systems	Administrators	Medical Support: Deliver Voice Messages and Collect Health-related	Human Health and Social Work Activities	No

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE sector	OSH implications
		healthcare and management of long-term conditions				Information		
Rabindranath et al.	2007	Continuous ambulatory peritoneal dialysis versus automated peritoneal dialysis for end-stage renal disease	3	Automated Medical Device: Peritoneal Dialysis Devices	Medical Health Professionals	Medical Procedure/ Automated Peritoneal Dialysis	Human Health and Social Work Activities	No
Roerecke et al.	2019	Comparing Automated Office Blood Pressure Readings With Other Methods of Blood Pressure Measurement for Identifying Patients With Possible Hypertension: A Systematic Review and Meta-analysis	31	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Rose et al.	2013	Automated versus non-automated weaning for reducing the duration of mechanical ventilation for critically ill adults and children	15	Automated Software: Closed Loop Systems	Medical Health Professionals	Medical Procedure/ Weaning	Human Health and Social Work Activities	No
Shang et al.	2013	Systematic review and meta-analysis of flow cytometry in urinary tract infection screening	19	Automated Medical Device: Urine Sediment Analyser	Medical Health Professionals	Medical Procedure/ Bacteria Screening	Human Health and Social Work Activities	No
Simões et al.	2019	Meta-Analysis of the Sensitivity of Decision Support Systems in Diagnosing Diabetic Retinopathy	18	Decision Support System	Medical Health Professionals	Medical Decision Support: Diagnosis of Diabetic Retinopathy	Human Health and Social Work Activities	No
Sng et al.	2018	Automated mandatory bolus versus basal infusion for maintenance of epidural analgesia in labour	12	Automated Medical Device: Automated Mandatory Bolus	Medical Health Professionals	Medical Procedure/ Analgetic Incision	Human Health and Social Work Activities	No
Stergiou et al.	2012	Automated blood pressure measurement in atrial fibrillation: a systematic review and meta-analysis	12	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Taggar et al.	2015	Accuracy of methods for diagnosing atrial fibrillation using 12-lead ECG:	10	Automated Software: ECG-interpreting Software	Medical Health Professionals	Medical Diagnosis/ Electrocardiograms	Human Health and Social Work Activities	No

Author	Year	Study	Number of base studies	Technology	Job affected by the system	Task	NACE sector	OSH implications
		A systematic review and meta-analysis						
Verberk et al.	2011	Blood pressure measurement method and inter-arm differences: a meta-analysis	22	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Blood Pressure	Human Health and Social Work Activities	No
Verberk et al.	2012	Automated oscillometric determination of the ankle-brachial index: a systematic review and meta-analysis	25	Automated Blood Pressure Monitor (oscillometric device)	Medical Health Professionals	Medical Diagnosis/ Oscillometric Determination	Human Health and Social Work Activities	No
Wang et al.	2020	How many crashes can connected vehicle and automated vehicle technologies prevent: A meta-analysis	73	Automated Software: Connected Automated Vehicle	Drivers	Driving (transportation)	Transportation and Storage	Yes
De Winter et al.	2014	Effects of adaptive cruise control and highly automated driving on workload and situation awareness: A review of the empirical evidence	32	Automated Software: Cruise Control	Drivers	Driving (transportation)	Transportation and Storage	Yes
Zhao et al.	2019	Effectiveness evaluation of computer-aided diagnosis system for the diagnosis of thyroid nodules on ultrasound: A systematic review and meta-analysis	5	Decision Support System: Computer-aided Diagnosis System	Medical Health Professionals	Medical Diagnosis/ Diagnosis of Thyroid Nodules	Human Health and Social Work Activities	No
Ziakopoulos et al.	2019	A meta-analysis of the impacts of operating in-vehicle information systems on road safety	44	Artificial Intelligence: In-vehicle Information Systems	Drivers	Driving (transportation)	Transportation and Storage	No

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

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