European Agency for Safety and Health at Work

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Advanced robotics and automation: implications for occupational safety and health

Report

European Agency for Safety and Health at Work

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1 Introduction and objectives

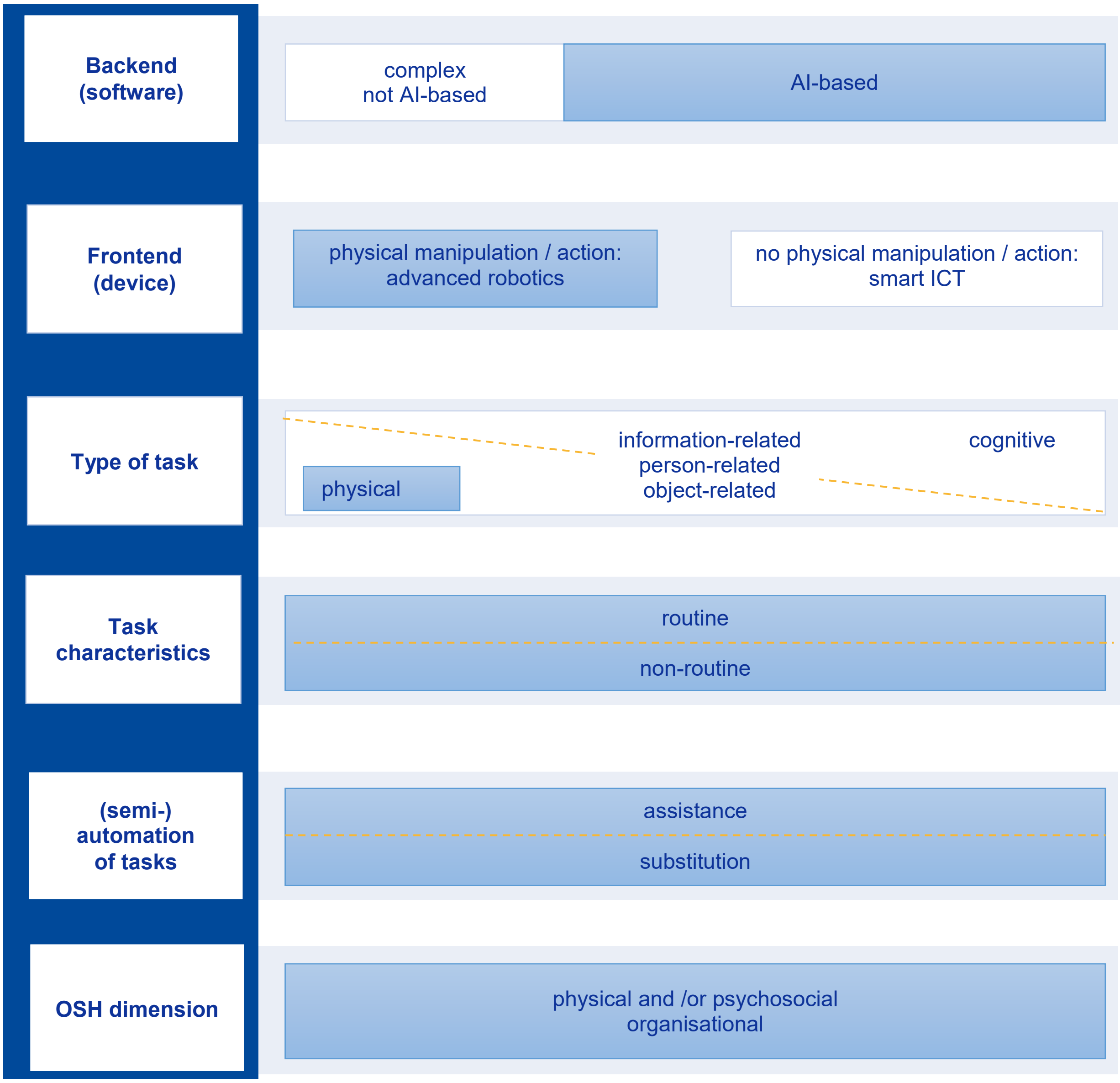
Digitalisation has led to a noticeable change for jobs and working tasks, leaving almost no field of work unchanged. The development of recent technologies, such as artificial intelligence (AI) and advanced robotics, has established new possibilities for task automation and revived the debate especially on work-related psychosocial and organisational aspects and on workers' safety and health. In order to address emerging risks and to highlight implications related to occupational safety and health (OSH) adequately, the European Agency for Safety and Health at Work (EU-OSHA) has launched the 4-year research programme 'OSH overview on digitalisation' with the aim to develop and disseminate further information on the challenges and opportunities for OSH associated with digitalisation. The OSH overview consists of five main projects 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 aim of this report is, following the taxonomy developed in EU-OSHA's report "Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health" (EU-OSHA, 2022a), to present OSH-related challenges and opportunities regarding the automation of physical tasks through robotic systems, including cobots. EU-OSHA's report "Cognitive automation: Implications for occupational safety and health" (EU-OSHA, 2022b), includes the role of advanced robotic systems and cobots in relation to the automation of cognitive tasks. For definitions of automation and robotic systems, refer to the above mentioned report (EU-OSHA, 2022a) as well, Chapter 3 and section 3.1, respectively. To support or substitute physical tasks, modern robotic technologies, like mobile robots, assembly robots and exoskeletal robots, are mainly deployed and the scope of physical tasks and functions they can support broadens steadily. The focus on tasks rather than jobs is a valid approach to follow as outlined in the above mentioned EU-OSHA's report (EU-OSHA, 2022a). The use of AI and advanced robotics has less induced entire job replacement but task changes or task replacement via reengineering and reorganisation (Brynjolfsson et al., 2018) that results in redefining and relabelling of their descriptions and expectations. The developed taxonomy (Figure 1) not only allows classification of the task's content but the application of different types of technologies as well as their critical assessment regarding OSH. It is therefore used in the subsequent analysis and presentation of results. This report additionally describes a variety of economic sectors and jobs in which physical tasks are fully or semi-automated. Finally, the impact of their automation through robotic systems on work-related physical, psychosocial and organisational OSH aspects will be described and, therewith, the risks, challenges as well as the opportunities for OSH to date and in the future.

Chapter 2 explains the methodological approach taken to gather relevant research findings on advanced robotics for the automation of physical tasks. This builds the groundwork for **Chapter 3** in which, based on the conceptual taxonomy developed in the report "Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health" (EU-OSHA, 2022a), the results of these systematic literature reviews are analysed and presented. The evaluation focuses on the task's content and the degree of automation. Specifically, it distinguishes between semi- and full automation of information-related, person-related and object-related physical tasks (Figure 1). **Chapter 4** applies the findings obtained so far on OSH dimensions. These include physical, psychosocial and organisational implications for the three mentioned contents of physical task automation, respectively. Therewith, it presents opportunities and challenges for OSH associated with the automation of physical tasks. **Chapter 5** presents concluding remarks and an outlook to the next phases within this project.

Figure 1: Taxonomy for advanced robotics for the automation of tasks with accentuation of categories relevant for physical task automation (EU-OSHA, 2022a)



2 Methodology

This chapter presents an overview of the applied methodology and the major data sources used to depict the relevant areas of literature regarding advanced robotics for the automation of physical tasks. This includes systematic reviews and meta-analyses as well as a review of grey literature and forward citation search to identify additional scientific work. The reviewed literature presented in EU-OSHA's report "Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health" (EU-OSHA, 2022a), forms the basis for further, targeted analysis in this report. Additionally a PEO-schemed (Population-Exposure-Outcome) search was performed with a focus on the automation of physical tasks and OSH-relevant human factors. The above-mentioned report (EU-OSHA, 2022a) identified state-of-the-art technologies and current trends as well as uses of systems for the automation of tasks. To complement the findings of both the above-mentioned report (EU-OSHA, 2022a) and the PEO literature search, an additional literature research on a variety of sectors was performed.

In addition to that, semi-structured interviews of a select group of experts in the field of advanced robotics were conducted to gain additional qualitative insight into the automation of physical tasks.

2.1 Literature research

The systematic literature searches were conducted in the following scientific and complementary databases, covering a wide range of research fields: *IEEEexplore, Ebscohost, Web of Science, PubMed* and, to a limited degree, Google Scholar. While the results of the first four databases are included to their full extent in the literature review, represented in the number of results, the first 20 pages of Google Scholar were searched complementarily to identify relevant studies that were not published in one of the other databases. For AI-based systems, the following search string was applied in the databases:

(‘artificial intelligence’ OR ‘AI’ OR ‘algorithmic learning’ OR ‘intelligent system’ OR ‘machine learning’) ***AND*** *(‘systematic literature review’/‘meta-analysis’)*

This identified a total of 2,509 potential papers out of which a total of 33 studies were selected for further analysis (22 systematic literature reviews, 11 meta-analyses). From this, four papers included direct or indirect implications regarding OSH (three systematic literature reviews, 1 meta-analysis). The included systematic reviews and meta-analyses are listed in the annex of the report “Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health” (EU-OSHA, 2022a). While the systematic literature reviews covered around 1,158 primary publications (not all papers mentioned the number of included primary papers), the meta-analyses include 815. Furthermore, some primary papers might be included in several systematic reviews and/or meta-analyses. Regarding advanced robotics literature, a total of 630 potential publications were identified, of which 57 studies were screened for their areas of interest (46 systematic literature reviews, 11 meta-analyses). Sixteen papers included direct or indirect implications regarding OSH (10 systematic reviews, six meta-analyses). The search string was:

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

While the systematic reviews covered around 1,844 primary publications, the meta-analysis covered 343. It has to be noted that some primary papers might be included in several systematic reviews and/or meta-analyses. The additional systematic literature review focused on the automation of tasks, independent from any specific technology. This allowed us to identify processes that the previous two reviews did not uncover. A new search string was constructed and applied in four different databases*: IEEEexplore, Ebscohost, Web of Science* and *PubMed*. In this review, Google Scholar was not used to supplement the results, as its mechanism does not accommodate the search string without substantial loss of detail and depth. The new search string contained the following keywords:

(‘automation of task’ OR ‘automated work’ OR ‘task automation’ OR ‘automated task’ OR ‘work automation’ OR ‘job automation’ OR ‘Level* of automation’ OR ‘degree* of automation’ OR ‘systematic automation’ OR ‘automation system’ OR ‘system automation’ OR ‘test automation’ OR ‘automat* task’ OR ‘automate repetitive’ OR ‘workplace automation’ OR ‘automation tools’ OR ‘smart automation’ OR ‘automation in manufacturing’ OR ‘industrial automation’ OR ‘factory automation’ OR ‘automatic production’ OR ‘automation of industrial tasks’ OR ‘automation architecture’ OR ‘process automation’)* ***AND*** *(‘meta-analysis’/‘systematic literature review’ OR ‘systematic review’).*

The literature research included in the report “Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health” (EU-OSHA, 2022a) regarding task automation yielded a total of 815 results across all databases and both conditions via 596 meta-analyses and 249 systematic reviews. Those results were then screened on title and abstract base for eligibility and duplicates were removed. After that, the full text articles were screened if necessary to determine whether they were suitable for the final selection. Regarding the meta-analysis, the final sample contained 45 studies, of which three contained direct OSH implications and one indirect. The remaining 41 form the additional base for the extraction of key information. The systematic literature review has a final sample size of 47, of which five have direct OSH implications and three indirect. This results in a final group of 11 papers with OSH implications.

Additional primary literature was gathered, in order to fill in and expand on the previous results, to address the research question of this task in more detail and depth. The search was done in the interdisciplinary databases *IEEEexplore*, *Web of Science*, *PubMed* and the meta-database *Ebscohost*. For all sources, a comprehensive combination of search terms was developed following the PEO scheme.

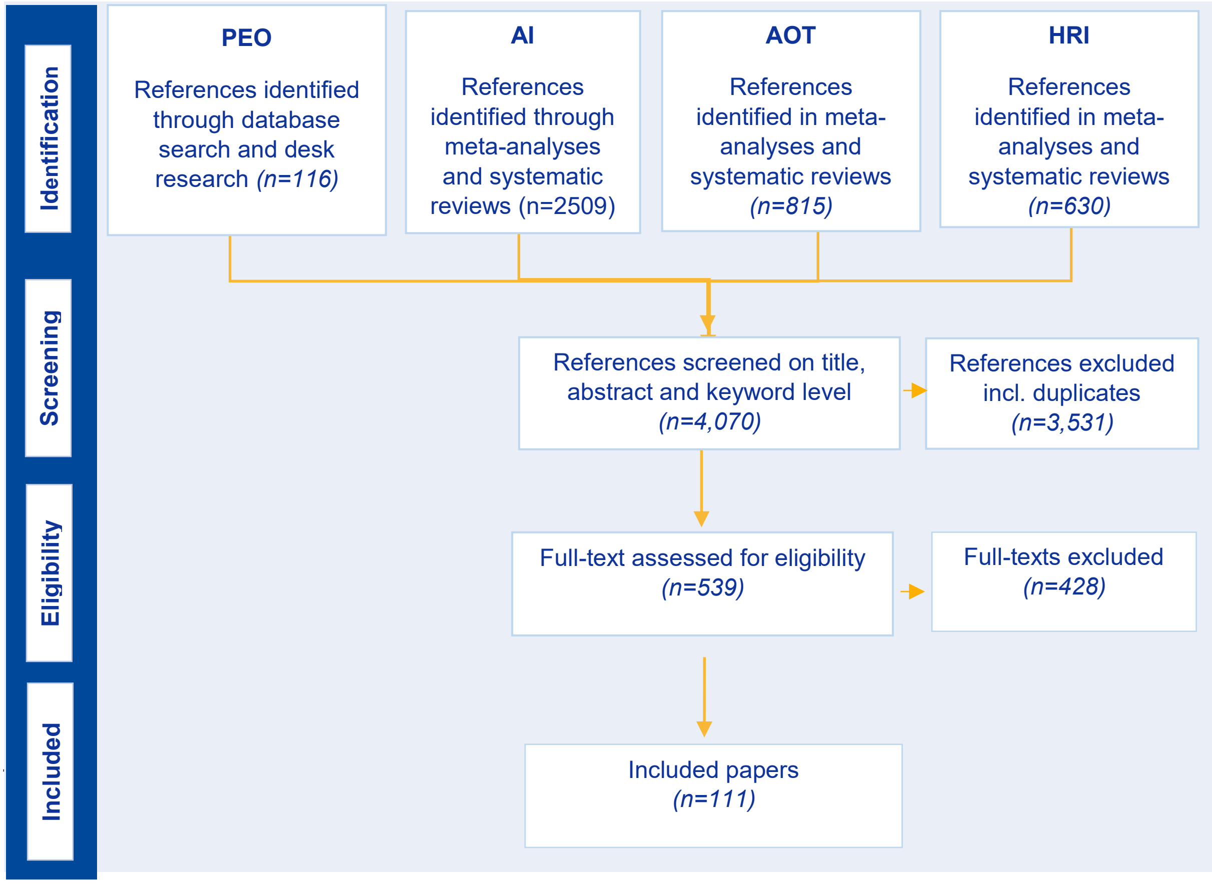
Intelligent robots was treated as the independent variable (exposure) and accordingly a set of terms representing the independent variables was developed. We used the same robot-related keywords as we did in the systematic literature review, as they proved to be effective. The dependent variables (outcome) was covered by a set of terms representing different human factors and ergonomics concepts. We applied a broad understanding of the field of ergonomics, including physical, cognitive and organisational ergonomics. Additionally, concepts specifically related to workers' safety and health were considered. For these search terms cognitive and physical tasks will be treated as the population of interest and will therefore create a set of contextual variables.

The final search string is presented below and was modified according to the specific database it was applied to. All categories of terms were combined using Boolean operators. Regarding the outcomes related to workers' safety and health, the published search terms from the project 'Mental health in the Working World - Determining the current state of scientific evidence' conducted by the Federal Institute for Occupational Safety and Health (BAuA) was used:

*('HRI' OR 'human-robot interaction' OR 'human robot interaction' OR 'cobot' OR 'robot collaboration' OR 'collaborative robot' OR 'robot cooperation') AND ('job control' OR 'decision latitude' OR 'feedback on the task' OR 'social support' OR 'social interaction' OR 'team work' OR 'isolation' OR 'working time' OR 'time pressure' OR 'work intensity' OR 'disturbances and interruptions' OR 'cognitive *load' OR 'over-reliance' OR 'trust' OR 'competences' OR 'skill*' OR 'mental health' OR 'well-being' OR 'wellbeing' OR 'workability' OR 'work ability' OR 'happiness' OR 'positive affect' OR 'positive emotions' OR 'satisfaction with life' OR 'life satisfaction' OR 'work satisfaction' OR 'job satisfaction' OR 'quality of life' OR 'sedentary work' OR 'awkward posture' OR 'lifting') AND ('cognitive task' OR 'knowledge based task' OR 'physical task*' OR 'manual task' OR 'assembly task')*

The search yielded a total of 42 results across all databases. Those results were than screened on a title and abstract base for eligibility and duplicates were removed. After that the full text articles were screened if necessary to determine if they were suitable for the final selection. In total, four additional studies could be identified to contain relevant information. Furthermore, additional desk research resulted in a selection of 72 primary publications to expand and enhance the insight from the previously identified studies.

Figure 2: Selection process for scientific literature



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

2.2 Interview methodology

Interviews are the main methodological tool for the qualitative research done for this report. Compared to surveys, semi-structured interviews allow for more flexibility and collection of detailed and nuanced information. Interviews conducted for this task are semi-structured interviews relying on a pre-established interview guide including common themes and questions. This ensures consistency and coherence between the interviews and facilitates the analysis of the results while enabling each interview partner to add new and relevant information. The interviewees were dedicated experts from EU Member States, international and EU bodies and associations, academia and the private sector.

In advance of the interviews, we contacted the interviewees to arrange the interview and to seek their consent for participation and the content of the interview being used in the study. We acquired written consent to record the interviews. In case the interviewee did not agree to the recording, the interviewer took the most important notes, but was supported by a junior team member who would only take notes, so that the interviewer could focus better on the conversation.

The interviews were planned to be carried out in person, by phone or by videoconference. However, COVID-19 countermeasures meant face-to-face interviews were not possible. In those circumstances, interviews were carried out either by phone or by videoconference. The interviewers carried out the interviews in the national language of the Member State where possible. Otherwise, the interview was conducted in English. The interviewers recorded the interviews and produced detailed notes of the interviews in English.

A total of nine interviews were carried out. In order to avoid overstraining interviewees and interviewers, interviews aimed not to exceed 90 minutes.

3 Advanced robotics and types of tasks

The following section presents the findings regarding the effects that automation of physical tasks can have on workers and their surroundings. To better illustrate the differences between the automated tasks, they are presented within a comprehensive structure according to the taxonomy developed within the project. First, the tasks are divided into groups of fully automated and those that currently fall under the state of semi-automation. Within these two groups each is further separated into the task being person-related, information-related or object-related, based on the object of work according to the focus programme 'Occupational Safety & Health in the Digital World of Work' established by BAuA (Tegtmeier et al., 2018). Each of these three subgroups then further differentiates between the task being either a routine task for the worker or a non-routine task. It has to be said that within the screened literature not every possible combination of categories is present. This in and of itself grants additional insight into which fields of application currently lean more heavily towards the automation of physical tasks, and where gaps are formed. This kind of automation also opens two possible avenues for benefiting the workers. On the one hand, these are physical opportunities – the robot can take over non-ergonomic activities from the human – on the other, these are psychological opportunities – the robot can take on monotonous and repetitive tasks that would allow the human to carry out more cognitive or creative tasks. In addition to that, we see a greater level of specificity when observing physical task automation through robotic systems. While some tasks are more prevalent or exemplified in a specialised context, but can potentially be applied in other working environments too, some robotic systems are developed to fit a specified task in a specific work environment and allow for limited generalisation. While the continuous development of robotic systems has allowed them to become more flexible in their application, the benefit for specialised machinery compared to a more multi-purpose robot can be seen in these kind of tasks. A potentially game-changing technological development refers to robotic systems that are purposely designed to work in direct cooperation or collaboration with a human in a defined workspace. Therefore, they are often referred to as cobots. Safety requirements for these specific systems are set in the standard ISO/TS 15066: Robots and robotic devices - Collaborative robots. The range of cobot applications includes systems with features like lightweight materials, rounded contours, padding and ‘sensory skins’ as well as sensors that measure and control force, speed and position (International Federation of Robotics (IFR), 2018; IFR, 2020). An overview of different types of advanced robotics including cobots is presented in the report “Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health” (EU-OSHA, 2022a).

3.1 Advanced robotics-based full automation (substitution) of tasks

In the following paragraphs, the results of our literature research regarding fully automated tasks are presented. According to the taxonomy (Figure 1), this group can be separated into the task being person-related, information-related or object-related.

3.1.1 Person-related tasks

The physical automation of person-related routine tasks is one area of application for the technology. The literature suggests that this kind of task automation in its nature leans towards more specific areas of application, such as the healthcare sector. This is further supported by the ESENER-3 findings, where when establishments were asked whether or not the potential impacts of various digital technologies on OSH were discussed, in 2019 this was the case more often in the healthcare sector than in all sectors (28% vs 24%). While some of these tasks are then uniquely automated for these fields, some can be generalised beyond their exploratory areas of application. However, for a more comprehensive overview of tasks, some are presented in relation to their application context.

Robotic assistance in healthcare is one of the more commonly known areas of application for this kind of technology. There are a number of tasks that either get assisted by or are fully automated through robotic systems in today’s healthcare practices. Kyrarini et al. (2021) present a comprehensive overview of tasks that are already automatable in today’s hospitals. Robotic nursing assistants can act as a teammate, helping nurses by performing non-critical tasks for them, elevating both mental and physical workload. There is a variety of tasks that fall under this category. One of them is needle insertion, either to draw blood or inject medicine. As the literature suggests, the process of needle insertion can be performed by a robot, to great success. The robot automates drawing blood and inserting intravenous therapy, while correctly identifying the best vein with sufficient accuracy (Kyrarini et al., 2021). Specialised nursing robots are capable of lifting patients from a bed into a wheelchair or helping them stand up, without the help of a nurse. Especially tasks of physical assistance like lifting patients have been identified through the interviews as well. This is a task that, depending on the physical and mental state of the patient, can be physically taxing for a healthcare worker (Kyrarini et al., 2021).

Within the field of nursing robots, we also see multi-purpose robots emerge, which help healthcare workers with a number of routines breaking the task specialisation of previous robotic systems, such as walking patients and fetching objects. (Kyrarini et al., 2021). Especially tasks in the area of retrieving specific objects are not unique to the healthcare sector, and will be examined more closely below. Drinking and eating assistance form another usually very time- and labour-intensive task in healthcare. However, there are now numerous robotic systems that can support patients in this field, to the point that the healthcare worker does not need to get involved anymore. Especially patients in need of assistance due to physical limitations, such as paralysis, can regain autonomy through robotic solutions. Some function via voice or vision command and others via joystick. Newer models can function with such accuracy that human assistance is not necessary anymore, not only returning autonomy to patients, but also elevating this task from healthcare workers. However, these systems are dependent on a certain level of input by the user, which makes them unsuitable for patients who need drinking or eating assistance due to cognitive impairment, such as Alzheimer’s disease (Kyrarini et al., 2021).

Moving away from nurses and caretakers, surgical procedures too have increasingly been subject to automation through robotic systems. Specialised surgical robots assist and support medical professionals in a variety of tasks. The setting of sutures during surgery is routinely performed by surgeons and a vital factor in the overall success of the intervention. The success of the procedure is largely determined by the quality of the placed suture. There are robotic systems capable of supporting the surgeon in this task. Although robotic devices offer a faster process, the results currently lack endurance when compared with the hand-sewn technique (Manolesou et al., 2021). So, while automatable from a technological standpoint, it will need further optimisation to find widespread use in the future. Another surgical task that sees automation is the extraction of tissue samples. So-called 'biopsyrobots' would automatically feed into the extraction site and remove the sample. The surgeon's remaining function in this process is limited to the active confirmation or correction, if needed, of the automatically generated plan of action from the robotic system (Marcus et al., 2018).

With task automation through robotic systems in the area of surgery, it is important to differentiate between robotic systems that are largely operated through the surgeon and those that perform tasks with a certain degree of autonomy. The former function as a technological extension of the surgeon, but display little to no physical autonomy. Currently, they are more commonly found in the surgical context. The latter is rarer, but as technological development makes robots more precise, reliable and capable of performing more complex yet reoccurring tasks, we could see an increase of task automation in this area in the future.

3.1.2 Object-related tasks

When it comes to object-related robotic tasks, the term industrial robot is applied in many cases. Often lacking a clear outline of what an industrial task is or combining several tasks in one publication, allowing more globalised statements for the sector, Dobra and Dhir (2020), Enríquez et al. (2020), Gholamian et al. (2007) and Kadir et al. (2019) all report on different aspects regarding robotic automation and industrial work. Some of the tasks mentioned include conveyer belt applied robotic systems performing pick and place or sorting tasks. Others refer to the implications of freely moving robotics in an industrial setting, and while not singling out robots with a task of object transportation from their publications, they do fall under this category. Iqbal et al. (2016) name tasks such as **welding, assembly, paint spraying, packaging and arranging, cutting, moving and sanding** as industrial tasks that can be fully automated by robotic systems. This is in alignment with tasks reported by the interviewed experts, who additionally named **heavy lifting**, precise physical activities such as **pick and place tasks**, and, specifically in manufacturing, the production of small-volume assembly items in a high mix of products/precision works. Again, the aforementioned tasks are not exclusively applicable to the work context in which they are listed in the literature. For example, the process of **packaging a product** can be found in a variety of jobs and sectors. The automation of transportation tasks is also applicable for a variety of work contexts, but in this case is exemplified through its role in the healthcare sector. A prominent group in the commercially available robots for hospitals helps with transportation tasks. They can retrieve and bring supplies to hospital rooms and nursing stations, deliver samples to laboratories and remove soiled linen bags (Kyrarini et al., 2021). Before functional deployment, the robot learns the locations of the relevant supply rooms and where the retrieved objects need to be delivered to. After this initial 'training', they are able to navigate fully autonomously and safely by avoiding static and dynamic obstacles, through special sensors. Some of these robots possess robotic arms, and therefore do not need to rely on the medical staff to load and unload the objects they deliver in the hospital. It has to be mentioned, however, that there are also versions of these robots that still need human assistance during these tasks. (Kyrarini et al., 2021). While illustrated with the contextual example of hospital work, these kinds of delivery tasks can find application in a variety of contexts, ranging from possibly post and package delivery systems to warehouse application or to assistance in restocking retail shelfs, to name a few. Hence, **logistics and transportation tasks** are prime examples for robotic automation of physical tasks. The technology needs a certain level of autonomy, for example to effectively navigate a warehouse. Simple, hardcoded paths trajectories would not provide the needed efficiency to justify the application of machines compared to human workers. However, newer generations of robotic systems are more flexible in their path planning and have sensors to enable their coexistence with human workers, without disrupting their workflow (D'Andrea, 2021). In the warehouse environment, a number of tasks have already been successfully fully automated. This includes loading and unloading of containers, stationary and mobile piece picking tasks, and delivery tasks. Among those tasks, 70-80% of labour in a warehouse is picking and packing items, and robotic arms are increasingly capable of performing this activity reliably (Gomez, 2019). Another dominant group of tasks are those that focus on moving items from a specific location to their new destination. In well-defined limited spaces, mobile robotic systems can operate to great success. New algorithmic developments like adaptive task planning furthermore enhance the autonomy and thus task performance of the robotic systems. Traditional warehouses use the picker-to-part method, where workers travel in the warehouse and collect the order. The introduction of transportation-focused robots changes that approach to part-to-picker, so that robots carry the requested item to the workers who are waiting at the pick or assembly stations (Bolu & Korcak, 2021). This eliminates a labour- and time-intensive task of warehouse workers, shifting their focus towards the more complex and non-repetitive aspects of their work.

Applications of robotics in mining are broad and include operating heavy machinery as well as lifting tasks, robotic dozing, excavation and haulage, as well as robotic drilling and possibly explosives handling (Plotnikov et al., 2020). These mining tasks can be categorised in three major groups: the first being tasks relating to exploration: carrying out mapping of mines, investigating the possibility of safe operation, carrying out instrumental operations, reconnaissance and assessing the situation after an accident. These tasks specifically remove the human worker from the operation site, be it for safety or efficiency reasons. They can be performed by autonomously moving robotic systems equipped with sensors to adequately assess their environment. The second category is rescue-related work: aiding people in a mining-related emergency, for example, clearing the way or debris after a cave-in or other accident; carrying out the loading of a person for their evacuation; and delivering necessary items for victims until they can be extracted from the danger zone. Both of these kinds of tasks have similar principals to other tasks that were previously discussed, namely the transportation of items and physical assistance of people. However, the operationalisation and used technology need to fit the context in which it operates. While performing a similar task, a robotic system deployed in a healthcare setting does not meet the criteria needed in a mining setting. The base function of the task is similar, but the circumstances make the execution so dissimilar that they should be acknowledged separately. The third category is operational tasks: performing various tasks in the mine, monitoring the state of the environment (concentration of combustible gases, temperature), moving objects, loading and unloading procedures, drilling, dismantling and transporting debris (Plotnikov et al., 2020).

3.1.3 Information-related tasks

The literature research identified both object-related and person-related tasks as primary areas of application for advanced robotic systems and cobots. Within the reviewed literature, there are no researched cases of information-related physical tasks performed by advanced robotic systems. However, when consulting use cases, robotic systems that use specific sensors to scan and analyse their environments can be found. These systems usually navigate through a worksite to identify obstacles, check machines for errors or temperature ranges or perform routine safety patrols. They can be operated manually, via a remote control for spot checks, or follow a hard coded path. They aid to provide a primary analysis of their area of employment, and can help determine if human intervention is needed. This way, workers are only send out e.g. to repair a machine when it is determined that a worksite needs human attendance. Specialists can then enter the worksite with information on the problem and already bring needed equipment.

While there are use cases for this type of information-related use of advanced robotic systems, there is a lack of research on their impact on OSH, both on a cognitive and physical level.

3.2 Advanced robotics-based semi-automation (assistance) of tasks

While some robotic systems already possess the technological sophistication to perform tasks fully autonomously, there are a number of tasks that benefit from partial automation, in which the human is still actively involved in the process. The following sections describe the current state of semi-automation of tasks.

3.2.1 Person-related tasks

Once again a number of semi-automated physical tasks can be found in a medical context. These tasks show comparatively greater specificity and are not necessarily transferable to other working contexts. The medical work environment contains a number of small physical tasks that are routinely performed on patients. Another nursing-related task for which robots have been used to assist with is getting dressed, both for clothes as well as shoes. When assisted by a user, who can be either a patient with the mental capacity to do so or a healthcare provider, these robots function well enough to automate parts of the clothing process. More complex clothing items have not been fully explored and might still need assistance by a healthcare worker. Other assistive robotic tasks in healthcare that require a higher degree of direct physical contact between the robot and the human have also been subject to automation, such as beard shaving, hair brushing and bathing. So far, these tasks however are only performed with a skilled worker overseeing and directing the process, or in laboratory settings. Nevertheless, with continuous improvement of robotic technology these tasks, too, could be fully automated in the future (Kyrarini et al., 2021). While the process itself can vary from patient to patient, manual patient handling in the form of moving and lifting is both a labour-intensive and frequently reoccurring task for nurses and medical staff. While there are non-robotic assistance devices for these tasks, they are often inflexible and difficult to use both for the nursing staff and the patient (Hu et al., 2011). However, robotic systems are in development and partial employment, which can assist with this sort of task. Current models are designed to be fully mobile and have bimanual manipulators to lift patients. They provide greater manipulator compliance, safety, flexibility and strength than the previous non-robotic assistance systems. When using the robotic system, nursing staff won't be required to carry the bodyweight, but can simply assist the patient to get up. This can be in the form of assistance with balance, as well as the supervisory and safety role in case the patient exhibits spontaneous movement and is in risk of falling or injuring themselves (Hu et al., 2011).

3.2.2 Object-related tasks

Object-related automation evokes images of conveyer belts with robotic arms next to them performing a variety of picking or assembly tasks. However, not all object-related work can or should be fully automated with the current standard of technology. Especially in the manufacturing setting, some tasks are intentionally moved from no automation towards a semi-automated state, through the introduction of robotic systems. Rauch et al. (2020), based on Tan and Arai (2010), quantitatively evaluated human-robot collaboration systems in cellular manufacturing. Based on standard assembly tasks, they performed a practical evaluation, considering a manual set-up and human-robot collaboration set-up. The specific task automated through and with the robotic system is an assembly task; a fairly typical example is manufacturing. Instead of the human operator assembling the product alone, a cobot assisted the process. This is accomplished by either providing needed work pieces to the human operator or securing the work piece in place. Due to the collaborative nature of the working situation, this can be classified as a semi-automated task. The collaborative set-up proved to have better overall performance measurements. These kinds of repetitive assembly tasks are a common occurrence in manufacturing settings, and depending on the specific task requirements either fully or semi-automatable. Advanced robotics in industrial and manufacturing settings carry out numerous tasks ranging from picking, packing and palletising, welding, assembling items and handling materials to product inspection (Matheson et al., 2019). Currently, these kinds of tasks are performed with varying degree of human involvement or supervision. Collaborative assembly of items is an illustrative example of semi-automation, while, for example, picking tasks leans more towards full automation. Once again, while these kinds of tasks are mostly discussed in a manufacturing context, it does not mean that the exhibited functionality of the task is restricted to this sector. Fundamentally, tasks like picking and placing an item, or holding a work piece for someone, can be carried out in a plethora of jobs. In the following sectoral analysis we will see that picking, placing and delivery tasks find purchase in a variety of contexts without changing the fundamental operationalisation of the task. These are examples of task types that are discussed more prominently in a specific work context, yet are generally applicable outside of this context. On the other side are tasks that are automated and applicable in a specialised sector. Some of these tasks relate closely to the area of construction work. Here, tasks such as automated robotic bricklaying, moving heavy items with a robotic arm and gripper operated by a construction worker, and concrete pumps equipped with specialised sensors that allow measurement of critical operational variables like orientation, angles, depths and distance, to adjust and then provide the suitable amount of concrete to the worker. Workers then only have to guide the system while dispersing the material. Some robotic systems are created to perform a coherent set of tasks, however they do not fully automate the process yet. Automated construction robots can pick up the brick, apply mortar and position them in the desired position. The work process then still requires a trained construction worker to work alongside the robot to smooth over the surface area before the robot places further bricks. From a technological point of view, this process can be fully automated, meaning that the entire brickwork of building could potentially be completed without any human intervention in the future (Gharbia et al., 2019). This is an illustrative example of tasks being automated through robotic systems to great specificity and efficiency for the worker; as a result, however, the technology becomes less flexible to be transferred to other potential uses.

3.2.3 Information-related tasks

As mentioned for the case of fully automated tasks, in the reviewed literature, there are no researched cases of information-related physical tasks performed by advanced robotic systems. However, investigation of actual implementations of robotic systems, have identified robotic systems that use sensors to collect data from the environment while having processing capabilities as well that could enable them to suggest actions, take actions or just ring an alarm. While there are use cases for this type of information-related use of advanced robotic systems, there is a lack of research on their impact on OSH, both on a cognitive and physical level.

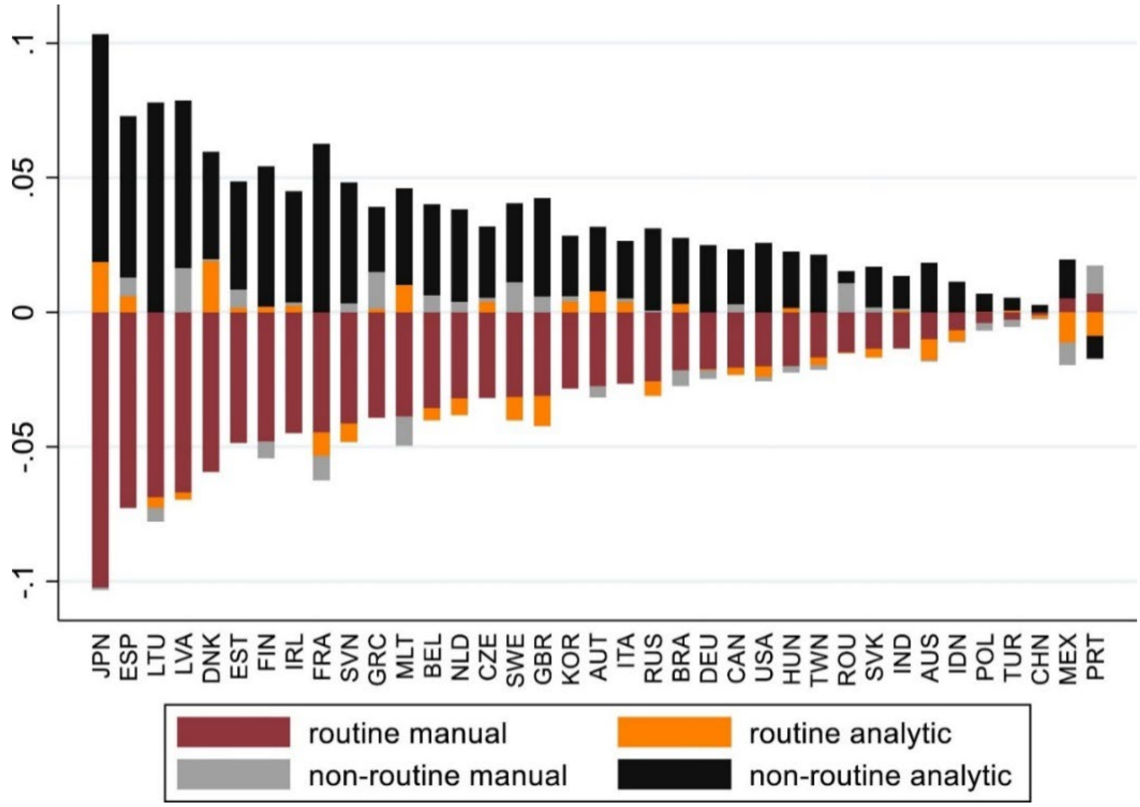
3.3 Impact on jobs

At this point in time, there is no debate about whether robotics, automated systems and AI will affect jobs and even render some obsolete. The defining questions of when, how and how many, however, find themselves under more speculation. Some estimate that in the United States (US) alone, 47% of existing jobs will be affected by the above listed technology within the next 5 to 15 years (Frey & Osborne, 2017). This number has been taken to imply a form of employment apocalypse, yet that is not what the authors were saying. They claim that their study looked at the susceptibility of existing jobs comprising 97% of the US workforce – to recent developments in emerging technologies such as AI and mobile robotics. It did not predict an exact timeframe, and it could neither explore nor account for the new sectors and roles that will arise in the years and decades to come, based on those technologies.

Next to the literature as a basis to ascertain which jobs will be affected by robotic systems in detail, it can be beneficial to first outline more clearly the general type of job that is expected to change. This impact group differs for robotic systems in comparison to other technologies, like information and communication technologies (ICTs). The impacted jobs have been found to be skill-biased, meaning they replace a more specialised but overall less complex skill, resulting in both a raising in productivity of high-skilled workers as well as lowering demand for low-skilled workers (Michaels et al., 2014). Robotic systems, however, are considered routine-biased, as their main application is to substitute workers performing routine manual tasks (Goos et al., 2014). Other than in the case of ICTs, the workers performing these routine tasks often have a middling level of education, such as repetitive industrial production tasks (Autor, 2015).

Viewed over the span of a decade, job growth has occurred for highly educated occupational groups with a more analytical focus and which possess the skills to quickly learn and adapt to new technological advancements. Similarly, it also occurred for those in lower-skill occupations, which focus more on manual and social labour. Technological advancement pushes those without technical skills from middle-skill jobs into low-skill sector jobs. This robot-incited displacement of human labour occurs under the presumption that occupations that engage in routine tasks found in middle-skill jobs are susceptible to replacement by automation through robots. These middle-skill jobs characterised by cognitively and physically routine tasks, such as traditional manufacturing, transportation services and office staff, among others, are more easily automated because they follow repetitive, finite procedures that can be carried out by robotic systems. de Vries et al. (2020) illustrate this shift from routine-based manual jobs towards non-routine analytical jobs on an international level in their recent publication (see Figure 3).

Figure 3: Depiction of the increase and decrease of job categories over a 10-year period in an international context (extracted de Vries et al., 2020)



This graph shows the development in the previously defined job categories between 2005 and 2015. According to the original publication of de Vries et al. (2020) the country-specific estimation regression coefficients are presented on the y-axis for each included country. Throughout the overwhelming majority of countries, within the last decade, routine-based manual jobs have decreased their share of employment, while non-routine analytic tasks have grown in proportion. Data analysis, specifically the calculated regressions, 'suggest a statistically significant and negative relation between changes in the routine employment share and global trends in robot adoption' (de Vries et al., 2020, p. 11. However, contrary to some beliefs that robotic systems will drastically decrease employment, de Vries et al. (2020) do not find a 'significant relation between industrial robot adoption and aggregate employment growth' (p. 11). They interpret these results as robots not having fully replaced jobs, but as they impact task demands, it shifted the jobs' focus away from routine manual tasks, leading to disruptive effects on employment. Retraining and reskilling of workers are seen as both a consequence and necessary step to continue growth in the industry (de Vries et al., 2020). This is then tied into the reoccurring narrative that the current changes due to robotic systems will lead to rethinking employees' educational goals, fostering the idea of continuous learning, and developing the right, adaptive and new skills (Kim & Park, 2020).

From this more general perspective on which kind of job is likely to be effected by task automation through robotic systems, we can focus on some of the most prevalent examples in the literature. Spearheading those are industrial workers (Dobra & Dhir, 2020; Gholamian et al., 2007; Gualtieri et al., 2021; Kadir et al., 2019). This job group is commonly associated with both physical and over-proportionally routine-based tasks, which increases their suitability for robotic automation. Overall, there are three general paths along which an industrial job might change through the introduction of robotic system. The first one is that a job might be rendered redundant through the automation, the second option is that the worker stays in their general position but their task profile changes to be assisted by the robotic system, and the third is that workers move to a higher-skilled or supervisory position through upskilling and training.

Workers whose job consists of a high proportion of repetitive physical tasks are at risk of facing either job loss or a reallocation of their central job focus. This can also entail retraining and re-education towards more complex tasks, next to any additional training they receive to successfully operate the robotic system. Although robots are capable of completing very complex tasks, if the financial gain made through this automation is not sufficient to cover the costs of the robots and their maintenance, human workers won't be replaced. This is in accordance with the above-made assumption that it is not necessarily the lower-skilled jobs facing the highest rate of automation. An increased reliance on technology to perform certain tasks is unavoidable, but it doesn't imply that all industrial processes will in the future be in the hands of robots. Many areas of the manufacturing industry will likely remain manual. Jobs in skilled areas requiring complex or spontaneous problem-solving, social intelligence or a high degree of adaptability will be occupied by humans for the foreseeable future, seeing parts of the workforce move towards more cognitive-based tasks. Workers will also become increasingly responsible for the servicing and programming of robotic systems in the manufacturing industry. As technological advancements proceeds, this will likely also lead to the creation of new jobs in the form of programming the robotic systems for the specific needs of the targeted manufacturing facilities. Hence, unskilled and repetitive tasks may become scarce as time progresses, but newer and better-paying jobs that require a higher skill level will simultaneously increase. What remains to be seen is the ratio to which manual jobs decrease, which percentage of the remaining workers are retrained or allocated into more supervisory roles, and how many new jobs are created. However, it has to be taken into consideration that not every worker has the capacity to fulfil the requirements of a supervisory position, or those of the newly created jobs.

People working in healthcare-related jobs will feel the impact of physical task automation as well. And this impact goes along with a number of prominent jobs, from physiotherapists (Liu et al., 2020; Oña et al., 2018; Zheng et al., 2019), surgeons and other specialised doctors (Manolesou et al., 2021) to nurses (Denault et al., 2019); the list of jobs discussed in the literature is in no way exhaustive. The whole healthcare sector is currently undergoing a transformation through physical tasks automation. Hospital jobs, which do not require at least a bachelor's degree, were found to be disappearing, indicating a shift towards more knowledge- and cognitive-based work (Terminino & Rimbau Gilabert, 2018). Nurses are probably among the possibly most-impacted groups. The current situation of an almost universal shortage of nurses is expected to become more problematic in the future as the older adult population grows (Qureshi & Syed, 2014). Robotics can play a role in assisting nurses to complete their daily tasks in order to provide better healthcare. Specifically the physical elements of their daily work, like moving and lifting patients with impaired mobility, can be especially straining and potentially dangerous. Nursing is a physically demanding job, illustrated by the rate at which healthcare workers experience musculoskeletal disorders. Their case number exceeded the rates observed among workers in construction, mining and manufacturing (Bureau of Labor Statistics, 2007). The main impact physical task automation through robotic systems is expected to have on nurses is that their overall physical strain reduces (Denault et al., 2019). This would also potentially free the staff's time and resources to focus on the more cognitive and emotional labour that is required for patient care.

Similar assistance in their work might be received by physiotherapists and to an extent medical staff, where robotic systems help with the physical recovery process of patients (Liu et al., 2020; Oña et al., 2018; Zheng et al., 2019). The patients' assessment and instruction, as well as parts of their physical training and therapy, are still performed by skilled professionals, however certain rehabilitation work is then assisted by robotic systems.

All of the above-described medical professions can benefit from physical automation through robotic systems. In all publications, the technology is framed in an assisting light, by improving working conditions or the quality of work, but not as a potential risk of replacement. This is noticeably different from other job profiles, that is, manufacturing jobs. One possible explanation for this framing is that these jobs are made up of a number of different tasks, varying between levels of complexity as well as their cognitive or physical nature. When a task in these jobs gets fully or semi-automated, the remaining task portfolio is complex enough so that no singular system could replace them.

Smart mines, which incorporate everything from drones and wearables to 3D printing, are becoming more commonplace. New technologies such as driverless trucks and trains and robotic drills can improve safety and efficiency for mining firms, but they can also lead to heavy losses of jobs in a sector that has traditionally required significant workforces. Fleming and Measham (2014), for instance, estimate that for every additional 10 jobs created in mining in a mining region in Australia, an additional four new jobs are generated in the same region. This estimation is based on Australian mining practices. However, the underlying implication is transferable to other regions with mining operations. They estimate that while low-skill routine jobs are disproportionally affected, the demand for high-skill workers will tend to keep increasing as automation technology would require a workforce capable of operating sophisticated machinery and computer coding. However, this misbalance of labour demand has two outcomes: the increase in demand of skilled workers will unlikely balance out the number of jobs to be lost for automation. The reskilling transformation from physical to more cognitively based jobs tends to decrease employment needs; and most of the high-skill labour is likely to operate automated machinery or manage robots (Fleming & Measham, 2014). Then again, the benefit of automation in mining is the increased safety and efficiency that this can bring to mine sites and workers' health. On the physical side of task automation, Sen et al. (2020) reviewed literature regarding work-related musculoskeletal disorders in the mining sector and ergonomic interventions. Their research revealed that mining jobs specifically would benefit from automation to reduce work-related musculoskeletal disorders and overall risk at the workplace. Mining work is among the most strenuous physical activities and comes with a variety of physical hazards. Next to external risk factors, such as tripping and falling up to lethal accidents, mining workers also suffer from the physical stress that job puts on their body. Typical tasks include operating heavy machinery as well as lifting tasks, depending on the level of automation already present in the mine. While the exact impact of specific technologies on tasks is not discussed in the publication, Sen et al. (2020) suggest robotic systems, autonomous haul trucks and other automated systems to reduce physical strain on mining workers, or to remove them from dangerous tasks altogether. While removing them from the hazardous workplace implies full task automation, robots might also simply assist in excavation or help detect gases and other materials. When a new technology is introduced to the mining workplace, operators need to be trained in using them. Additionally, many mining jobs are deployed in hazardous environments, so the replacement of human labour by machinery is a positive step for safety and health outcomes. With the increasing use of robots, mining will be a safer activity, benefiting workers' health and requiring lower levels of investments in human safety overall (Paredes et al., 2020). During the transitional phase between full and semi-automation of mining jobs, specific technologies, such as robotic systems worn as exoskeletons, can already offer health benefits to workers under heavy physical demands (Sen et al., 2020). While these technologies are less likely to reduce the workforce, as their functionality is based on supporting the human body, they are an important transitional step towards full automation in those very hazardous and dangerous environments.

Warehouses can also be dangerous environments. Common safety hazards for employees are slipping, tripping or falling from heights, and accidents occurring while operating or working around equipment like scissor lifts and forklifts. Severe injuries can occur in the case of pallets falling over or racking collapsing on a worker. There is an inherent risk associated with working at heights, which can't be eliminated even by a trained workforce. By using robots to reduce the need for employees to work at heights or to operate high-risk equipment such as forklifts, operators could achieve a significant workplace safety benefit. Besides the direct benefit of replacing tasks that pose a risk to humans with robots, the long-term benefit can be seen in reducing the overall physical demand of the job. Ideally, the technological improvements lead to improved working conditions for warehouse workers. The smart warehouse of the future would leverage the best of robotics technology to perform repetitive, dangerous or remote tasks while employing the human workers' ability to act on insights, perform higher analytical tasks and possibly contribute to the improvement of the production processes (D'Andrea, 2021).

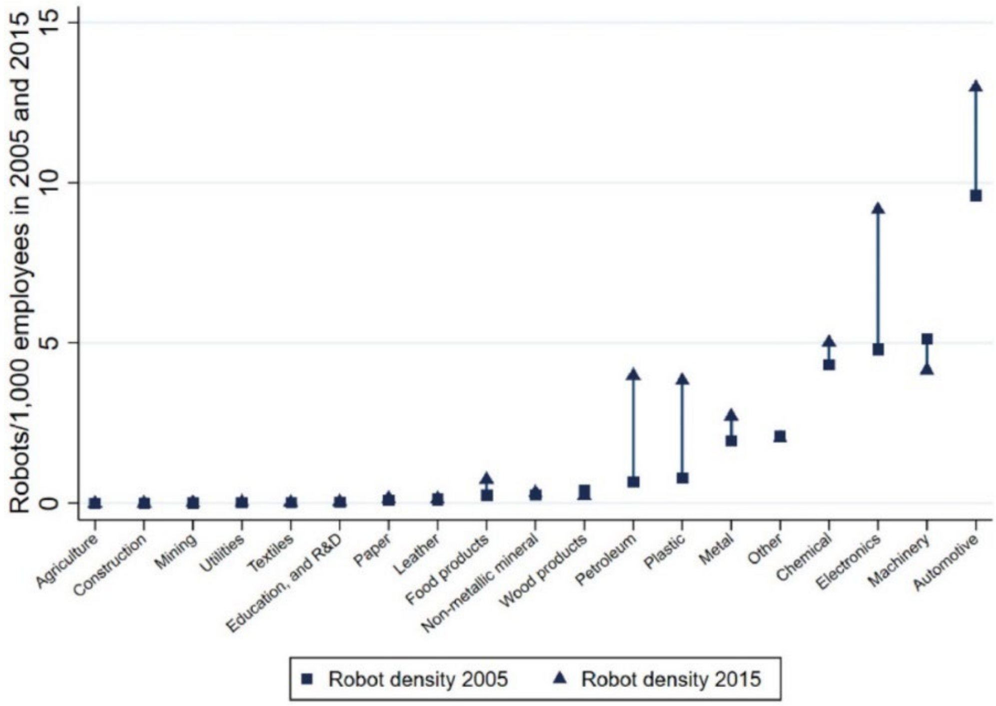
Construction workers, too, belong to a job group facing potential changes in their overall work structure through robotic systems. One of the main advantages of using robotics in construction lies in their potential to assist construction workers during repetitive or dangerous construction tasks in an autonomous manner, or with little worker supervision. This, however, is only possible as robotic systems have become more flexible in recent years and less dependent on a stationary environment. This has the potential to reduce exposure to environmental hazards and increase safety for workers, while also increasing productivity. Thereby, robotic systems present the potential to benefit the whole construction industry (Gharbia et al., 2019). While some tasks are currently still performed by construction workers, such as laying the very foundation of buildings in the form of placing bricks, they will become fully automated in the future. During a transitional period, construction workers will gain assistance in these tasks from robotic systems and then continuously shift towards a more supervisory role over the robot as it performs more subtasks of certain work assignments. A key benefit is that, being mobile, the robots can construct buildings on site, thus reducing transportation costs, material wastage and potential time frame of the whole process. A construction worker's job would then include setting up the robotics system on site, possibly supplying the system with raw material and supervising the process, only intervening when necessary. In essence, they become responsible for all standard functions that are required to ensure the uninterrupted development of the automated construction processes.

This shift however also includes that the construction workers will have to acquire new skills on how to both handle and supervise the machines that are used on site. This reskilling might also be a continuous process as automation progresses and newer, more complex and capable robotic systems will be developed and potentially employed in their work environment.

3.4 Impact on sectors

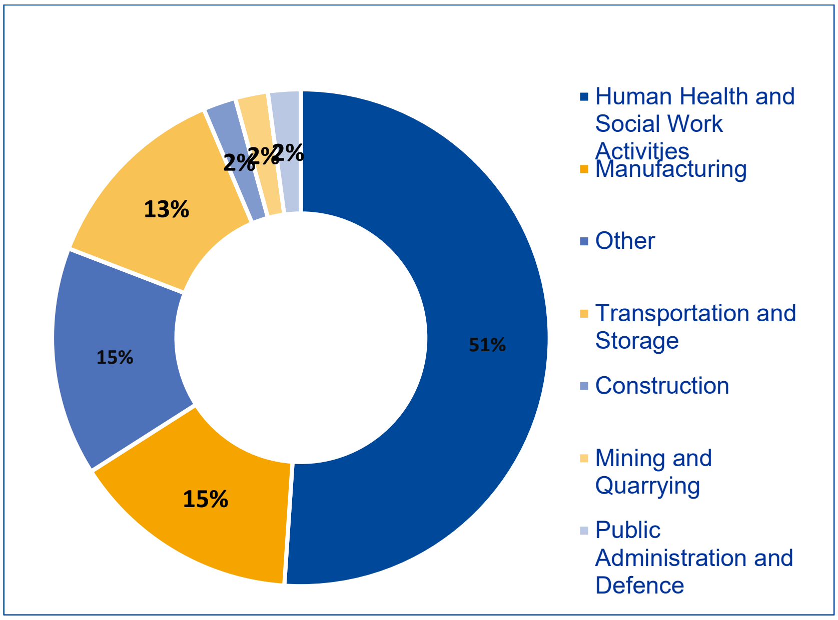
The sectoral analysis presented in EU-OSHA's report "Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and occupational safety and health" (EU-OSHA, 2022a), already revealed the area of **human health and social work** as a prime sector for automation through AI and advanced robotics, followed by **education and professional, scientific and technical activities** as indicated by the analysed literature and interviewed experts. While these results give an indication on which sectors the scientific literature focuses on, they do not represent the entirety of affected sectors. In an additional literature analysis focusing specifically on sectoral impact of industrial robots used for the automation of physical tasks, a variety of additional sectors have been identified.

Figure 4: Relative change of robotic density in the given sectors over a 10-year period (extracted from de Vries et al., 2020)



de Vries et al. (2020) utilised data from the IFR to illustrate the changes in robotic density per 1,000 employees, sorted by industry between 2005 and 2015. While they do not employ the NACE sectors but the ISIC rev 3.1, the results cannot be matched one to one to the literature research results. However, the sectors of **automotive and electronics** are both among the strongest growing sectors in de Vries et al. (2020). Also the **plastic, petroleum and chemical** sectors have experienced an increase in robotic density over the last decade. These results are of high value, as they capture a development over time rather than an assessment of the current situation.

Figure 5: Automation of physical tasks - NACE sector distribution according to scientific literature



The extracted sectors from the literature review help complete the picture of sectorial robotic distribution further. The literature distribution shows a different focus from the results on robotic density found by de Vries et al. (2020). Here, the focus lies on the **human health and social work activities** sector, followed by the **manufacturing** sector. In addition to that, **transportation and storage, construction, mining and quarrying** are specifically mentioned (see Figure 5). These results reflect that the scientific focus currently lies on the human health and social work sector in which the technology is not yet as prevalently used, and secondarily on an established field like manufacturing.

The distribution of automated physical tasks among sectors (Figure 5) 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**. The plethora of possible applications for robotic systems indicates that in the near future the installation of robots in this working environment will gain momentum. Efficiency gains through the use of automation will become more noticeable, leading the systems to play an important role in assisting healthcare professionals to complete their daily tasks. By automating some of the physically intense tasks, healthcare workers might also experience a health benefit through these systems. Noticeable for the human healthcare and social work sector is that not only mid- or lower-skilled jobs are affected, as specifically surgeons, too, are likely to experience increased robotic presence in their working environment. Overall, the healthcare sector is growing and is showing a noticeable potential for widespread introduction of robots in the day-to-day operations. At the same time, research indicates that the sector is taking away jobs from the healthcare professionals fast and passing it on to robots (Qureshi & Syed, 2014). Especially as physical tasks get increasingly automated, the sector has the potential to invest in training and development of their human resources, so as to keep their skills and knowledge up to date, which in turn would enable healthcare professionals to work in tandem with robots and benefit from their support. On a sectoral level, healthcare and social work is likely to continue to grow in its importance and also as a major field of application for robotic systems.

Secondly, the **manufacturing** sector is strongly affected. This cannot only be found in scientific literature but is emphasised by the experts as well as the National Focal Points consultation. The experts agreed upon the fact that the manufacturing sector is the main one regarding the deployment of advanced robotics at the moment. There are numerous examples of almost fully automated factory settings in areas such as the automotive industry. But the capabilities of the technology can expand beyond that sector to other forms of production. Where robotic systems formerly needed to follow a set path or pattern, current iterations use technology such as vision systems to detect the orientation of parts and materials. They can additionally integrate information from multiple sensors and adapt their movements in real time. These technological developments allow them to take over more advanced and complex tasks, for example, by using force feedback to mimic the skill and perception of a trained human worker. The entire manufacturing process will hence become more data-driven, giving robotic systems even more space to advance. This will shift the space and role of workers in manufacturing even further. Manufacturers will have increased freedom to decide which tasks to automate through robotic systems and which to conduct manually. These choices can be influenced by a variety of reasons, ranging from financial decisions to social perception of the company (Demir et al., 2019). This also implies that the extent and speed with which robotic systems change the manufacturing landscape might vary.

More general implications for the sector are that safety and efficiency are expected to increase though human-robot collaboration with cobots (Gualtieri et al., 2021). The option to put robots and people side by side and to reallocate tasks between them also increases productivity, as it allows companies to rebalance production lines in case of demand fluctuation. The workforce will likely benefit most from the decreased physical strain through the automation of physically demanding tasks and increased safety of the work environment by being removed from potentially harmful situations (Gualtieri et al., 2021). While historically there has been job loss due to the elimination of certain positions through robotic automation, in the future, humans are likely to still be present in a supervisory capacity, to ensure that there is no malfunctioning and other disruptions in the production process. Another development in this sector could arise directly from the sinking labour costs of automation. As lower labour and production costs have in the past been factors in manufacturers opening or relocating their sites to different countries, the shift to a more robot-based production with decreased human labour cost might influence this decision in the future towards more in-country production, where the majority of the human workforce is in supervisory positions. The exact role of this factor in future organisational decision-making remains to seen, as it is a multi-factorial and complex process. Regardless, the sector as a whole is likely to benefit from increased automation and improved robotic systems through a more efficient workflow, higher productivity and reduced safety risks for the remaining human workers.

The general sector of **transportation and storage** is also addressed quite frequently in scientific literature and also mentioned by the experts. The logistics market in particular is undergoing rapid changes due to the increase of e-commerce, mass customisation and just-in-time philosophy. EU-OSHA's recently published discussion paper 'Supply chains and their present and future implications for occupational safety and health' focuses specifically on developments in this area (EU-OSHA, 2020). While the current state of technology describes mostly semi-automated warehouses, speculations regarding fully automated modern logistics centres can be found (Pang et al., 2019), and in some cases already be observed in action. Due to the increased activity of e-commerce, this trend will likely continue. A prominent example is selected warehouses in Asia that are fully automated and instead of the theoretical need of 400 to 500 human workers to operate by traditional means, they employ around 1% of them. And these employees do not partake in any transportation or storage-related tasks but provide on-site service for possible machine malfunctions (Hornyak, 2019). This illustrates a shift that the transportation and storage sector will possibly face in the future.

A shortage of skilled workers, with simultaneously rising labour demand, in a physically dangerous environment, is a driving force pushing the **construction industry** to increasingly look towards robotics and automation (Cai et al., 2019). Concerning the current state of automation of construction, maintenance and inspections through robotic systems for on-site usage, are for the most part at a prototype stage or applied in the research context. The automation of tasks through robotic systems on construction sites is expected to increase productivity, as they are faster and are not affected by physical exhaustion. Within the sector there is also likely going to be a shift in the specific kind of skilled worker that is needed. Instead of drafters there might be a need for workers with more digital skills, able to handle more complex systems. Overall, robotic systems can reduce the reliance on manpower in the construction industry and minimise hazards to workers, speed up processes, reduce waste, shorten construction timescales and reduce costs, thereby contributing to the growth of the sector.

The process of labour substitution by automation and robotics is increasing in modern **mining** processes. Next to the reviewed literature, the interviewed experts also identified the mining sector as a likely area to observe increased interaction between workers and robotic systems in the future. Next to supportive robotic technology, the introduction can also lead to labour replacement. This is likely to continue and even accelerate in the coming years due to technological advances and cost reductions in the technology. Traditional mining practices are heavily relying on physical labour and at the same time they were early fields of application for robotic systems, with the first driverless locomotives introduced in the 1970s (Lopes et al., 2018). This also provides a possible explanation as to why in the decade analysed by de Vries et al. (2020) the number of robotic systems has not significantly increased. Automation that took place before the observed time period cannot contribute to those numbers. And if the task requirements have not changed since the implementation of a robotic system, once these tasks are automated there might not be the need for additional robotic systems. As mining practices are facing new challenges, robotic systems can provide beneficial solutions for both the employer and the employee. Increasing mine depths and thus increased environmental hazards such as high temperature, physically dangerous working environments (e.g. cave-ins, falling hazards), and working in remote areas (e.g. far away from cities and emergency support), among other aspects, have negative impacts on a worker's safety and health (Lopes et al., 2018). Robotic systems offer the potential to reduce or solve some of these issues. In addition to that, the sector might experience increased efficiency and reduced costs after introducing more robotic systems, while the human workforce in the mines decreases. However, for this change to be effective and efficient for all parties involved, the transitional process must be undertaken with certain precautions. Miners are often part of the 'loss of jobs' group as they perform low-skilled and repetitive labour. Simultaneously, to steer and maintain the robots, high-skilled programming and engineering jobs are created and thereby create a demand for these kind of workers. Socially responsible companies will have to invest in education and training of their workforce, to provide them with the skills needed to perform in the changed work environment, and adjust their jobs task profile towards less routine manual work and towards more analytical tasks.

Less frequently observed in scientific literature but emphasised by the experts are the sectors **construction, agriculture, forestry and fishing**. EU-OSHA also recently published their 'Review of the future of agriculture and occupational safety and health' (EU-OSHA, 2021), addressing the digitisation of the sector, including the use of AI and robotisation as relevant factors. However, de Vries et al. (2020) places these sectors amongst the lowest density sectors regarding robots per 1,000 worker distribution. These sectors do not lack physical tasks with the potential for automation, however there could be numerous reasons for their underrepresentation both in the literature and general usage reports. According to the interviewed 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 the workers with tasks that involve handling heavy loads (e.g. automated cranes) or, a relatively new development, the exoskeleton. The agriculture, forestry and fishing sector (NACE Rev.2 classification) is quite developed regarding autonomous systems and there is a rapid increase of innovation of these technologies in the sector. All of them present unique environmental challenges for robotic systems, such as exposure to water and no readily available power sources. Nevertheless, the development of technologies in this sector is considered very important to Europe by the experts and is expected to expand in the near future.

4 OSH implications

Based on the reviewed literature we can identify certain areas of interest regarding the current scientific discourse and OSH-related topics discussed most when it comes to the automation of physical tasks through advanced robotics. To provide a better overview on the implications discussed in the literature we categorised them in the sections below. According to the presented taxonomy, OSH implications can primarily impact psychosocial, physical or organisational aspects.

4.1 Psychosocial effects

The ability of machines or assistant technologies to carry out a vast number of functions that once could only be performed by humans has generated a substantial research domain within human factors and ergonomics research (Parasuraman et al., 2000). Within scientific literature the use of automation technologies has driven discussions on which and how many functions should be automated, the design of systems, as well as unintended and unanticipated effects of automation. Intended benefits from implementing automation technologies like increased efficiency, improved safety or optimised workload may not always be realised and can be counterbalanced by human consequences associated with inadequate use, poor system design or inadequate training (Parasuraman & Manzey, 2010).

A great amount of automation research has been conducted in and originated from aviation and military research domains, commonly addressing cognitive tasks. However, many psychological aspects are also discussed independently from the specific task type and can to some extent be applied to physical tasks likewise. Underlying principles of automation issues and effects are generalisable to some extent to the specific interaction form of humans and advanced robotics used for the automation of physical tasks. On the one hand, the overlap of human use of automation with human use of robotic systems allows us to better understand the principles of human-robot interaction (HRI). On the other hand, distinctions and robotic-specific features can be emphasised. The scoping review on human-machine interaction and health at work presents relevant categories of human-machine interactions for the analyses of consequences in relation to the automation of tasks. As described in the review, it is not beneficial to refer to human-machine interaction as a whole when addressing OSH-related consequences, but to rather address individual dimensions in relation to human-machine interaction. These relevant dimensions will also be applied to HRI, as a specific form of human-machine interaction. The identified dimensions are *function allocation* (section 4.1.1), *interface and interaction design* (sections 4.1.2 and 4.1.3), as well as *operation and supervision of machines and systems* (section 4.1.4) (Robelski & Wischniewski, 2018). Although the presented work is not robotic-specific, the categories developed within the review can serve as guiding elements in order to outline OSH risks and benefits associated with advanced robotics and the automation of physical tasks. For this analysis, the additional category of *task design* was added. Most OSH-related consequences will be somehow related to all three categories, though. Nevertheless, they provide an overview as to which broad aspects, in relation to advanced robotics used for the automation of physical tasks, are relevant for which OSH risk or benefit.

4.1.1 Function allocation and human consequences

The aspect of function allocation within the automation of tasks requires that the working task itself determines the allocation of function between humans and machines, in this case advanced robotic systems (Robelski & Wischniewski, 2018). Automation itself is not an 'all or nothing' solution but rather a continuum where different functions to varying degrees can be automated (Parasuraman et al., 2000). The function allocation process itself and especially the resulting tasks left to the human are important sources for OSH-relevant factors to consider. In traditional automation scenarios the task allocation process, including subtasks, is performed and executed once and most likely to stay in the designed way. However, as more flexible, more capable even AI-based robotic systems may take greater parts in the automation of tasks, the scheduling of tasks becomes more dynamic (Nikolakis et al., 2018). There are a number of psychological aspects to consider, which can be influenced in real-time ad hoc task allocation, like perceived process control, mental effort, perceived fairness, task identity and acceptance of the allocation result, flow, and self-efficacy or satisfaction (Tausch et al., 2020). However, currently the application of ad hoc and dynamic function and task allocation in the workplace is very rare. Pilot applications can rather be found in laboratory settings. Applying flexible and dynamic allocation processes currently faces a number of obstacles and challenges. First of all, cost-efficiency is a challenging factor. Flexibility in task execution of both, human and robot, requires a very high degree of technological development. Very often robotic system capabilities are still very limited compared to human abilities. A recommendation regarding the robotic and human capabilities is that the working relationship between the two should be optimised as far as possible. Since robots excel at carrying out repetitive work accurately and quickly and people have higher capacity for creative work, taking decisions, and flexible and adaptive work, combining these strengths creates the best-possible benefit from the relationship between the two (Steijn et al., 2016). If, however, robotic abilities raise to the human level or exceed those, the question arises, from an economic point of view, for whom it will be more cost-effective to perform the task. Here we could see a strong economic favour towards full automation rather than semi-automation. Furthermore, executing different tasks, for example, in a manufacturing setting, might also require robot retooling, which again can be challenging on time and costs. Furthermore, the current process on risk assessment faces challenges when being applied to such dynamic work systems. Risk assessment processes would need to be as dynamic as the task allocation itself or would be required for all foreseeable uses of the robotic system that in itself lowers the flexibility in system use.

A. Automation complacency and automation bias

Within the human factors literature, a number of automation-induced phenomena or challenges have been discussed extensively throughout the past decades. The most common challenges associated with human-automation interaction include complacency, decision biases, reduced situation awareness, unbalanced mental workload, mistrust and over-reliance (Parasuraman et al., 2007). Some of these aspects have explicitly been considered within the specific automation form of HRI. The different challenges will be described here briefly and their specific relevance in terms of using advanced robotics for the automation of physical tasks outlined.

A common phenomenon in relation to the automation of tasks is automation complacency. It is defined as 'a poorer detection of system malfunction under automation compared with under manual control' (Parasuraman & Manzey, 2010). It is generally found in multitasking environments such as in aviation, where operators have to perform automated and non-automated tasks as well as supervise automation. It is most frequently understood as an attention allocation strategy where greater attention is paid to the manual (non-automated) task at the expense of the automated task (Parasuraman & Manzey, 2010). This attention allocation strategy can – consciously or subconsciously – be determined by high levels of operator trust towards the automation technology. The effect is reduced when automation reliability does not remain constant over time but varies. Also, studies show that expertise and training do not have mitigating effects on the occurrence of complacency (Parasuraman & Manzey, 2010). However, training procedures on multitasking might be able to reduce these effects. Automation complacency has been identified as a major contributing factor in accidents mainly within aviation but also other domains (Parasuraman & Manzey, 2010). It is therefore a relevant basic aspect to consider when it comes to the automation of tasks.

A second well-explored and documented automation phenomenon addressed in scientific automation literature is the risk of automation bias and two types of related errors: omission and commission errors. Omission errors occur if the user does not respond to a critical situation related to an alert function (Parasuraman & Manzey, 2010). An example is a worker who misses restocking material for a machine in time because the assistive system misses indicating the right time. Commission errors are related to specific recommendations by the automation system and are described as following the advice of the system although it is incorrect (Parasuraman & Manzey, 2010). An example for this error type would be picking a wrong product from the warehouse shelf as indicated by the assistive system that was not updated to the new warehousing organisation of products.

As summarised by Parasuraman and Manzey (2010), there is consensus within scientific literature that there are three main factors contributing to the occurrence of automation bias. The first one refers to a tendency of humans observed in decision-making processes, to follow the road of least cognitive effort. The second factor describes the tendency of users to overestimate performance and authority of automation systems. Users might even ascribe greater performance and authority to the assistive system than to other humans or themselves. There is evidence that this effect is likewise observable when using advanced robotics, as workers tend to cede control authority to a robot for the allocation of physical tasks (Gombolay et al., 2015). The third factor contributing to automation bias is a phenomenon also observable in shared human tasks. It is the diffusion of responsibility leading to 'social loafing', a tendency of humans to reduce their own effort when working with others (Parasuraman & Manzey, 2010). Again, there is some evidence indicating that the interaction with robotic systems induces the reduction of own efforts (Gombolay et al., 2015). Assigning more tasks to the assistive technology may itself not be of concern, even an intended goal for using the system in the first place. However, some research indicates that interacting with advanced robotics changes the feeling of responsibility for a task. Kim and Hinds (2006) observed that a greater robot autonomy led people to attribute more blame to the robot. Interestingly, this pattern could not be observed for credit for success (Kim & Hinds, 2006). Related to the feeling of responsibility is the sense of agency, the perceived relationship between one's own actions and external events. Some results indicate that performing a task with an advanced robot has the potential to reduce the sense of agency (Ciardo et al., 2020).

The so-far described phenomena, automation complacency and automation bias, are mostly discussed in relation to cognitive tasks within scientific literature. This in particular is the case for automation bias. A similar pattern is observable in scientific literature addressing different automation consequences and phenomena explicitly in HRI scenarios possibly involving cobots[1] (see, for example, Cosenzo et al., 2006; Parasuraman et al., 2007; Wright et al., 2018). The addressed applications often refer to the military context, more specific command and control systems, which again rather relate to cognitive tasks (like convoy management, information acquisition and analysis). Yet, the fundamental effects automation can have on the human user should be considered in any type of automation. Furthermore,

[1] Cobots being robotic systems that perform cooperatively or collaboratively in human-robot interaction.

as outlined above, some contributing factors leading to automation-related phenomena do hold the potential to become even more relevant within HRI. From an OSH perspective it is important to consider that both automation complacency and automation bias can lead to inappropriate use of the system. This might take the form of neglect regarding maintenance or overestimating the capabilities of the system. Depending on what kind of task is automated, both behaviours can expose workers to risks. If a robotic system that supports lifting tasks, for example, in the medical sector, is overloaded, it can lead to possible malfunction, posing the risk of falling for the patient and healthcare worker.

Compared to the other human consequences related to the automation of tasks, an exception for the concept of trust in automation is strongly noticeable. Within the identified literature a large number of studies address trust in automation in relation to HRI.

B. Trust

Trust in automation, regardless of the specific automation technology, automation level or particular task, is an important factor in human-machine interaction and often determines automation usage (Parasuraman & Riley, 1997). There are a vast number of definitions of trust, also stemming from different disciplines. Each emphasise different aspects, describing trust as a belief, attitude, intention or behaviour. According to Lee and See (2004), trust can be understood as 'the attitude that an agent [automation technology, i.e. advanced robotics] will help achieve an individual's goal in a situation characterised by uncertainty and vulnerability'. An adequate level of human trust towards the interacting system promotes an appropriate system usage (Hancock et al., 2020; Parasuraman & Riley, 1997). Extreme forms of trust can lead to adverse effects. Overtrusting or excessive trust, for example, can lead to automation complacency (Hancock et al., 2020; Parasuraman & Manzey, 2010), whereas insufficient trust may lead to neglect of the technology (Hancock et al., 2020). Overtrust and distrust are always considered in relation to the actual system capabilities, also considered as calibrated trust (Lee & See, 2004). Trust is highly related to the reliability of an automation technology or robotic system (Hancock et al., 2020). However, if trust is miscalibrated, problematic interactions occur. Humans are 'found to misuse (over- or under-rely on the robot), disuse (stop using the robot all together), or abuse (use the robot for purposes other than as designed) their robotic counterpart, respectively' (Hancock et al., 2020, p. 1201). Miscalibrations can have severe effects, for example when an operator decides to no longer monitor a robotic system although some oversight would be needed. In contrast, an operator might strictly monitor a robotic system and neglect other relevant tasks.

A considerable amount of studies have investigated antecedents for trust in robotic systems. There is consensus that antecedents significantly influencing human trust towards robotic systems can be human-, robot- or context-related and therefore have to be considered carefully when using robotic systems for the automation of tasks (Hancock et al., 2011; Hancock et al., 2020; Oleson et al., 2011; Schaefer et al., 2014). Among human-related factors exerting effects on human trust towards robots are user satisfaction, expectancy and comfort with robots. Robot-related factors can further be divided into performance factors, like reliability and failure rates, and attributes, such as the degree of anthropomorphism and physical appearance. Within performance, the related factor dependability shows a negative correlation with trust, meaning as dependability of the human on the robot increases, trust decreases. In relation to robotic attributes, the literature shows that robot personality-included factors, such as positive facial expressions, empathy, likeability and sociability, show positive relations with trust (Hancock et al., 2020). Within context-related factors, the aspect of team collaboration, describing the constitution of a team, shows a positive relation to trust. Furthermore, the literature shows that task difficulty has a significant effect on trust. More difficult tasks evoke higher levels of trust towards robotic systems. A reason for this might be reduced workload for the human as the robot might take over some challenging tasks. As mentioned earlier, but also observable in different studies, the reliability of a robot also shows strong positive and significant impact on trust. The more reliable a robot is, the more the human can rely on it to perform in a way that meets their expectations (Hancock et al., 2011; Hancock et al., 2020). A significant source of influence revealed by the literature is proximity. The closer the location of the robot to the human, the higher the degree of trust (Hancock et al., 2020). This finding is especially relevant for remote, teleoperating scenarios, which then especially should consider other trust-enhancing aspects. Furthermore, the aspects of experience with a robot and anthropomorphism show a positive relationship with trust, indicating that more experience and higher degrees of anthropomorphism lead to greater trust towards the robotic system. Human trust towards the robot is also greater when robots fulfil user expectations and when users experience greater satisfaction.

Overall, Hancock et al. (2020) come to the conclusion that factors relating to the robot have the strongest impact on trust compared to factors relating to the human.

Within the robot-related antecedents a robot's attributes and its performance have the strongest impact on trust. As results from different meta-analyses have shown, trust plays an important role for OSH. Its influences on the use of a system are far-reaching, relating to such fundamental functions as to trust a system to reliably perform the task it has been given and therefore to use it continuously. If, for example, a worker does not sufficiently trust a robotic system to hold heavy work pieces, they might lift them themselves, risking short-term or long-term physical injury. It is important not to only consider trust enhancing aspects but to also have in mind that some aspects might have detrimental effects on task completion or other issues (Hancock et al., 2020). A social and highly anthropomorphic robot might be more enjoyable to work with, however anthropomorphic features are not always beneficial for a successful HRI. Furthermore, the adverse effects of too-high levels of trust must not be neglected. This holds especially when combined with a limited understanding of how the automating technology is operating. This can lead to dangerous situations like unexpected behaviours, not recognising automation failure or too slow responses to automation failure (Papadimitriou et al., 2020). This aspect is also closely linked to the issue of adequate training in relation to the use of automation technology.

4.1.2 Task design

The working task is a key element within social-technical system theories and models, where it can be seen as the linking element between human, technical and organisational components. Furthermore, the importance of task design and working task characteristics is directly related to the automation of tasks as the very nature of automation lies within redesigning the working task of a working system. A direct consequence of the function allocation process is the design of the remaining working task (job content) left to the human. One major characteristic of the design of working tasks is related to the amount and quality of decision latitude or job control given to the human worker.

A. Job control

The concept of job control, which includes the dimensions of decision latitude (also referred to as decision autonomy), timing and method control, itself has a long history in occupational psychology. The positive effects job control can have on workers' wellbeing, motivation, satisfaction and mental health, especially helping to outbalance high job demands, are very well described in scientific literature (Bakker & Demerouti, 2007; Karasek, 1979, 1998). Especially in areas like physical manufacturing tasks, where the level of job control naturally is lower due to standardisation and quality control efforts, timing and method control are influential factors in workers' mental health, motivation and satisfaction (Rosen & Wischniewski, 2019). The application of robotic systems can hold the risk to even further decrease levels of job control. A tight and non-flexible coupling of human tasks to robotic performance could lower task performance flexibility and increase a machine-determined work rate. Both aspects have the potential to be associated with a number of adverse psychosocial effects like emotional exhaustion, nervousness or irritability, an overall poorer mental health and less intrinsic job satisfaction (Robelski & Wischniewski, 2018; Rosen & Wischniewski, 2018).

In relation to changing task characteristics and changed levels of job control when using advanced robotics for the (semi-) automation of tasks, the interviewed experts also mentioned the risk of lack of self-efficacy arising from new or modified tasks. This can have the effect that the workers no longer feel as competent and independent in relation to their work and their work environment. Workers may develop a feeling of lower self-efficacy, because the tasks are more predefined and they have less leeway in defining the task, that is, a reduced level of job control. It is furthermore stated that these low levels of control and dependency on the robotic systems, which in scientific literature is also known as technological coupling (Corbett, 1987), may lead to a feeling of only supporting the robot's work and decreasing the subjective value of one's own work.

The importance of job control is underlined when considering the role it plays in the development of burnout. As most of the discussed technology is still comparatively new, no long-term studies exist on their specific relationship with burnout and job control. However, the general relationship between these two concepts is well supported in the literature (see, for example, Park et al., 2014) and should therefore be considered when talking about advanced robotics and their impact on OSH.

In contrast, the possibility for workers to perform certain working tasks with a flexible robotic system might hold the opportunity to increase levels of job control, if certain design recommendations are followed (Rosen & Wischniewski, 2018). However, if task and system boundaries are not made clear, one could face the risk of letting job control or decision latitude become too large, which again can result in decreased wellbeing or stress.

B. Feeling of control

Task characteristics defined by the level of job control can be perceived differently by human workers. Therefore, closely linked to the concept of job control is the subjective sense of control, which is also a well-established concept in psychology (Spector, 1998). Perceiving control over one's work environment can alleviate the effects of stressors in the workplace and a positive relationship has been shown between the subjective feeling of control and health as well as wellbeing (Spector, 1986). The increasing autonomy of intelligent systems and smart robotics gives space to the question of how much workers want and need to be in control of the robotic systems they work with and how it affects the way robotic systems should be designed. The sense of control can be divided into perceived control and desired control, where perceived control refers to the perception of who is realising an intended action and desired control describes the worker's expectation of how the action is realised. There is some research that describes the sense of control in HRI, especially when accounting for different levels of autonomy in the robot. Perceived control lowers as the level of autonomy of the robots increases; this did not seem to correlate with participants' desired control (Chanseau et al., 2016). Being able to realise intended actions through a chosen actor and then receive the expected outcome with the robot would result in a higher sense of control over the working situation. Growing autonomy of robotic systems might incentivise workers to allocate tasks towards them, which the system is capable of performing, without losing their sense of control over the situation.

However, there is evidence indicating that high levels of robotic autonomy are also associated with lower levels of feeling of responsibility. This effect seems to be even stronger for occurring errors but not for success factors (Kim & Hinds, 2006). Nevertheless, both a lack of feeling in control and low levels of felt responsibility are risks associated with the allocation of tasks and the resulting working task within HRI. The risk of losing control, whether it is a subjective feeling or an objective circumstance, was also explicitly mentioned by the interviewed experts. The experts further stressed that the 'human in control' principle should be regarded as a leading design guideline. Therefore, when designing workspaces in which robotic systems and humans work closely together, the worker should retain their sense of control over the working situation, rather than feeling like their actions are controlled by the robotic work process. Having the human in control enables the worker to take actions especially in unforeseen situations and can even prevent accidents. This design request is closely linked to the aspect of system transparency and the design principle of self-descriptiveness. Both aspects will be described in section 4.1.3 on interaction design.

C. Work intensity and deskilling

In relation to the design of working tasks and a very often discussed and addressed psychosocial working condition is the aspect of work intensity, for example as described in relation to job control in the Job-Demand-Control Model (Karasek, 1979, 1998) or the broader Job-Demand-Resources Model (Demerouti et al., 2001). Closely linked to the concept of technological coupling, in the literature but also explicitly addressed by the interviewed experts, the question is raised as to whether introducing robots to workplaces will lead to work intensification. On the one hand, this relates to the question of how tasks are quantified in terms of time resources and if sufficiently addressed in the new working system. On the other hand, this also addresses the aspect of skill level required to perform a certain working task. Effects on skill level and preservation of certain skills are addressed in scientific literature and were also stressed by the interviewed experts. The scientific literature describes the potential risk of robotic systems causing deskilling effects on the workforce as workers do not complete the full task anymore and therefore lose comprehension of the complete process. The reduction of skill variety is also addressed in the potential polarisation of jobs (see, for example, Hirsch-Kreinsen, 2016), a hypothesis very often discussed in relation to the automation of tasks and digitalisation of work systems. In a simplified way, it states for jobs with low-skill level requirements that the automation of complex routine tasks will cause the job to focus on even more simple tasks rather than enabling the human to perform tasks that require a higher skill level. Closely linked to this is also the issue of qualification and, even more, how workers develop a subjective feeling of being qualified and capable of working with robotic systems. As will be described in section 4.1.4, in the paragraph on fear of job loss, the fear of not being qualified to work with newly introduced systems for the automation of tasks can be considered as a relevant risk.

4.1.3 Interaction design

Within scientific literature there are a number of robotic interaction design aspects that are discussed in relation to different OSH aspects. Robotic design aspects and interaction design can be associated with different attributes. They can, for example, be related to the outward appearance and embodiment of the robotic system (e.g. anthropomorphic or zoomorphic design), robotic behaviour and movement or interaction, as well as communication styles and channels. Within the area of robotic movement behaviour, aspects like velocity, acceleration and deceleration, trajectories, and approaching or passing strategies fall into the scope of consideration. Communication between human and advanced robotics can be designed to various degrees. Research has been conducted on comparing the effects of different communications channels. One example is the effectiveness of combining several modalities like gesture and speech (Berg & Lu, 2020). Other attempts focus on specific verbal interaction scenarios, for example, when robotic systems need to communicate their limitations and request aid from the human interaction partner (Backhaus et al., 2018). These different interaction design aspects are to varying amounts associated with OSH risks and opportunities. The similarity that interaction design research shares is the attempt to identify attributes and characteristics that enable a smooth and natural interaction. The overall aim is furthermore to increase the feeling of wellbeing, acceptance, trust, positive emotions, a positive user experience or workflow (see, for example, Honig et al., 2018). Likewise, dysfunctional levels of workload, irritation, strain or disruptions shall not be induced by the interaction or even reduced, where possible. However, robotic design aspects are not stand-alone considerations and must always contemplate the addressed context and working task. This will be presented especially in relation to the aspect of anthropomorphic robot design, which probably has received the highest attention within interaction design literature.

A. Anthropomorphic robot design

The aspect of embodiment and more precisely anthropomorphic robotic design is largely addressed within scientific literature. Especially in recent years it has regained major interest as more human-like systems have entered the commercial market. As we have seen, anthropomorphic robot design can have positive effects on trust towards robots. Furthermore anthropomorphic design features like eyes or facial expressions can foster a more natural interaction, acceptance and likeability especially in social robotics (Fink, 2012). However, using human social cues as a means for a smooth HRI does not only have advantages. First of all, there is no linear relationship between robotic anthropomorphism and associated likeability or acceptance. In fact, as brought forward by the uncanny valley theory, human likeness only increases empathy and likeability up to a certain degree (Mori et al., 2012). Once a robot has reached a certain degree of human likeness, it can rather cause strong negative emotions like eeriness (Mori et al., 2012). Secondly, but probably more important, are the negative consequences anthropomorphic design can impose on human expectations but also on task performance. Anthropomorphic design features will trigger human expectations regarding robotic capabilities and behaviour (Złotowski et al., 2015). If a system has features like eyes, we expect the robot to be able to process visual cues; if a robot has ears, we expect it to be able to process auditory cues. In general, anthropomorphic features will lead workers to ‘unintentionally attribute non-existent “reasoning” or “recognition” capabilities to robots’ (Murashov et al., 2016, p. 7). This can result in irritation or even a significantly perceived lower reliability in industrial settings (Roesler et al., 2020). It is important to note that anthropomorphic cues should always be considered with possible attributed functions. Furthermore, if anthropomorphic cues are not task-related, that is, serving to improve task performance, or used for supporting the coordination of the interacting partners, they should generally not be applied. This is especially the case for industrial applications (Roesler et al., 2020).

Especially in interactions where precise knowledge of the robotic features and, for example, communicative capabilities is important to the task, the unintentional attribution of other features based on anthropomorphic design choices could pose an OSH risk. As an example, being able to halt a robotic motion via voice command versus only via directly typed input changes how close a worker has to be to the system to interact with it. If wrongly assumed voice commands are possible, the system might not halt in time. Anthropomorphic design is not only limited to embodied features like facial components or body structure. It can also relate to robotic movements or communication strategies. Especially for physical pick and place tasks, evidence is given that anthropomorphic robot movements compared to purely robotic movements enable humans to respond to the movement significantly faster and with greater accuracy (Kuz et al., 2014). This is a finding that certainly can be relevant for handover and (collaborative) positioning tasks. This could result in the actions being performed more smoothly with fewer additional movements on the human side to adjust to the robotic system.

B. Dialogue principles in HRI

The anthropometric design of advanced robotics embodiment can be regarded as quite robot-specific, even unique. However, in relation to interface and interaction design, more traditional aspects and the overall existing knowledge on advantages of ergonomic design apply. One standard to consult when addressing interaction design has to do with the interaction principles (former dialogue principles) formulated in the EN ISO 9241-110. Interaction principles and general design recommendations can guide the development and evaluation of user interfaces, leading to improved usability. The priority with which the interaction principles are applied depends on the purpose of the system, the users of the system, the tasks, the environment, the specific interaction technique used and the consequences arising from use. The way they are then employed depends on what kind of system is being used. The seven principles 'Suitability for the user's tasks', 'Self-descriptiveness', 'Conformity with user expectations', 'Learnability', 'Controllability', 'Use error robustness' and 'User engagement' form a basis of general design recommendations for different interactive systems (ISO 9241-110:2020). While they have been identified to be important and useful for designing system interaction in the context of Industry 4.0 (Fischer et al., 2017) and have proven to be an adequate tool for user evaluation of robotic systems (Rosen et al., 2018), the literary basis on their application in robotic system interaction is still rare. Especially the new degree of automation that advanced robotics bring into a workplace introduce a new quality to the interaction, which could be assessed and improved by applying the dialogue principles early in the development process. Furthermore, as described by Rauch et al. (2020), new work environments will challenge cognitive abilities such as coordination, supervision and decision-making more than previous physical tasks. For this reason, cognitive and sensorial aid needs to be provided to prevent information overload and its negative effects on the operator, also when mainly performing physical tasks. The quality and effectiveness of the addressed cognitive and sensorial aids are directly related to the aspect of interaction design and how well a system incorporates the described design principles.

C. Transparency and responsibility in HRI

Especially as robotic systems expand in capabilities and autonomy, developers and also legislators need to consider the facet of responsibility and accountability in the interaction. Humans hold robots accountable for their mistakes (Kahn et al., 2012), at least more than other objects. While the idea of transparency in an interaction with a system has intuitive appeal, few studies have examined the impact of transparency on HRI specifically. Kim and Hinds (2006) found that transparency had a greater influence on user perceptions of the robot when the robot had greater autonomy. Users placed greater blame on the robot and less blame on others when errors occurred in the work process. This suggests that transparency increases in importance as a robot's autonomous capabilities increase. Transparency stands for a more comprehensive treatment of information, including system state indication that an operator may need when dealing with autonomous systems, especially under high stress, workload or uncertainty. If transparency is lacking, the user may view the robotic system as unreliable, when in reality the provided information is misunderstood or not presented in a sufficient form. In that case, even routine behaviours can be interpreted as errors, if the operator lacks the information to understand the reasoning process behind the actions (Kim & Hinds, 2006). And given the imperfect track record of automation, it is imperative that researchers and developers consider the transparency of HRI to allow individuals to properly assess their reliance on these systems, particularly as technology gets more complex and is used in increasingly complex scenarios (Lyons, 2013). However, one should not simply assume that more information delivered by the system is necessarily better for the user. Too much information might not increase the transparency of a system but lead to an information overload and result in an inability to select and process critical information (Finomore et al., 2011). Hence, creating sufficient transparency in HRI is an important yet complicated endeavour with noticeable consequences for the interaction between operators and the system.

Incorporating design principles to a sound state, providing sufficient system transparency or even enabling individualised interaction strategies taking into account very personal and individual preferences and characteristics will definitely ensure a seamless interaction. Technical requirements for individualisation or a smooth and user-friendly interaction are often related to the deployment of a variety of robotic sensors. Being able to react and behave in the intended or tailored to an individual way requires the robotic system to collect and analyse environmental data as well as data regarding the interacting human. However, seamless interaction supported by well-known design principles can conflict with adverse effects like infringing users' informational privacy or contributing to the feeling of alienation and loss of control (Fronemann et al., 2021). A feeling of alienation and loss of control, for instance, can be caused when a robotic system adapts its behaviour autonomously without notifying the user, who might not be able to predict and understand this adaptation (Fronemann et al., 2021). Again, this interaction design-related risk emphasises the importance of transparency regarding system operations, actions and behaviour to reduce potential adverse effects. Excessive data collection can furthermore lead to actual or perceived monitoring of workplaces and employees' performance and behaviour. This can lead to negative impacts on motivation, satisfaction, organisational trust or stress, even if principles of data protection according to the General Data Protection Regulation (GDPR) are met (Funk et al., 2020). This very ambiguous aspect of individualisation and smoothness of interaction, holding risks and opportunities likewise, was also explicitly mentioned by the interviewed experts. It was pointed out that especially cooperative or collaborative interaction scenarios could benefit from the advances, if the robot for example would sense certain aspects of the human, for instance, bodily weaknesses. However, the described possible risks must not be neglected.

4.1.4 Operation and supervision

The dimension of operating and supervising a system can be regarded as a direct consequence resulting from the function allocation process and the specific interaction design (Robelski & Wischniewski, 2018). Although the different addressed dimensions aren't strictly distinctive, there are some psychosocial risks and challenges that are rather associated with the actual or forthcoming use of a robotic system than the aspect of function and task allocation or interaction design.

A. Attitude and experience towards and with robots

The relative novelty of robotic systems in the workplace leads to an inevitably inexperienced and unaccustomed workforce when it comes to the interaction with them. This lack of familiarity can influence their attitude towards them and colour their initial experience. Even more, initial attitudes can be shaped by external sources like newspaper reports, which can be biased towards negative pictures regarding robotic systems at the workplace (Riemer & Wischniewski, 2019).

We know that use and experience can change workers' perceptions of and attitude towards robotic systems. With increased familiarity, the novelty of these systems decreases as preconceived ideas about their capabilities and behaviours evolve towards a more realistic picture (Sanders, 2019). Both trust and acceptance are likely to increase as attitudes are shaped by exposure to a system (Hancock et al., 2011). This effect however seems linked to the actual experiences of robots acting in a physical space to decrease negative attitudes toward robots. Nomura et al. (2011) found that the negative attitudes towards them decreased as experiences of interacting with robots increased. This was not specific to a working environment; however, as familiarity has been repeatedly stated as a positive influence on the attitude towards these systems, it can be assumed that similar effects will take hold in a working environment. However, in the current manner, experiences of and with robotic systems are comparatively short-term. There is a lack of data on the long-term development of attitudes towards them once workers have years of experience. As the short-term effects seem to be beneficial for workers, companies that intend to employ robotic systems in their work environment should take this into consideration.

One of the interviewed experts also described experiencing very reluctant attitudes towards a robotic system more precisely an exoskeleton, from the affected workforce during a piloting phase. This was even the case although the usage was purely voluntarily and helping to lift heavy loads. However, workers were not willing to change their original working process or to add additional tasks in order to charge, maintain or store the exoskeleton. However, it has to be noted that the presented reasons by the workforce might have been influenced from other effects. Especially with the use of exoskeletons, the risk of low acceptance due to stigmatisation or reduced comfort can occur.

B. Social support

Social support in the workplace, for example, from team members and colleagues, is considered a major factor influencing wellbeing and satisfaction. Research has shown mitigating effects of social support on perceived work-related stressors and a reduction of experienced strain (Viswesvaran et al., 1999). The (semi-) automation of tasks that previously had been performed by humans might eventually lead to new teaming structures. So far, it remains unclear how and if adding robotic systems to working systems will influence existing team structures and possibly influence perceived social support. A possible risk could be a decrease in perceived social support as the interaction with human team members might decrease. However, currently, this phenomenon is not yet extensively addressed in scientific literature.

C. Fear of job loss

While the narrative of introducing autonomous robotic systems as a sort of co-worker frames the technology in a humanising light, some workers will not perceive them as a beneficial technology, but as a potential risk to their employment. While the exact percentages of jobs that are highly or entirely automatable are not set in stone, some estimations place this number at around 14% (Pouliakas, 2018) and at around 40% of workers who will experience major changes in their work. Changes through the automation of the workplace can lead to fears of unemployment and financial insecurity (McClure, 2018). Currently, workers have already begun to recognise that becoming technologically literate is essential in the increasingly digital workplace (Smith, 2015). However, this mentality does not give insight to whether it resulted from the positive outlook of improving one's working situation or from the fear of job insecurity if a worker fails to attain new skills that are still relevant after others have been automated through the system. Reichert and Tauchmann (2011) investigated levels of psychological distress for workers with job insecurity and found that employees with little job security suffer from poorer psychological health. Furthermore, the effects of job insecurity are exacerbated for workers who have pre-existing mental health problems. In addition to that, not every position is affected equally through robotic systems, as the above-described tasks and jobs illustrate, therefore not every worker has the same likelihood of experiencing the fear of job loss once a robotic system is introduced into a firm. Workers in higher positions, who are less likely to be affected negatively by the introduction of robotics, such as managers, professionals and the highly educated worker, fear robots at work less than manual, blue-collar workers and people with lower education (Dekker et al., 2017). Kozak et al. (2020) assessed that job insecurity due to automation through robotic systems is not an irrational fear of the unknown but rather a rational reflection of automatability risks of tasks to which workers are exposed. They stress the need for further implementation of skill development policies for the labour force to combat both actual job loss and the subjective fear of it. Providing workers with new skill sets could simultaneously facilitate their adaptations to requirements of the new work environment in a digital economy and provide them with a subjective sense of security (Kozak et al., 2020).

4.2 Physical effects

The physical impact of task automation through robotic systems can be categorised into two categories: the potential and intended benefits and the possible risks.

4.2.1 Physical benefits

Within the group of positive impacts we see one major area being the distancing of human workers from dangerous or strenuous environments (Gharbia et al., 2019; Sen et al., 2014). Construction sites and mines, for example, pose inherent physical danger to workers, ranging from tripping and falling risks to even more severe dangers. Removing human workers from those dangerous tasks can reduce the risk of injury. The other group of positive effects comes from robotic systems physically supporting workers in specific tasks, in which the continuous or repeated physical strain poses a health risk (Kyrarini et al., 2021). Many generic tasks automated through robotic systems, such as lifting a work piece or even transportation of an item around the workplace, can fall under this category. The repeated lifting of patients in a healthcare setting is also an example for the affected task. Work-related musculoskeletal pain and injuries are common among nurses. Hence, the automation of especially strenuous tasks can greatly benefit their health.

The subsection of object-related physical impact is probably the most easily associated with robotic systems among all the categories. It evokes an image of a robotic arm lifting a heavy work piece, which previously had to be stabilised manually, having the worker lift dozens of kilograms. Gualtieri et al. (2021) use their review to highlight the current research on designing safe and ergonomic collaborative robotic work cells. Regarding physical ergonomics, specifically task scheduling, motion planning and control, they suggest that the work cells should allow a reduction of physical workload by changing the work cycle and the robot system's performance according to the operator's physical conditions, benefiting the workers' physical wellbeing. This is in line with the interviewees' interpretation of how a robot can impact a worker, since it could remove, under certain circumstances, physical strain and reduce risk exposure. Especially in terms of physical risks in work situations that include an object as part of the task, the robot can operate in dangerous situations and thereby alleviate the physical stress on the worker. An example was that it can lower the weights they may need to carry; it can help the human avoid unhealthy posture and thereby avoid musculoskeletal disorders. Nelles et al. (2019) reviewed 30 studies and extracted eight instruments to measure human wellbeing in HRI. While their primary focus is on presenting these instruments, they also summarised the results of the original studies. This allows some insight into which factors affect wellbeing, both positively and negatively. Physical wellbeing seems to be improved by partly automated workplaces or physical assistance during strenuous tasks. This result is in line with previous findings. However, as these observations are not part of their main research, their completeness and generalisability cannot be assumed. Gualtieri et al. (2021) too, describe several OSH-related methods that have been developed in the context of HRI at the workplace. They gathered literature and observed the prevalence of certain safety measures. Their baseline is a workplace in which human and robot work together in a shared space including an object that gets manipulated through the work process, sometimes without additional fencing. One concept is contact avoidance to ensure operators' safety (in terms of mechanical risk) by pre-empting dangerous contacts using preventive methodologies and systems. Within this concept, the most developed research themes for Contact Avoidance are Motion Planning and Control, Sensor Systems for Object Tracking and Safety Management. For Motion Planning and Control, the main contents refer to human-motion prediction, trajectory modification and motion control strategies. For Sensor Systems for Object Tracking, the main contents refer to the development and integration of monitoring and computer vision systems for human localisation, workspace control and gesture recognition.

4.2.2 Physical risks

Next to positive shifts with regard to a worker's physical condition, experts also point out, that new technology could lead to new kinds of physical hazards. As many robotic systems currently perform a task that somewhat involves movement, possibly movement with an additional physical load, collision risks have been highlighted repeatedly. While a collision between worker and robotic system itself already poses a health risk, the potential for injury increases when the robot is handling an object or has a sharp or pointy gripper attached. The speed of the robot as well as the mass of it and its load will determine the impact on the human body and potential severity of the accident. Therefore, before employing a robotic system these scenarios have to be assessed and mitigation strategies must be developed, as required by the obligations of a risk assessment according to Article 9 in the Health and Safety at Work (Framework) Directive 89/391.

Furthermore, the experts addressed a number of physical risks that can be associated with the use of robotic systems in the workplace. They will be described briefly in the following paragraph, however it has to be noted that the addressed risks are not per se robot-specific and are dealt with in the applying Directive 89/654/EEC - workplace requirements as well as the Machinery Directive 2006/42/EC as well as applying Type-A standards (basic safety standards) and Type-B standards (generic safety standards). In the following, a number of occasions leading to physical risks are listed as described by the interviewed experts.

Errors in the control functions can cause the robot to stop or start unexpectedly, which can cause a harmful situation. Unintentional movements can hit the human being or trap the person between the robot and a fixed part, for example, squeezing the hand. Here, excessive force from control errors is the main risk. Therefore, limits for the force of contact need to be set. It is important to consider that these kind of control errors can occur at both the design and operation stage and they often fall back on a malfunction of the software, but might also possibly be caused by human error. Another risk factor is possible mechanical failures: if there is no proper maintenance, there might be an error in the hydraulics or electrical parts, leading to possibly the same outcomes as a control error. Failure to the electrical power system, too, can cause a robotic system to malfunction, for example, due to disruption of power supply. If this risk is considered prior to integration of the robot into the workspace, countermeasures can be taken to prevent this sort of risk. As with most electrical machines, robotic systems introduce a potential fire risk to the workplace. This can be triggered by overloading the robot, because of electrical overload, or an improper electrical installation or maintenance. Here, authenticity of the electronic components when the robot is being maintained is important to ensure a continuously safe working environment. Furthermore, as robotic systems operate, workers might be exposed to additional risks of vibrations. Proper maintenance of the machine is very important: the robot should be installed in the right way in a certain place or on the floor, so that any possible vibrations won't result in it moving or dislocating parts. Additionally, the experts also highlighted environmental sources around the robot as physical safety and health risks: electromagnetic or radio frequencies can interfere with the software of the robots and increase potential injuries to the workers. Lastly, as technology becomes more and more interconnected and relies more heavily on distributed communication between systems, cybersecurity is being mentioned as a contributing factor to physical risk while working with a robot. To ensure that robotic systems are indeed not being influenced in their movement by outside sources, software security is an important aspect to consider, for the prevention of potential outside influences, which may cause the machines not to behave in a safe way. One way to account for these factors is the introduction of robot-specific risk inventories and evaluations. 'Organisations can be assisted in this using methods such as electronic questionnaires and checklists. A codified questionnaire can help with risk inventories and evaluations, and can also benefit awareness and compliance towards prevailing legislative and regulatory aspects' (Steijn et al., 2016, p. 44).

4.3 Organisational effects

Although the implementation of new technologies in the workplace has become both a reoccurring phenomenon for workers and a necessity to increase competitiveness for organisations, the gathered information reflects that when it comes to robotic systems employers should approach this process with intention and structure to maximise the expected benefits for the workforce. Robotic systems pose a degree of freedom and autonomy that previous technologies did not possess; hence, the organisational changes that their implementation is expected to trigger might vary from previous technology. At the same time, experts express that some known organisational considerations should still apply.

4.3.1 Introduction process and change management

Clear and direct communication as well as participation approaches can provide employees with the appropriate level of information as to why, how and when changes to their workplace and routine will take place. This serves two purposes. Firstly, it informs workers regarding their tasks, policies and other organisational changes to which they will have to adapt and, secondly, it prevents perceived separation of the workers affected by the changes and those who incited the changes, creating a more coherent unit. Empirical research suggests that the existence of a formal communication avenue in organisations introducing a change initiative reduced uncertainty and enhanced commitment (Bordia et al., 2004; Hobman et al., 2004). Communicating future changes to employees can reduce feelings of uncertainty towards the rationale behind the change. Furthermore, clear and direct communication has also been found to promote change and supportive behaviour from workers (Bordia et al., 2004). While these concepts were not specifically outlined with robotics in mind, but rather with organisational changes through technology in general, their importance is reflected in the interviews' assessment. In addition to communication prior to the implementation, the work area in which the robot will be employed needs to be rearranged and the tasks of the workers newly defined. Before any implementation that will require changes in work processes, a company should consider additional safety devices and gather know-how for different situations of use of the robotic system. Problems can arise when companies buy the robotic system before analysing the workplace and creating an appropriate work environment. To facilitate that, one should first create a use case for the robotic system and then analyse it as needed. It can also be beneficial to have a designated team in place that thinks about relevant and new issues, such as working with the robotic system continuously, involve human factor and ergonomics specialists, and possibly ask support from accident insurance institutions. Once integrated into the workflow, companies have a number of tools at their disposal to ensure OSH at a workplace with a robotic system and enhance smooth collaboration. Here especially, the aspect of risk assessments was stressed by the interviewed experts. Furthermore, the experts named risk management, training of employees, monitoring and supervision of the worksite, and procedures for good maintenance as potential tools.

4.3.2 Cybersecurity

Noticeably, a majority of research regarding safety and robotics has focused on various aspects of HRI. This is reasonable as robots often are generally large heavy machines, which, when working close to humans, could pose a physical risk. The possibilities of those have been examined above already. However, as robots become more widespread, the impact of human safety with regard to cybersecurity needs to be addressed. As with most embedded systems, robots too could be targeted; the gravity for human safety being highly dependent on what kind of robotic system gets attacked. The impact of a cyberattack on a military robot can have far-reaching consequences, but also intentional malfunctions in surgical robotics could pose a risk to both surgeon and patient. Next to physical harm caused by a hacked robotic system, data privacy could also be breached if cameras of a robotic system are accessed by a third party (Clark et al., 2017).

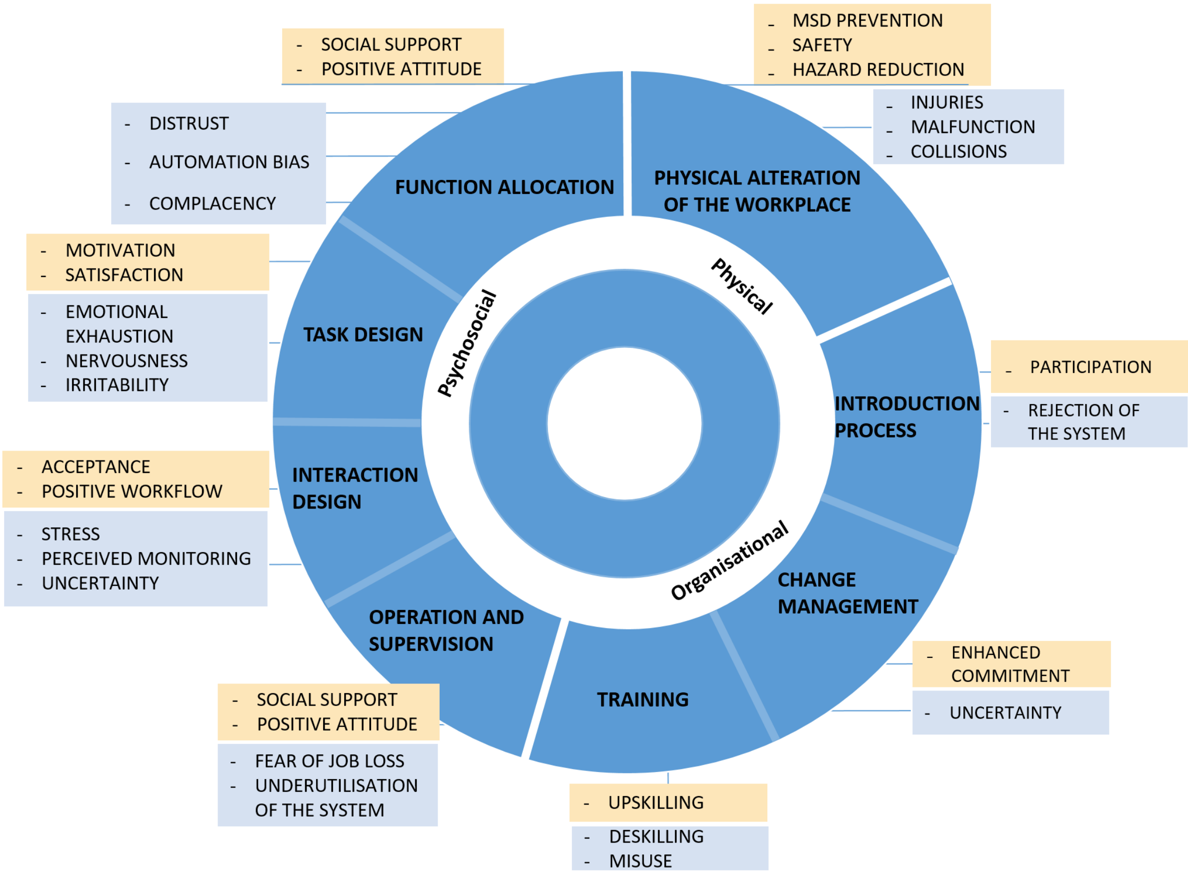
Hence, when employing a robotic system, there need to be adequate systems in place to prevent an attack on them. The recently enacted European Cybersecurity Act establishes a cybersecurity certification framework. While this is not specified for advanced robotic systems, it could be used to define cybersecurity requirements for robots, although concrete cyber-physical implementation requirements are not yet described (Fosch-Villaronga & Mahler, 2021). In the meantime, it is within everyone's interest to develop preventive measures against common attack methods like viruses, worms, software trojans and buffer overflow. With regard to the increased connectivity of systems, partially related to the Internet of things, firmware code is stored in flash memory to allow operating system upgrades remotely via the Internet. These upgrades open device drivers and operating systems to attacks (Clark et al., 2017). These possible target points should be considered by manufacturers when creating robotic systems, but in the maintenance and usage also do depend on the users to comply with certain safety measurements, too. While procedures like not delaying updates, or granting untrusted sources access to a system, are in no way new, or limited to robotic systems, their importance should not be understated.

4.3.3 Need for training

Next to external organisational changes, there are other more worker-oriented factors that should be considered when deriving an organisational change in relation to a robotic system. The interviewed experts remarked that familiarity is of utmost importance when working with a robotic system. However, as familiarity with the new system can only be created over time spent working in the new setting, sufficient and adequate training is necessary. This training should be specific to the robotic system and the work situation in which it will be employed. The need for specialised training falls under another category of organisational change expected from introducing robotic systems to the workplace, more than previous technology. One of the biggest organisational changes these work environments will have to face is the demand for re- and upskilling. This entails training the staff in working with the new robotic technology, while simultaneously avoiding deskilling and the loss of other crucial competences. Several sources in the interviews stressed the need for reskilling, or upskilling and the danger of deskilling in the workforce. Considering these factors and providing the needed opportunities for employees might also increase their participation in the organisational changes. Employee participation in implementation and decision-making has been found to enable supportive behaviour from employees (Gagne et al., 2000).

In order to address OSH-related risks and opportunities associated with the (semi-) automation of physical tasks with advanced robotics, including cobots, relevant dimensions and their effects were analysed. Figure 6 presents an overview of the relevant identified dimensions in relation to psychosocial, physical and organisational aspects and possible associated OSH-related risks and benefits.

Figure 6: Overview of OSH-relevant dimensions and effects



4.4 Standards

Apart from Type-A standards (basic safety standards) and Type-B standards (generic safety standards) that also apply if relevant, there are currently three machine safety standards (Type-C standards) for robotic systems.

- ISO 10218-1: Robots and robotic devices - Safety requirements for industrial robots;
- ISO 10218-2: Robots and robotic devices - Safety requirements for industrial robots; and
- ISO 13482: Robots and robotic devices - Safety requirements for personal care robots.

Furthermore, there is a relevant technical specification to be named as well as a relevant technical report:

- ISO/TS 15066: Robots and robotic devices - Collaborative robots; and
- ISO/TR 9241-810: Ergonomics of human-system interaction — Part 810: Robotic, intelligent and autonomous systems.

As described in the relevant German standard DIN EN ISO 10218-2:2012-06, part one (10218-1) refers to the robot itself. Part two (10218-2) refers to the robotic system, that is, the working or production system or line a robot is used in. This working system can furthermore include other machines beyond robots, which again have their own Type-C standards. Also relevant for a robot that is part of an integrated production system is ISO 11161: Safety of machinery – integrated manufacturing systems.

ISO/TS 15066: Robots and robotic devices - Collaborative robots is an addition to the abovementioned standards for collaborative industrial robots. ISO 13482: Robots and robotic devices - Safety requirements for personal care robots refers to mobile robot assistance, movement-supporting robots and person-transporting robots. The standard excludes industrial robots covered by ISO 10218 and medical robots, as well as toys, military applications and robots that move faster than 20 km per hour (DIN EN ISO 13482:2014-11).

In relation to the content of the standards, the interviewed experts addressed the following aspects:

- ISO standards are conservative: no touch between the human and machine is allowed.
- ISO standards for working environment and workload are not yet revised for unfenced robots.
- Biomechanical limits of ISO TS 15066 are limited to pain onset. There are requests regarding limits for injury onset.
- Lack of focus on situational awareness and user friendly instructions.
- ISO standards do not regulate the material a robot is made of.
- ISO standards do not regulate which tasks a robot can or cannot carry out.
- Modes of operation and application are not sufficiently described.
- The issue of cybersecurity is not very well explored.
- Conditions of use in the actual workplace are not adequately addressed in the standards, especially the implementation process.

Regarding the application of standards, the experts pointed out that end users do not have enough knowledge on robots and on the guidelines to implement them as well as that managers aren't aware about the standards, and which exist and which apply.

To summarise the experts' opinions on standards in relation to robotic systems, it has to be noted that they do see room for improvement in the existing standards regarding specific aspects, however currently there is no need for additional standards, as expressed by the experts. This reflects the current number of fully integrated HRI applications we currently observe in Europe, as, for example, indicated by the results of the ESENER-3 data as in 2019, only 3.5% of all interviewed enterprises (n=1,611) reported using robots with direct interaction capabilities (EU-OSHA, 2022a).

4.5 Risk assessment

The specific OSH impact of introducing an advanced robotics or AI-based system into a workplace is often hard to gage and varies upon the specific system, automated task and environment. The same applies for the overall risk of introducing and implementing such systems into the workplace. In recent years, there have been first drafts of cobot-specific risk assessment tools (e.g. Stone et al., 2021; Raza et al., 2021), however there are few tested and published tools publicly available. Within the research of this project, specific OSH risks of advanced robotics and AI-based system have been identified. While there are risks specifically associated with the use of advanced robotics, risk assessment tools that cover both risk identification and risk analysis for them are currently rare and often not readily available. The EU-OSHA recently published a policy brief on the specific impact of new technologies, like cobots, in agriculture and forestry, highlighting that risks and benefits can be very specific to sectors and applications (EU-OSHA, 2021). Guidelines and regulations in this area exist, like the guideline for the safety limits of machinery (e.g. ISO 12100) as well as technical specifications for robotic systems (e.g. ISO/TS 15066), but when it comes to collaborative robotic systems or robotic systems which use AI, these can be too non-specific for the use case at hand. Some of these risk assessment tools use the above mentioned guidelines as a foundation (Raza et al., 2021), while others use e.g. process-failure mode effect analysis to arrive at concrete suggestions to reduce risk at the workplace (Stone et al., 2021). These assessment tools are an important first step to facilitate the introduction of advanced robotic systems in different working environments. However, the existing tools are comparatively new and still need to prove their applicability and reliability in different use cases. Risk assessment tools also face an additional challenge, associated with frequent changes of the environment in which many cobots operate. The EU-OSHA's recent report (2018) on new and emerging occupational safety and health risks associated with digitalisation, acknowledges that 'rapid reconfiguration of work processes in response to demands for and expectations about customisation from consumers may mean that the risk profile of a factory changes frequently' (p.53).

Nevertheless, accurate and in depth risk assessment of a technology in the workplace is vital to ensure OSH, and the lack of assessment tools capable of providing this for advanced robotic systems, cobots and AI based systems for the automation tasks, needs to be considered going forward.

5 Conclusion and recommendations

When analysing the types of tasks and automation degree for which advanced robotics applications are currently used, we see a strong focus on routine person-related and object-related tasks for semi-automation and full automation respectively. Within person-related tasks, we find many nursing tasks, including lifting or assisting patients with food or drinks. Furthermore, surgical and other medical tasks like sewing or intravenous processes are partly or fully supported. Within object-related tasks, there is a strong focus on tasks common in the manufacturing sector, warehousing and crafts. Tasks that are found to be fully automated are industrial tasks like welding, assembly, paint spraying, packaging and arranging, cutting, moving and sanding. Furthermore, we find packaging as well as transportation and delivery tasks in different areas like manufacturing, hospitals and warehouses being fully automated. Assembly tasks are object-related tasks, which are found to be partly assisted by advanced robotics.

Regarding the risks and opportunities for OSH associated with the overall automation of tasks, there is already an extensive and elaborate body of scientific literature including well-known concepts. However, as the history of advanced robotics, being able to closely interact with humans in occupational setting, is rather young, there are fewer publications on this specific technology and topic. The chosen approach was to identify transferable knowledge as well as scientific evidence of relevant aspects that so far has been thoroughly investigated.

One primary finding is that within scientific literature OSH risks and opportunities currently do not or only very rarely consider a task approach. There is a clear lack in studies addressing HRI and associated OSH risks and opportunities in purely physical tasks. Many aspects regarding HRI and their effects on the human operator/human interaction partner have been considered in studies either not clearly differentiating between the addressed tasks or have been explicitly investigated within settings using social robotics. Often, the associated tasks are not further described or related to cognitive tasks. Nevertheless, the observed effects remain relevant for the automation of physical tasks using advanced robotics, as especially in this area we might see a stronger evolution of robotic systems capable of a number of tasks, where they don’t only, for example, assemble parts but are also used for the provision of process information or transporting tasks and therefore have more interacting moments. Hence, the findings that are presented can be regarded as general findings up to some extent, applicable to all robotic applications. The approach most research takes is a stronger technology-related approach focusing on the attributes and abilities a specific robot has. For example, studies describe whether it is a social robot, humanoid robot or an industrial robot but do not necessarily take a real task or real application scenario into consideration.

From scientific literature we were able to identify four different dimensions for HRI that can be associated with different OSH-related risks and opportunities: function or task allocation, task design and interaction design as well as operation and supervision. These dimensions are not strictly discrete and do show dependencies among each other. Nevertheless, they provide a solid framework in order to analyse and allocate the origin from different OSH-related risks and opportunities.

All dimensions in some way influence aspects related to the (rather short-term) experience of the working situation. We know from occupational psychology that the experienced cognitive, emotional and physical states to some extent do have the potential to influence wellbeing, mental health and physical health of workers in the long run. For some HRI dimensions we have identified, there even is evidence of being directly related to physical health as they can, for example, influence the occurrence of accidents.

Regarding the dimension of function or task allocation we see that these processes might become more dynamic as robotic systems hold the promise of flexible use. Assuming an appropriate technological readiness and suitable use cases for such application, not only the result of a function allocation process but the process itself, will pose risks and opportunities for OSH. If both are performed well, it can increase system performance, reduce errors, optimise workload, and increase motivation, satisfaction and wellbeing. However, associated risks with function allocation include a number of human consequences like complacency effects, decision biases, reduced situation awareness, unbalanced mental workload, mistrust and over-reliance. What we do see very often is that relevant concepts are interrelated, that one aspect has several effects on different outcomes, and that some effects will not prevail stable over time but might change as an individual's work with a robotic system progresses. For example, higher degrees of automation might reduce the mental workload of an operator but can also result in a loss of situational awareness and, worse, performance failure (Onnasch et al., 2014). Depending on the work context, this can result in a number of health and safety risks. However, Winter et al. (2014), too, found that situational awareness can be affected once a system becomes more automated; however, they found an improved safety performance once this freed attention was directed back into monitoring the task. But they noted that this does not happen automatically, and if the situational awareness is directed away from the task, negative consequences might ensue.

In relation to task design as a consequence of the function allocations process, especially the risk of low levels of job control and associated with that low levels of feeling in control, low self-efficacy, low satisfaction, motivation and wellbeing have to be stressed. High levels of robot autonomy were also associated with the risk of lowering the feeling of control and, furthermore, the feeling of responsibility for the working task. A tight coupling of the worker to the robot's task additionally has the risk of increasing stress.

It is challenging to identify the characteristic features distinguishing advanced robotics from non-robotic automation technologies in order to derive very robotic-specific OSH risks and challenges. While some aspects, to some extent, do also apply to non-robotic technologies, we were able to identify one aspect in relation to robotic systems that seems quite unique. This refers to the dimension of interaction design and more precisely to the aspect of anthropomorphic robot design. A large number of studies have addressed this aspect and it is strongly related to OSH risks and opportunities. Anthropomorphic cues can benefit the interaction process between humans and robots. However, this is mostly relevant for social robotics. Especially in relation to physical tasks, anthropomorphic features pose the risk of irritation and false attributions, if not explicitly dedicated to a task-relevant function.

Furthermore, the application of well-known design principles will also benefit the overall interaction process. Their absence, however, is associated with adverse effects. It has to be noted that the importance of some design principles might shift, especially as the demand for transparent robotic design and behaviour is crucial to prevent possible risks like reduced feeling of responsibility and accountability, and over- or under reliance as well as a feeling of alienation or loss of control. Furthermore, it has to be noted that albeit individualised and smooth robotic behaviour and actions are beneficial for a pleasant interaction, there are some risks associated with that, like the actual or perceived monitoring of workplaces and employees' performance and behaviour.

Some OSH-related risks and opportunities are more strongly connected to the actual direct use or the forthcoming use of a robotic system. There is evidence that attitudes towards and experience with robotic systems influence the actual use and especially user acceptance. Furthermore, the risk of fear of job loss can be triggered especially if workers have no experience with robotic systems and introduction processes do not consider this fear.

With the use for advanced robotics especially in hazardous and dangerous working environments there is a clear opportunity to be emphasised. Robotic systems firstly provide the potential to completely remove humans from these unfavourable circumstances. Secondly, especially in assembly and lifting tasks, robotic systems can improve physical health related to musculoskeletal disorders. Physical risks like collision or ones related to mechanical or electrical failures are also mentioned. However, they again are less robotic-specific but do apply to any machinery at the workplace.

In relation to organisational effects we especially see the relevance of the introduction process, or the change process associated with introducing advanced robots into the workplace. If this process is not considered carefully in terms of an adequate task analysis, worker participation, communication strategy, and an ongoing evaluation and monitoring process, companies will face the risk of low acceptance, rejection and disuse of the system. Also important is the aspect of appropriate training for workers to prevent the risk of deskilling and loss of crucial competences.

There is one aspect that has been studied to an extraordinary higher degree than any other aspect in HRI. This is the human consequence of trust in robots. The fact that successful cooperation is influenced by the trust between the cooperating parties is well known in occupational psychology with regard to human-human interaction (Costa et al., 2001). Teamwork becomes more efficient and overall performance increases when team members trust each other. In relation to trust, robotic traits like mobility, anthropomorphic and zoomorphic design, multimodal interaction possibilities, and multi-purpose usage for proximal and remote applications may suggest that human trust towards robots differs compared to trust towards regular automation technology (Hancock et al., 2011; Hancock et al., 2020). Compared with other human consequences attributable to the interaction with advanced robotics, the issue of trust currently has been studied most within scientific literature. Direct comparisons between trust towards robotic systems and trust towards non-robotic technologies are scarce. However, distinct features incorporated in robotic systems, like robotic design and behaviour or comprehensive interaction possibilities, have proven to be influential on human trust towards robotic systems. Hence, there seems to be evidence that trust towards robotic systems does differ from trust towards non-robotic technologies. Such an allegedly clear picture cannot be found for other human consequences.

Not enough trust in a robotic system can have negative consequences for the interaction, but excessive trust in the robot can also result in these. In contrast to a lack of trust, one could assume that very high trust in the robotic system has positive effects. This is true only to a limited extent, as excessive trust in the robot can also result in negative consequences. If there is excessive trust, the duty of care towards the robot, for example, is neglected (Hancock et al., 2011), which can lead to further damage or, if a defect is not noticed, damage to the work piece or injuries to people. If the degree of trust that is placed in the robot matches the capabilities of the robot, efficient and safe collaboration can take place (Hancock et al., 2011). If operators trusts the robot, they follow suggestions made by it and accept information provided (Hancock et al., 2011). This means that informed decisions can be made and interaction can be carried out without additional complications. With a good trust fit, it is possible to benefit from the advantages of human-robot collaboration (Sanders et al., 2011). While the concept of appropriate trust in a robotic system seems intuitive, several researchers suggest that it is a multi-factorial, highly individual concept that needs further research to be fully understood (see section 4.1.1). While these papers highlight the importance of adequate trust in an automated or robotic system, the dangers of automation bias, and concrete strategies on how to mitigate or avoid them, concrete models on how to achieve that goal have not been developed. Explicit training about automation bias and adequate training with the systems is encouraged, however it is difficult to define general principles here, as this training needs to be adjusted to the robotic system and the specific working situation.

We were able to identify relevant HRI dimensions from which specific OSH-related risks and opportunities were derived. These more general OSH observations regarding robotic systems help in understanding that regardless of application context, some fundamental criteria should be considered. Even if the single effects of the addressed dimensions can vary from workplace to workplace, it is advised to always consider them. It is important to keep in mind that for any user to fully benefit from the system they need a sufficient level of trust towards it. This can result in direct effects, like fully benefiting from the system's intended effect of cognitive support, to more indirect effects by avoiding the consequences of automation bias, in the form of over reliance or loss of skill. The allocation of tasks between the robotic system and the human worker has to be considered carefully. When introducing a new system to a workplace, everyone in contact with it should be made aware of the capabilities and realistic limitations of the system. Users should be given training to not only understand the technology but also see how their work changes due to it. In addition, understanding the system and maintaining it not only in its physical embodiment but also its software-related components are vital for ensuring that measures towards cybersecurity can fully function. In that context, enforcement could become really challenging for traditional labour inspectorates. Taking the addressed OSH risks and benefits into careful consideration will result in a human-centred application of advanced robotics for the automation of tasks.

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