European Agency for Safety and Health at Work

Automation of cognitive and physical tasks in the health and social care sector: implications for safety and health

Literature Review

European Agency for Safety and Health at Work

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

Authors: Laura López Forés (Open Evidence), Lucie Lechardoy (Open Evidence), Cristiano Codagnone (Open Evidence), Lode Godderis (KU Leuven), Anke Boone (KU Leuven).

Project management: Kate Palmer, Maurizio Curtarelli - European Agency for Safety and Health at Work (EU-OSHA).

This literature review was commissioned by the European Agency for Safety and Health at Work (EU-OSHA). Its contents, including any opinions and/or conclusions expressed, are those of the authors alone and do not necessarily reflect the views of EU-OSHA.

Luxembourg: Publications Office of the European Union, 2024

PDF ISBN 978-92-9402-327-8 doi:10.2802/692689 TE-02-24-537-EN-N

Table of Contents

List of Tables

List of Figures

1 Introduction and objectives

The objective of the study is to provide an overview of the state of play, the tasks and good practices related to the use of artificial intelligence (AI) and robotics for the automation of physical and cognitive tasks in the health and social care (HeSCare) sector.

The specific objectives of the project are:

- to make available easy-to-access information on the impact of the automation of cognitive and physical tasks in the HeSCare sector;
- to identify and further investigate the motives for the adoption of the specific technologies in the HeSCare sector and its implications for occupational safety and health (OSH) (as described in the literature); and
- to provide information to support the development of resources for the European-wide Healthy Workplaces Campaign 2023-2025 “Safe and healthy work in the digital age”.

The technologies in the scope of the study are AI-based systems as well as complex non-AI-based robotic systems according to the taxonomy developed by EU-OSHA.[1] The geographical scope is the EU-27 with examples from outside the EU if relevant (for example, from leading countries in robotics such as Japan, South Korea and the United States). The study covers the state of play and research from the last five years to ensure that the information is up to date with the latest technological, economic and social developments.

2 Methodological approach

A literature review was conducted following a systematic approach. The review includes academic articles published in peer-reviewed journals from the databases ISI Web of Science, Scopus and Business Source Complete (EBSCO). To complement the resources identified in the academic databases, the study team also conducted searches in Google Scholar and PUBMED. The initial search string used to identify relevant literature was:

“Artificial intelligence” OR AI OR automation OR robot OR cobots OR algorithm* OR RPA OR “human-robot interaction” OR “human-machine interaction”*

AND

“Occupational safety and health” OR OSH OR psychosocial OR organisational OR work OR health OR safety OR “physical environment” OR “work design” OR ergonomic OR well-being OR “mental health” OR “work organisation” OR “work management” OR “workforce characteristics” OR “job quality” OR “job content” OR skills OR productivity OR autonomy OR training OR risks*

AND

“healthcare sector” OR “social care sector” OR nurse OR “medical staff” OR “residential care” OR caretaker OR caregiver OR “hospital activities” OR “human health activities” OR doctor OR surgeon OR radiologist OR physicist*

In a second step, a combination of certain key words was used with the aim of yielding more tailored results. For instance, additional searches were conducted to obtain results for sectors or professionals for which there was less available information (e.g. sector Q87 residential care activities). Furthermore, as the insights found on the OSH impacts of automation in the HeSCare sector were mostly positive, searches were run including other terms such as: technostress, work intensification and privacy.

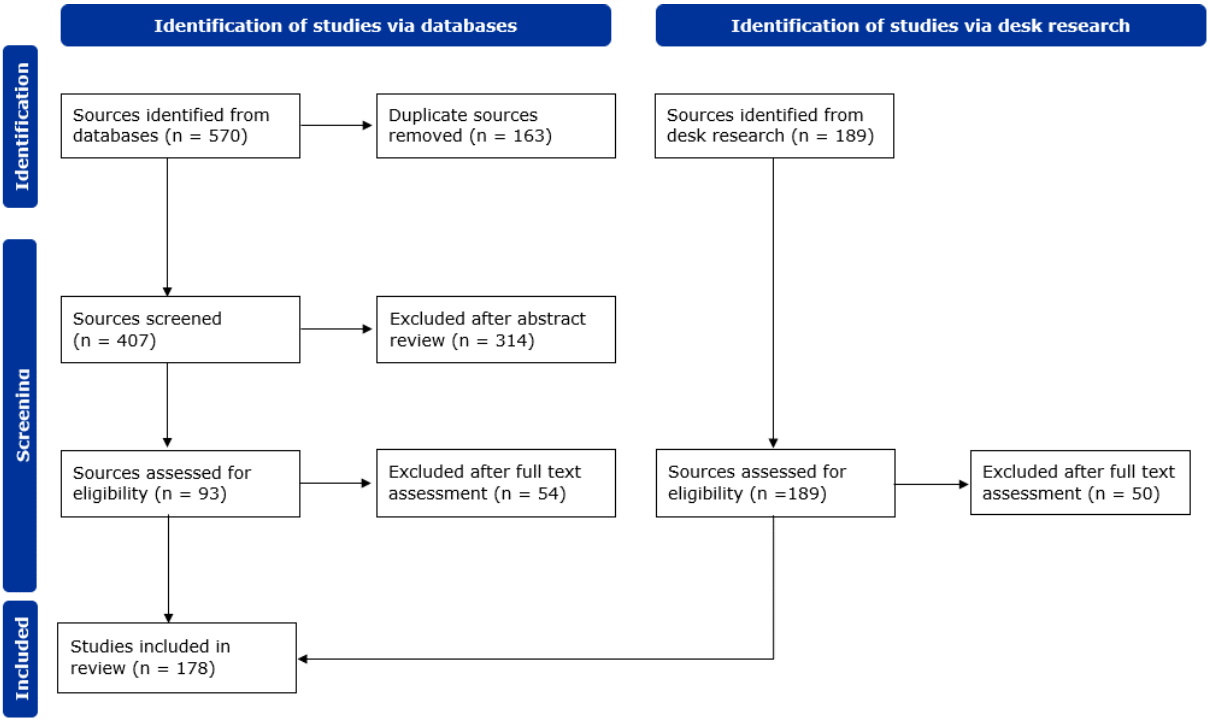
Only sources published after 2015 were retrieved to make sure to take into account the latest technological advances in the HeSCare sector. No restriction on settings and language of information

[1] EU-OSHA – European Agency for Safety and Health at Work, *Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and Occupational Safety and Health*, 2022. Available at: https://osha.europa.eu/en/publications/advanced-robotics-artificial-intelligence-and-automation-tasks-definitions-uses-policies-and-strategies-and-occupational-safety-and-health

sources were applied, while as expected, most literature identified was published in the English language.

To complement the search on academic databases, additional sources were sought through desk research. Desk research included works and publications from 'grey' sources, customised Google search engines, institutional websites and snowballing from identified relevant literature. Through snowballing, several relevant additional sources of information were identified from the bibliography of relevant publications.

Figure 1: Selection process for scientific literature



The introduction of the search string in the three databases returned 570 articles (i.e. 263 articles in Web of Science, 238 in Scopus and 69 in EBSCO), of which 163 were discarded as duplicates. After abstract screening, 93 sources were read in full text, of which a total of 54 were finally included in the review. Additionally, 189 articles were identified from desk research and added to the list of sources to be read in full. Of these articles, 139 were included as references in the review. Therefore, a total of 178 studies were included in the literature review.

Based on the insights of the literature review, a preliminary selection of 10 examples of automated or automatable tasks was made from within a list of 20 examples. The examples were selected to ensure a balanced representation in terms of geographical coverage, sub-sector of activity, type of worker, type of technology, type of task affected and OSH dimension affected. Five of the automated and automatable tasks were then selected as good practice examples. Further desk research was conducted to retrieve information on OSH implications, workers' experience, and barriers to and drivers of implementation of those technologies. A total of 54 additional sources were identified to provide further information on the selected examples on top of the sources reported for the literature review above.

3 Definition of the sector and the technologies under study

3.1 The HeSCare sector

The human HeSCare activities sector in Europe is key in providing and promoting health and wellbeing for European citizens and communities, including its workforce. The HeSCare sector is characterised by a **high degree of diversity, both in terms of the types of activities carried out and the organisations involved in providing the services** (European Commission, 2018). The sector encompasses: human health activities (NACE code Q86), from large hospitals and clinics to small private practices and community health centres as well as non-governmental organisations; residential care activities (NACE code Q87) such as nursing homes; and social care providers (NACE code Q88) including home care services, and social support organisations.

The HeSCare sector is an important contributor to the European economy and a major employer. In 2021, the HeSCare sector employed around 21.9 million people in the EU, accounting for about 11% of total employment.[2] According to Eurostat data, the number of employees in the HeSCare sector grew by 11.5% between 2014 and 2021.

The importance of the HeSCare sector is likely to further increase because of the rising demand for care services driven by an ageing population coupled with longer life expectancy. In recent decades, Europe has indeed been experiencing a profound demographic shift characterised by a rapidly ageing population accompanied by low birth rates. Longer longevity has been driven by improvements in healthcare (Grundy & Murphy, 2017). According to Eurostat data, the proportion of the EU population aged 65 and over has been increasing in the last decade, from 18% in 2012 to 21.1% in 2022.[3] The ageing of the population will systematically require additional investments, such as the need to adjust welfare and public health systems to cater for the growing demand for accessible, high-quality healthcare and long-term care that is affordable (European Commission, 2023a).

In parallel, the HeSCare sector is also impacted by the cross-sectoral phenomenon of an **ageing workforce** — 34% of the current workforce in the HeSCare sector is nearing retirement age.[4] Ageing implies that healthcare workers may have a reduced ability to perform certain tasks as their motor, vision or hearing skills change. Older workers are therefore more vulnerable to OSH risk factors, which calls for health promotion interventions (Bonzini et al., 2023).

The upward trend on the demand for healthcare labour will be confronted with a shortage in healthcare workforce supply. In this respect, the supply of healthcare personnel is expected to decrease as the baby boom generation of doctors, nurses and other healthcare staff approaches the retirement age in the coming years (OECD, 2023a). In addition, in many European countries, the HeSCare sector is characterised by low levels of employee retention due to the challenging working conditions, difficulties in human resource management, high chronic fatigue, poor quality of care or lower work satisfaction (European Commission, 2023b; Lavoie-Tremblay et al., 2022). According to a joint report by the OECD and the EU, another common challenge across Europe relates to the difficulties in recruiting and retaining doctors in remote and sparsely populated areas (OECD, 2022).

According to Eurostat data, the number of physicians and nursing personnel has increased in recent years. In 2020, there were 399 physicians available per 100,000 inhabitants, compared to 350 in 2015, a 14% increase between both years.[5] Similarly, the number of nurses per 100,000 inhabitants increased from 633 in 2015 to 847 in 2020.[6] On the other hand, the number of caring personnel per 100,000 inhabitants decreased by 9.48% between 2015 and 2020, from 539 to 488 in 2020.[7] Whereas the

[2] Eurostat (2023). Employment in EU in 2021 across sectors. Eurostat. https://www.cedefop.europa.eu/en/tools/skills-intelligence/sector-employment-occupations?year=2021&country=EU#1 (last accessed 7 November 2023).

[3] Eurostat (2023). Proportion of population aged 65 and over. https://ec.europa.eu/eurostat/databrowser/view/tps00028/default/table?lang=en (last accessed 23 November 2023).

[4] Cedefop (2023). Health & social care. Cedefop – European Centre for the Development of Vocational Training. https://www.cedefop.europa.eu/en/tools/skills-intelligence/sectors?sector=06.16#6 (last accessed 11 December 2023).

[5] Eurostat defines practising physicians following ISCO 88 (code 2221) as medical doctors who apply preventive and curative measures, improve or develop concepts, theories and operational methods and conduct research in the area of medicine and health care. EU average calculated manually from country data available. No data available for FI, EL, LU, PL, PT, and SK. Data for DK, CY and SE corresponded to 2019. Source: Eurostat (2023). Health personnel (excluding nursing and caring professionals) - historical data (1980-2021) – code hlth_rs_prs1. https://ec.europa.eu/eurostat/databrowser/view/hlth_rs_prs1__custom_8634928/default/table?lang=en (last accessed 22 November 2023).

[6] Eurostat defines nurses as qualified nursing professionals including associate nurses that generally work under the supervision of other health professionals. EU average calculated manually from country data available. No data available for BE, FI, FR, IE, LU, PL, PT, and SK. Data for DK, CY and SE corresponded to 2019. Source: Eurostat (2023). Nursing and caring professionals - historical data (1980-2021) – code hlth_rs_prsns. https://ec.europa.eu/eurostat/databrowser/view/hlth_rs_prsns__custom_8637798/default/table?lang=en (last accessed 22 November 2023).

[7] Eurostat defines caring personnel as health care assistants in institutions (ISCO 08 code 5321) and home-based care workers (ISCO 08 code 5322). EU average calculated manually from country data available. No data available for CY, FI, FR, and SE. Data for DK, DE and EL corresponded to 2019. https://ec.europa.eu/eurostat/databrowser/view/hlth_rs_prsns__custom_8637798/default/table?lang=en (last accessed 22 November 2023).

number of physicians and nurses has increased in recent years, the growing healthcare personnel may not be sufficient to cover the rising demand for care. According to the OECD (2023a), 'the demand for healthcare and long-term care workers appears to be outstripping supply' (p. 15). To address the shortage in healthcare workforce, many countries have in the past decades resorted to health worker migration. In this respect, healthcare professionals from eastern European countries have historically moved towards western European countries that offer better salary levels and working conditions (Sowa-Kofta et al., 2019). This has aggravated existing labour shortages in eastern Europe while migration flows are not expected to fill the labour gap in western Europe.

The healthcare sector is also characterised by being female-dominated. While **women account for the vast majority of the healthcare workforce**, that is, around 80% (Eurofound, 2020), they still represent a small proportion of leadership and senior positions (Mousa et al., 2021). According to joint work by the World Health Organisation (WHO) and the International Labour Organisation (ILO) (2022), the average wage of female healthcare workers is 20% below the average one for men. On top of that, women in the healthcare sector face particular challenges affecting their OSH. According to Cattaneo and Pozzan (2020), on average, women healthcare professionals conduct three more hours of unpaid work per day than male healthcare workers. As women still take on more home and family responsibilities than men, they find it more challenging to cope with long working hours to find the right work–life balance. This has been argued to increase their exposure to higher stress levels that may lead to lower job satisfaction and burnout (Cattaneo & Pozzan, 2020).

The COVID-19 pandemic has helped further acknowledge the relevance of the HeSCare sector within Europe's economy and society. HeSCare workers became crucial players at the forefront of the outbreak, risking their own lives to save others (Greenberg et al., 2020). As a matter of fact, frontline healthcare workers had a significantly increased risk of COVID-19 infection, even among those who adequately used their personal protective equipment and followed OSH guidelines (Nguyen et al., 2020). The responses to the pandemic have also shifted the ways in which primary care operates. For example, according to Rawaf et al. (2022), 'the pandemic improved access and coordination in many settings of primary care, balanced against resourcing and information flow issues, and a reduction in the comprehensiveness of services' (p. 1).

Additionally, **healthcare expenditure in Europe is on the increase**. According to Eurostat data, healthcare expenditure in the EU increased by 18.19% between 2014 and 2019.[8] The rise in healthcare expenditure has been attributed to several factors, including significant advancements in medical technology, the high costs of pharmaceuticals and the increasing administrative expenses associated with healthcare systems (Goryakin et al., 2020). The ageing of the population, and the parallel surge in the use of age-related medical procedures and treatments, such as those related to chronic diseases, is also a factor in the growing costs (Marešová et al., 2015).

Amid the challenges that the healthcare sector is facing, the **deployment of advanced technologies may be crucial to guarantee the sustainability of the sector**. In order to meet a growing demand for healthcare services coupled with the shrinkage of the workforce, healthcare systems will need to find ways to increase efficiency and productivity without compromising quality. In this context, the integration of AI-based systems and advanced robotics holds important positive promises for workplace progress and growth in productivity as well as for workers' OSH (EU-OSHA, 2022a). In general terms, advanced technologies can enhance productivity by taking over time-consuming and repetitive tasks, while they can also improve logistics and management flows.

To some extent, the adoption of these technologies may be inevitable given current global trends. In that regard, individuals are likely to ask for technology-enhanced services similar to the ones applied to other sectors that they are already benefiting from (Bohr & Memarzadeh, 2020). Additionally, the deployment of AI technologies in the healthcare sector is expected to significantly enhance cost savings without sacrificing quality or access to services (Sahni et al., 2023). According to Bohr and Memarzadeh (2020), cost reductions will mainly stem from focusing on health management rather than disease treatment. In other words, technologies will help in disease prevention and early detection to ensure a timely treatment as well as efficient follow-ups.

[8] The latest available data corresponded to 2020, but we decided to include the data for 2019 as the year 2020 was particular in terms of healthcare expenditure due to the COVID-19 pandemic. The percentage increase between 2014 and 2020 was of 24.24%.

Despite the potential benefits of implementing advanced technologies in the healthcare sector, the sector is still lagging behind in terms of technology adoption. In this respect, while huge health datasets are available to train AI models, health data are commonly unstructured within different systems and formats (Sahni et al., 2023). Furthermore, the use of health data is particularly sensitive so that before any deployment of AI-based systems, it is pivotal to guarantee personal data protection. Similarly, the use of AI technologies in clinical practices also faces several other legal and ethical challenges. Gerke et al. (2020) summarised in an academic article these challenges that relate, among others: to the ability of applying the principles of informed consent to AI applications; to ensure unbiased and fair systems; or to establish who is liable for the actions taken by advanced technologies.

Additionally, another barrier to the adoption of such technologies in healthcare refers to the difficulties at the time of recruiting the resources necessary for their effective deployment (Panch et al., 2019). The global shortage in AI experts is driving wage premiums that are difficult for healthcare institutions to afford, often implying that they are unable to attract talent.

3.2 OSH in the HeSCare sector

According to the European Survey of Enterprises on New and Emerging Risks (ESENER) (EU-OSHA, 2019), **the main OSH risks faced by the HeSCare workforce are musculoskeletal (MSK) and psychosocial risks**. MSK risks may include regularly lifting patients, pushing heavy medical equipment, performing repetitive movements, and prolonged standing and sitting. These risks, which stem from the physically demanding nature of care work, create a significant concern due to their prevalence and the potential impact on the wellbeing of workers. MSK risks can result in MSK disorders, injuries from poor patient handling, as well as long-term health implications such as chronic muscle pain and disability.

Additionally, HeSCare workers commonly face several **psychosocial risks**. These include, among others, violence and harassment at work, emotional demands and exposure to traumatic events such as dealing with people at the end of their lives, high-stress levels from heavy and intense workloads, including burnouts and mental health issues, patient-related stressors from challenging patient behaviours, and organisational factors such as inadequate staffing or lack of support (Bernal et al., 2015). In addition, workers in the HeSCare sector are more exposed to adverse social behaviour, and they experience the most organisational change and job insecurity of all sectors (Eurofound, 2021). These risks are also combined with the need to systematically multitask, work in shifts (including night shifts) and a lack of control over work.

The HeSCare sector has also been associated with low wages and **precarious working conditions** (Pappa et al., 2020) **which may exacerbate the mental health conditions of workers**. According to the European Working Conditions Survey, a fundamental concern of the HeSCare sector includes its job profiles and **poor working conditions** (Eurofound, 2021). The sector's job profiles are often of a lower standard compared to other sectors, with high work intensity, emotional demands and low health quality, which negatively impact workers' health and wellbeing (Eurofound, 2021).

HeSCare workers are also considerably exposed to **biological, chemical and physical risks**. Biological risks, common in healthcare environments, include exposure to biological agents such as blood-transmitted pathogens and infectious microorganisms. Similarly, chemical risks can include daily exposure to hazardous chemicals and drugs transmitted through inhalation or dermally in laboratory work, through patient treatment or in cleaning products like disinfectants. Finally, physical risks in the workplace include excessive noise in hospitals and dental clinics, especially in intensive care units, and frequent slips, trips and falls among carers, ambulance staff, nurses and cleaners.

OSH risks are on the rise when considering trends from 2009 to 2019 of the ESENER surveys. For example, the number of establishments reporting repetitive hand or arm movements as a risk rose from 51% in 2014 to 66% in 2019 (EU-OSHA, 2022a). Moreover, in 2019, 58% of establishments reported prolonged sitting as a risk and 57% of establishments reported lifting or moving people or heavy loads as a risk. All three risks described are above average compared to other sectors and industries. Similarly, risks related to dealing with difficult customers/patients are particularly common in the HeSCare sector (78.5% in 2014 and 83.5% in 2019). Risks related to time pressure (51% in 2014 and 58% in 2019) and risks from long or irregular working hours (28% in 2014 and 31% in 2019) are also above average compared to other sectors. Furthermore, in 2019 more establishments reported biological and chemical risks than the average for all sectors (47% of HeSCare establishments compared to 36% of establishments in all sectors) (EU-OSHA, 2022a).

The digitalisation of the sector, and specifically the **automation of working tasks, is increasingly considered a significant factor in supporting OSH management** by providing efficient and effective solutions to strenuous tasks (Sætra & Fosch-Villaronga, 2021). This automation may contribute to preventing many OSH risks such as MSK disorders or reducing psychosocial risks by eliminating the burden of tedious work. However, the use of AI-based systems may also create new risks related to the fear of job loss, deskilling and lack of appropriate skills (Konle-Seidl & Danesi, 2022). In the next section, we summarise the state-of-the-art evidence on the OSH implications of AI and complex-non-AI systems in the healthcare sector.

3.3 Technologies and their applications

The ever-changing nature of work is being driven, more than ever, by technological developments and innovations. In this sense, the automation of tasks in the HeSCare sector has the potential to revolutionise the way healthcare is delivered. AI and the automation of tasks are terms notably difficult to define. Below we present the definitions of AI-based systems from the OECD and the European Commission that were used in previous EU-OSHA research (EU-OSHA, 2022b).

The OECD updated its definition for AI-based systems in 2023 as ‘a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment’ (OECD, 2023b, p. 7).

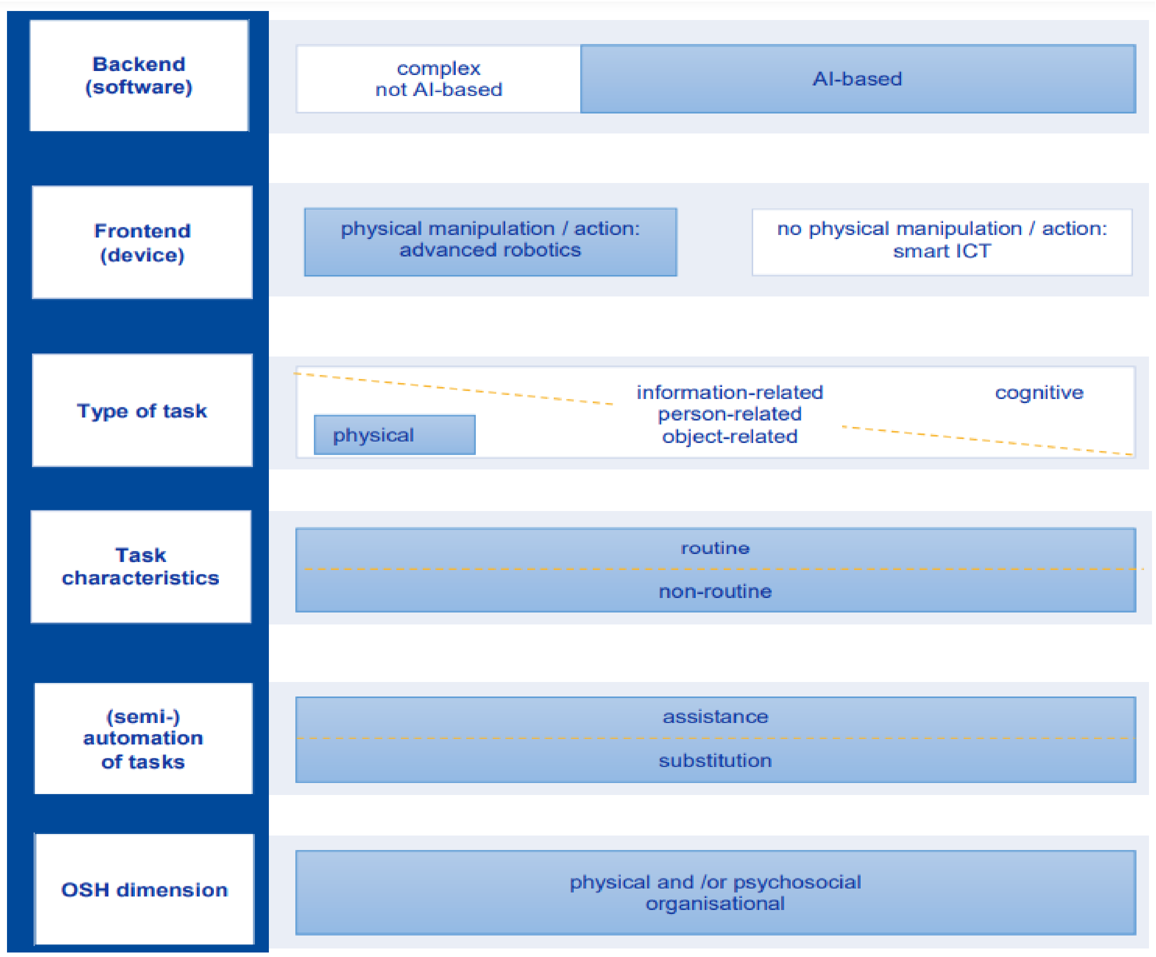
The independent High Level Expert Group on Artificial Intelligence (HLEG-AI) of the European Commission defined AI systems as those ‘that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals. AI-based systems can be purely software-based, acting in the virtual world (e.g. voice assistants, image analysis software, search engines, speech and face recognition systems) or AI can be embedded in hardware devices (e.g. advanced robots, autonomous cars, drones or Internet of Things applications)’ (HLEG-AI, 2019, p. 1).

Based on the definitions for AI systems provided above, and to better understand the implications that advanced technologies have on workers’ OSH, EU-OSHA has built a detailed taxonomy (EU-OSHA, 2022c). Figure 2 presents this taxonomy broken down by type of technology, type of task, task characteristics, the degree of automation and the OSH dimension.

The taxonomy differentiates between **AI-based systems and complex non-AI-based systems** (EU-OSHA, 2022c). The aim of this differentiation is to expand the taxonomy to encompass technologies that fall under the scope of addressing task automation, even if they are not strictly AI-based (EU-OSHA, 2022b). **Complex non-AI-based technologies** often exhibit advanced capabilities, but from a purely technical standpoint do not contain genuine AI. Instead, they carry out their designated tasks based on predetermined and predefined actions within the system’s programming architecture from the outset, such as is often the case with collaborative robots (EU-OSHA, 2022b). **Collaborative robots** refer to a specific type of advanced robotics that work alongside human workers as collaborators to accomplish tasks, enabling further forms of human–robot interaction (Hentout et al., 2019).

Under EU-OSHA’s taxonomy, a distinction is made between cognitive and physical tasks at work. When considering the implications of automation in the HeSCare sector, it is essential to recognise the differences between these tasks. On the one hand, **cognitive tasks** refer to mental activities that involve thinking, reasoning, decision-making and information processing (Kester & Kirschner, 2012). In the HeSCare sector, healthcare professionals regularly engage in intense cognitive tasks throughout the day to ensure proper diagnosis, treatment planning and patient care. For example, healthcare providers repeatedly make critical quick decisions based on patient data, medical history and clinical assessments, as well as addressing complex medical cases, identifying treatment options and adjusting care plans that require analytical thinking. These key cognitive tasks are accompanied by continuous information processing and the need for effective communication with patients, families and colleagues, putting an extra strain on the cognitive demands of workers. On the other hand, **physical tasks** encompass activities that require manual labour, mobility and hands-on patient care. In the HeSCare sector, physical tasks involve direct continuous and direct interaction with patients, such as administering treatments, performing medical procedures and providing physical support. Other strenuous physical tasks include patient handling, patient care such as bathing, dressing and feeding, or infection control such as adhering to strict hygiene and sanitation protocols.

Figure 2: Taxonomy for AI-based systems and advanced robotics for the automation of tasks (EU-OSHA, 2022b)



According to the taxonomy, task categorisation then falls between fully automatable and semi-automatable tasks; person-related, information-related or object-related based on the object of work; and divided into routine and non-routine tasks, which is central in assessing their potential for automation of both physical and cognitive tasks at work (EU-OSHA, 2022b).

The taxonomy differentiates OSH implications within three main categories: physical, psychosocial and organisational. Physical aspects cover outcomes concerning physical wellbeing, such as accidents and the development of MSK issues. Psychosocial aspects involve factors like emotional wellness, drive, pressure and exhaustion. Finally, organisational aspects are linked to health management metrics, such as efficiency and employee absence. The interaction between each task category and technology has the potential to influence any of the three OSH dimensions.

This classification system offers a comprehensive and visual outline of important aspects to consider when categorising or evaluating advanced robotics and AI-based systems. This includes differentiating between the system's backend and frontend representation, the type of task assigned and the key characteristics of that task (EU-OSHA, 2022c). Additionally, it assesses the level of automation that can be provided by the system and which OSH dimensions can be affected by it (EU-OSHA, 2022c). It is evident from the taxonomy that these factors can manifest in various combinations in the workplace. The taxonomy provides a framework for organising and visualising the characteristics of a particular system and the focus of its operation.

4 State of play of automation of tasks in the HeSCare sector

The use of AI technologies in the HeSCare sector dates back a long time; already in 1950 physicians made the initial attempts at improving diagnoses using computer-aided programmes (Secinaro et al., 2021). Since then, the deployment of automation technologies has been rapidly expanding in the HeSCare sector and currently is one of the megatrends that concerns the sector as mentioned in the introductory sections. As a matter of fact, previous EU-OSHA research showed that most examples on the automation of tasks were found in the human health and social care sector (EU-OSHA, 2022b).

The application of such technologies is used to automate a wide range of tasks from patient care and diagnosis to the performance of administrative duties in staff management. In the following sections we provide an overview on the state of play of the (potential) implementation of AI-based systems and complex non-AI-based robotic systems for the automation of tasks in the HeSCare sector. We differentiate between the automation of physical and cognitive tasks, and provide further classification based on EU-OSHA taxonomy to differentiate between person-, object- and information-related tasks.

4.1 Automation of physical tasks

In terms of automation of physical tasks, the use of AI-based and complex non-AI-based systems is primarily to perform **person-related or object-related tasks**. In the majority of instances, these systems are AI-based robotic applications that can take the form of robotic arms or autonomous mobile robots (AMRs). These robots work alongside human workers to assist or substitute them in the performance of certain tasks, and therefore could be encompassed under the category of **collaborative robots**. These robotic applications are in fact used to handle and transport both objects (e.g. medical instruments, patient samples, food) as well as people (e.g. patients). In most of the cases, these technologies are used to substitute workers in the performance of **routine** tasks that are physically demanding for the healthcare workforce.

4.1.1 Person-related tasks

One of the oldest and most frequent uses of robots in the healthcare sector is as **surgical robots**, with the first applications dating back to the late 1980s (George et al., 2018). The most common example of surgical assistive robots is the ‘Da Vinci Surgical System’ — in 2022, 6,000 Da Vinci systems had been deployed and used in 8.5 million operations worldwide (Mayor et al., 2022). Surgical robots often consist of robotic arms that are controlled through a console by surgeons seated near the operation table. The console provides the view of the surgical area, enabling the surgeon to augment the view further than the human eye’s capability. The robot is controlled by the surgeon using master controls that directly translate the surgeon’s movements to the robot moving the instruments. The master control embeds tremor-filtration software that enables surgeons to move instruments with smoother precision. Automating surgery through such robots can therefore enhance precision, flexibility and control during the operation and allows surgeons to better see the surgical site, compared with traditional techniques (Goh & Ali, 2022).

Surgical robots have been developed for **minimally invasive interventions** such as laparoscopic procedures (Longmore et al., 2020). Likewise, **robot-assistive surgeries** have been developed for procedures that demand **high levels of precision** such as spine surgery (Barrio Lopez et al., 2023) and skull base neurosurgery (Singh et al., 2022). Surgical robots can also facilitate orthopaedic surgeries by providing robotic support to accurately prepare the bone, improving the ability to reproduce alignment, and by restoring normal kinematics (Yang & Seon, 2023). Another application of surgical robots refers to their application to **control the orientation of catheters and guidewires** through mouses or joysticks at a control station (Chen et al., 2023).

There is still ongoing research for the safe use of robots in more invasive surgeries still performed via open manual procedures, such as **tumour resection** (Price et al., 2023). In some cases, research shows that robotic resections are as effective as open and laparoscopic resection procedures (Magistri et al., 2019), while in other cases current systems on the market still require specific improvements to be effectively used (Boehm et al., 2021). In some cases, the application of surgery robots is still limited due to the robots’ **lack of instrument dexterity or endoscope manipulation** that this type of interventions requires (Kim, de Mathelin et al., 2022).

Beyond assistance in surgical interventions, surgical robots have been developed to specifically **automate certain surgical tasks**. For example, surgical robots are being trained with data stemming from human-based demonstrations to autonomously perform suturing tasks by correctly moving, positioning, inserting and pushing needles (Schwaner et al., 2021). Likewise, robotic arms have been developed to **autonomously perform endoscope video positioning tasks** while the surgeon performs the bimanual coordination and navigation task (Gruijthuijsen et al., 2022). Another development in surgical robots refers to **tissue manipulation tasks** such as connecting two different tissues or closing an incision by placing both sides of a tissue in a way that enables homogenous suture distance for improved healing (Shin et al., 2019). Advances in surgical robots have also enabled the automation of **pattern cutting tasks** by applying the optimal tension on a tissue while cutting through a predetermined trajectory (Shahkoo & Abin, 2023).

Other robotic applications aim at reducing the amount of repetitive and physically demanding tasks that workers routinely perform. For instance, many robots help in performing tasks such as **lifting and moving patients** in dependent situations several times a day (Persson et al., 2022). Such robot lifting devices usually take two forms: either they are wearable devices such as exoskeletons that augment the weight that the healthcare worker can normally lift, or they take the form of robotic arms that help lift users (Wright, 2018). Lifting robots can **either substitute or assist human workers** in safely and efficiently doing routine tasks such as transferring, manually lifting and repositioning patients between beds, lifting patients from a bed into wheelchairs and helping patients stand up without the help of nurses (Sivakanthan et al., 2019).

Recent technological advances have resulted in devices in the piloting phase to **autonomously transport patients** within healthcare facilities. **AMRs** are robotic devices with embedded sensors and AI software helping them define the environment around them and act consequently (Fragapane et al., 2020). AMRs are therefore able to autonomously move around facilities. A particular prototype of AMRs refers to **connected driverless wheelchairs** that can **autonomously transport patients** from the inpatient service to the operating room (Baltazar et al., 2021). These autonomous robots receive transportation requests to pick up patients at their beds, and to navigate autonomously through different floors, avoiding obstacles and communicating with elevators to leave patients at their designated operating room.

Robotic applications have also been developed to **substitute** healthcare workers in the performance of **routine tasks** such as **sample collection**. For instance, robotic arms have been used to **automate swab testing**. The robotic arms are able to identify the region of interest in patients to take the sample and then safely secure it in a container (Kaiser et al., 2021). Similarly, AI systems have been developed to **collect blood samples** from patients and to analyse them to provide diagnostic results. The robotic arm localises blood veins with ultrasound imaging and image analysis to place the needle in the centre of the indicated vein to draw the sample (Leipheimer et al., 2019).

In addition, robots have been used to **automate several rehabilitation and physical therapy tasks**. Robots can perform repetitive tasks more consistently than humans, which is beneficial in rehabilitation where the repeated practice of certain movements is often needed (Li et al., 2021). For instance, since 1994 **robotic-assisted therapy** has helped to improve upper limb mobility in post-stroke rehabilitation (Li, Fu et al., 2022). The use of such rehabilitation robots has been hitherto prescribed for disabled patients for whom it is difficult to attend regular clinical visits for treatment. Hence, recent advances in robotic-assisted therapy have investigated the feasibility of deploying such devices for home-based rehabilitation.

Rehabilitation robots can also assist in walking or motion studies by improving a patient's walking ability and movement function while providing a way to **track progress over time**. This offers objective measurements of the effectiveness of the rehabilitation programme (Smirnova et al., 2022). Furthermore, rehabilitation assistive robots have been found to **improve adherence to treatment** while enabling prompt detection of critical conditions by clinicians (Irfan et al., 2023).

4.1.2 Object-related tasks

In recent years there has been an increase in the use of **AMRs** to help in the performance of routine tasks that are not directly related to the healthcare profession, such as **transporting (heavy) medical equipment** (Kriegel et al., 2022). AMRs are also used to **help in hospital logistics** and to perform material handling tasks such as the delivery and retrieval of supplies. For instance, AMRs are used for the **transportation of medicine** to the patient in a locked drawer (Fragapane et al., 2020); in other cases, AMRs have been used to **deliver meals to patients** and return the dishes to the washroom after mealtimes (Holland et al., 2021). The use of this type of technology, which has grown since the COVID-

19 pandemic, is also used to pick up and deliver lab specimens and for ancillary services, waste collection and mail delivery, as well as for housekeeping services (Aydinocak, 2023; Fragapane et al., 2020).

Another recently introduced use of AMRs is their use for automation of the **transport of sterile instruments**. Sterile instruments tend to be expensive, therefore as a cost-saving strategy, many hospitals circulate these instruments across their facilities several times a day after being properly cleaned, disinfected and checked for functionality after each use (Fragapane et al., 2023). Hence, to minimise the risk of contagion, hospitals are making use of **AMRs to transport sterile instruments** in a cost-effective manner (Mehta et al., 2023).

Robotic applications have also been used to assist in routine tasks such as the **disinfection and sterilisation of rooms and equipment** in hospitals, especially after the COVID-19 pandemic. In this respect, the use of ultraviolet-based (UV-based) disinfection robots has the potential to make the disinfection process faster and more efficient (Mehta et al., 2023). UV-based disinfection robots are AMRs that take the form of a lamp irradiating UV germicidal irradiation. This radiation is hazardous for human skin; therefore, such robots include motion sensors that automatically shut down the lamp when they detect a human.

Disinfection robots can therefore complement routine manual cleaning that is sometimes insufficient to eliminate pathogens form contaminated surfaces (Füszl et al., 2021). In this respect, disinfection robots have proven to be effective in reducing hygiene failures for terminal room disinfection between two successive patients (Casini et al., 2023). However, at present they still cannot entirely substitute these manual tasks (Diab-El Schahawi & Zingg, 2021).

In relation to the substitution of person-related tasks described in the previous section, robotic applications have also been deployed to improve workflows related to blood collection processes by **picking up and labelling blood collection tubes** (Wang et al., 2022). Similarly, other robot applications can transport and remove samples, while others can sort the samples for further clinical analysis (Holland et al., 2021). These robots can also make sure that the temperature of the blood samples is adequate.

In the operating theatre, several pilots have been conducted to further help the surgical team in **handling and passing surgical instruments**. Notably, a robotic arm has been developed that can identify the position of instruments on the surgical table and to efficiently and accurately hand them to the operating surgeon by processing their voice commands (Muralidhar et al., 2021). With meticulous attention to maintaining a sterile surgical environment, these robots are programmed to adhere to strict protocols, thereby reducing the risk of contamination and surgical site infections. Similarly, in surgical assistive tasks, some developed robots are able to **automatically deliver anaesthesia** to patients after a prior measurement of the depth of the anaesthesia (Zemmar et al., 2020).

AI systems have also been developed to replace nurses in performing **patient assistive routine tasks**. For instance, there are **meal assistance robots** that **help feed meals to patients** who are unable to feed themselves (Kim, Jeong et al., 2022). Meal assistant robots consist of robotic arms that use deep learning technology to identify where the food is located on a food tray while at the same time using face recognition technology to locate the patient's mouth. Caregivers or nurses can control the robotic arm via a tablet while their assistance is only needed for the initial setting up and finishing of the meal (Choi et al., 2023).

Pilot programmes are also being conducted to develop mobile robotic platforms that assist patients in fetching objects or for temperature measurement, as well as to support patients while they are using their walkers (Lundberg et al., 2022). **Automated dispensing systems** have also been increasingly used in the healthcare sector. These AI-driven systems can deliver reminders for and dispense medications for seniors, ensuring timely and correct dosages while reducing the need for repetitive tasks by nurses (Takase et al., 2022).

4.2 Automation of cognitive tasks

Our literature review showed that all the instances of automated or automatable **cognitive tasks** refer to the deployment of **AI-based systems**. These systems normally take the form of **software embedded in the computer equipment** or other portable device (e.g. laptop, tablet) that the healthcare workforce normally uses. All of the instances of technologies used for the automation of cognitive tasks that we have identified relate to a large extent to the **automation of routine tasks**; in particular, AI-based systems that can help in either assisting or replacing human workers to mainly perform **person-related and information-related tasks**.

The majority of the technologies used to assist in **information-related tasks** can be grouped under the term **decision-making support systems**, as they are able to analyse millions of data observations to help healthcare professionals in, among other tasks, diagnosing the patient, managing patient data or improving patients' treatment. In the case of the technologies used in **person-related tasks**, the automation of tasks refers to **interaction with patients** mainly via the use of **chatbots or social robots**.

4.2.1 Person-related tasks

Chatbots and conversational agents operate via the application of natural language processing (NLP) to understand user inputs and to provide responses based on predefined rules and the contextual understanding gained from the data they are trained with (Garcia Valencia et al., 2023). Chatbots can therefore be used to **replace or assist healthcare professionals in their communication activities with patients**. For instance, AI-driven chatbots have been used for the **automation of appointment scheduling** (Woodcock, 2022). Chatbots have also been used to improve the communication with patients before and after kidney transplant operations (Garcia Valencia et al., 2023). In the pre-transplant phase, the chatbot is able to provide personalised and understandable information to the patient on the procedure. During the post-transplant phase, the patient can communicate with the chatbot to solve any doubts on their medication after the operation (e.g. consequences of missing a medication dose, potential effects of another prescribed medicine). Similarly, previous EU-OSHA research (EU-OSHA, 2022d) reported that voice-based virtual assistants were able to support Alzheimer patients by providing them with dietary recommendations.

Given the increasing burden of mental illness worldwide coupled with a shortage of mental health professionals, there has been an emergence of **chatbots for therapy purposes**. For instance, according to a review conducted on emerging AI-based chatbots (Pham et al., 2022), such applications have been used to automate the monitoring of symptoms, to coach individuals in times of emotional distress and to provide therapeutic conversations with their users.

In the case of automated conversational agents for **patient coaching**, there exists mixed evidence on their positive impact on patients' outcomes. In some cases, patients engage more with the conversational agent as they feel less judged by a machine; in other cases, the use of conversational agents has been related with higher dropout rates (Prochaska et al., 2021). A particular successful example of automated conversational agents refers to its use to **reduce problematic substance use**. Notably, the conversational agent Woebot-SUDs is accessed by patients through a mobile application and provides them with conversational tailored support in moments of craving (Prochaska et al., 2021). Woebot-SUDs was found to help reduce the incidence of patients' self-reported consumption of problematic substances (e.g. alcohol, marihuana).

Another particularly interesting application refers to the AVATAR therapy that consists of a digital simulation (i.e. avatar) that reproduces the distressing voices of patients diagnosed with schizophrenia spectrum (Garety et al., 2021). The therapist can transform their voice into the avatar voice through a console to have a three-way dialogue. Initial tests of the therapy tool found it to significantly reduce the frequency of the distressing voice in patients.

Other applications of chatbots have been used **to identify outpatients with major depressive disorders**. In particular, conversational agents in the form of software-driven virtual humans have been used to conduct face-to-face interviews to identify depressive disorders following pre-established criteria (i.e. DSM-5) (Philip et al., 2017). A speech recognition software allows the conversational agent to encode the responses given by the patient, which are later classified by an algorithm based on the pre-established criteria.

In some cases, chatbots and automated conversational agents can be embedded in a human or pet-like form to provide companionship and emotional support to patients. These types of robots are referred to as **social robots** as they interact directly with patients. A literature review conducted by Ragno et al. (2023) found that social robots have been applied to **support healthcare workers in a variety of tasks**, including the treatment of several mental disorders, to educate patients on their medical issues and to perform patient monitoring. For instance, a specific application refers to the use of social robots 'to help autistic patients in improving their speech and social abilities' (Ragno et al., 2023, p. 18). The use of such robots has alleviated the workload of healthcare workers while reducing their exposure to challenging patient behaviour (Christoforou et al., 2020).

4.2.2 Information-related tasks

In recent years, there has been an expansion in the use of AI systems to **guide clinicians' decision-making** in several fields of healthcare. Notably, AI-based systems can analyse large volumes of data across different modalities to detect diseases and guide clinical decisions (Secinaro et al., 2021). In this manner, AI systems can help in the **automation of routine tasks** that in the past required human intervention (EU-OSHA, 2022d, p. 13). Such AI systems are available via computer-based programmes that healthcare professionals can access through the device they normally use. According to van Smeden et al. (2021), prediction models fall within two major categories: (i) diagnostic prediction models that estimate an individual's probability of a specific health condition being currently present; and (ii) prognostic prediction models that estimate the probability of developing a specific health outcome over a specific time period.

The **use of AI to inform diagnosis** has great potential as algorithms can interpret large numbers of medical images (i.e. X-rays, MRIs, computed tomography (CT) scans) by identifying patterns and anomalies that may be difficult for the human eye to detect (Oren et al., 2020). For example, for **early cancer diagnosis**, AI computer-based programmes can assist clinicians in screening asymptomatic patients at risk of cancer, investigating and triaging symptomatic patients, and diagnosing cancer recurrence more effectively (Hunter et al., 2022). As **AI clinical decision support systems** still have inaccuracies or provide misdiagnoses, they currently inform and assist **rather than automate doctors' diagnosis tasks**. In a growing number of cases, it has been found that the hybrid AI and human team outperforms both agents taken alone in terms of accuracy (Leibig et al., 2022; Reverberi et al., 2022).

Another routine task that could be automated thanks to the use of AI systems refers to the **development of personalised treatment for patients**. This application has emerged as potentially transformative — offering the promise of superior treatment outcomes for patients (EFPIA, 2019). For instance, algorithms can **analyse patient data to recommend tailored treatment plans** based on individual genetic makeup and medical history (Blanco-Gonzalez et al., 2023). AI systems can also help health professionals to keep them up to date on the advances in the medical field with a constant real-time analysis of medical information stemming from journals, textbooks and clinical practices (Shortliffe & Sepúlveda, 2018).

AI systems have also been used to help doctors to perform certain routine medical interventions. Examples include **image-guided interventions**, where AI algorithms can analyse medical images in real-time to **guide medical procedures**, such as catheter placements and biopsies (Tang, 2020). Within the operating theatre, such AI applications are embedded in the console used by the surgeons to provide them with continuous information on the optimal way to continue the intervention. Such AI systems therefore provide clinical data to the surgeon by monitoring and analysing patients' vital signs, by instrument/hand tracking or by measuring electrosurgical energy usage (Hashimoto et al., 2018). The use of such systems helps surgeons in their decision-making processes during the surgical interventions, enhancing patient outcomes (Kazemzadeh et al., 2023).

Another novel application of AI systems for the **automation of routine tasks** came as a response to the high influx of patients in hospital facilities during the COVID-19 pandemic. In order to better manage the flow of patients, several hospitals deployed AI systems for the **automated triage of patients**. For instance, in a university hospital in Belgium, an AI-powered robot detected whether an individual walking into the hospital facilities had high temperature or was not wearing a mask via temperature measurement cameras and ultrasonic sensors (Murphy, 2020). In either or both of the cases, the robot alerted the individual and/or the healthcare personnel. In the United Kingdom, an AI-based screening model could perform COVID-19 tests that analysed routinely collected patient information such as blood tests and vital signs. The model provided information to assist in directly streaming those who tested positive to a COVID-19 positive clinical area to avoid risk of contagion (Soltan et al., 2022).

The automated triage of patients has since then been expanded to **improve the management of overcrowded emergency departments**. Predictive algorithms are commonly used to determine if a patient in the emergency room needs to be admitted or not or to identify high-risk patients from the large proportion of non-urgent cases (Jiang et al., 2021). Automated triage systems can also assess the need for critical care and detect abnormal medical conditions or acute morbidity (Fernandes et al., 2020).

In general terms, the application of AI in emergency departments is promising in dealing with the increased challenges of departmental flow and the need for fast and accurate decision-making for high-acuity patients (Grant et al., 2020). In this respect, AI systems have the capability to help **adapt to real-**

time emergencies. For instance, AI systems can support centres by assessing the need to ask for extra resources from other hospital facilities nearby (Alser et al., 2023). In this manner, healthcare professionals can avoid delays in care for critical cases and are able to provide the adequate resources and capacity required to treat certain cases. AI-based systems can also predict major adverse cardiac events in patients with chest pain in the emergency department (Zhang et al., 2020).

In addition, AI has enabled more sophisticated **remote patient monitoring (RPM) systems**. These systems can substitute healthcare workers in doing **routine tasks** related to the monitoring of patients' conditions in either hospital settings, residential facilities or at home. RPM systems rely on different technologies such as wearable devices or contact-based sensors to measure relevant parameters to control for patients' health conditions (Shaik et al., 2023). RPM systems analyse the data collected using machine learning methodologies to, in a second step, **predict or classify patients' data**. The system in parallel can estimate any abnormal event in the near future based on pre-established threshold values of the health data parameters collected (Shaik et al., 2023).

According to previous EU-OSHA research, these AI-powered monitoring systems 'are paving the way for the scaled-up development of "smart homes"' (EU-OSHA, 2022d, p. 12). **Smart homes** are defined by VandeWeerd et al. (2020) as 'residences equipped with ambient sensors and computing technologies that monitor the activities and well-being of occupants in their homes' (p. 2). Smart homes thus enable individuals to live more independently without the need for hospitalisation while at the same time freeing up caregivers from their increasing workload.

Another substantially **time-consuming routine task** performed by healthcare professionals refers to **administrative processes**. In fact, previous research has indicated that physicians in ambulatory settings allocate 49% of their time to electronic health records (EHRs) and administrative tasks and only 33% to direct clinical interactions with patients and staff (Sinsky et al., 2016). For this reason, there have been several advances in recent years to develop AI-based technologies to automatically perform these tasks to **alleviate healthcare professionals' administrative burden**. A particular example refers to the **automation of medical reporting** using NLP systems. Initial developments in the field were related to technologies that could **automatically extract clinically relevant information** from patient- and clinician-recorded dialogues (Rajkomar et al., 2019). More recent technological advances have enabled the **automatic generation of a consultation report** through NLP tools that can be checked by practitioners before uploading it in the EHRs (Maas et al., 2020).

NLP systems have also been used in emergency departments to **draft a patient chart** based on a recording of a patient–physician interaction as it occurs (Grant et al., 2020). Another application of NLP relates to the **extraction of structured relevant information from medical reports**, and in particular from radiology reports (Casey et al., 2021). Similarly, AI systems can alleviate the **administrative work burden** by, for instance, **automating the management of EHRs**, where AI can help streamline the organisation of patient records and improve data accuracy and accessibility while reducing workloads (Honavar, 2020). Another example refers to the use of robotic process automation (RPA) to recognise medications using barcodes to **automate the prescription-filling process** (Wiljer & Hakim, 2019). Such RPAs can automatically do the process thanks to computerised administrative medication data they are trained with.

5 OSH implications in the automation of tasks

The use of advanced technologies in the HeSCare sector is rapidly growing, with the potential to enhance patient outcomes while tackling the current and future challenges the sector is facing. Whereas the automation of physical and cognitive tasks in the healthcare sector presents several opportunities, significant OSH concerns may also arise from the adoption of these technologies. In this section, we provide an overview on the OSH implications of the automation of physical and cognitive tasks. According to the presented EU-OSHA taxonomy, OSH implications can relate to physical, psychosocial or organisational aspects. At the same time, these technologies can be used for a wide range of applications, implying that sometimes the boundaries between some of these aspects are blurred with some applications having both physical and psychosocial implications at the same time.

5.1 Physical implications

The vast majority of physical implications refer to the automation of **routine physical tasks** that HeSCare professionals conduct daily. The automation of such tasks has direct physical effects on the worker, while in the case of the automation of cognitive tasks the physical implications are mostly indirect.

Physical implications can be divided into two distinct subgroups: MSK and physical risks, and exposure to biological and chemical risks.

5.1.1 MSK and physical risks

The automation of physical tasks has mainly been reported to **reduce physical fatigue and the incidence of MSK disorders** in the HeSCare workforce. For instance, surgeons conducting laparoscopic surgeries regularly report MSK disorder symptoms, mainly in their neck and shoulders (Dalsgaard et al., 2020). The use of **assistive surgical robots** entails that surgeons do not need to use their hands to directly access the body, so that smaller incisions are made in comparison to conventional surgery. Therefore, surgery robots are argued to help reduce MSK disorders. A systematic review on the MSK impact of robotic-assisted surgery conducted in 2020 showed that robotics provided superior **MSK benefits** while reducing workload compared to laparoscopy procedures for both surgeons and trainees (Wee et al., 2020).

However, there is also evidence on how robotic surgeries can lead to **MSK discomfort and injuries** experienced by surgeons. In this respect, a study analysing 309 survey responses from surgeons using robotic systems to assist their surgeries in 40 countries worldwide found that surgeons **still experienced considerable physical pain** and discomfort in their neck, shoulders and back (Patel et al., 2023). These issues were related to the **ergonomic design** of the surgeons' console. Further research showed that female and small-handed surgeons reported to experience more pain and discomfort when using robotic hand controls (Hislop et al., 2023). Hence, whereas surgical robots have improved overall MSK health, more anthropometric tool design to adapt the tool to the workers' diversity of physical characteristics and features is needed to improve surgeons' experience.

Another physically demanding task that is largely related with healthcare professionals' **MSK disorders** refers to the **lifting and moving of patients**. Manual patient handling is associated with lower back pain, which is the main contributor to occupational health problems, and the most common, affecting nurses (Brinkmann et al., 2022). The use of robots to assist in moving patients has been demonstrated to **reduce the physical burden of nurses and caregivers** (Persson et al., 2022). A study analysing the effect of using a collaborative robot for patient manual handling tasks with 11 participants found that the use of robots significantly **reduced the force exertion in the caregiving process** by up to 51% (Brinkmann et al., 2022). Their use also led to a significant reduction in men's spine muscle activity of up to 55%. Another study conducted with 10 caregivers showed that the use of lift-assist robots led to a **significant reduction in shoulder, back and knee muscle activities** compared to the manual handling of patients (Kong et al., 2023). Similarly, robots that assist in patient washing and bathing (including patient lifting and transportation) also **reduced biomechanical load and physical stress**, while improving worker safety and increasing overall care efficiency (Aslam et al., 2015).

Similarly, the use of robotic applications to **transport instruments and equipment provides hospital workers support in this task and reduces the physical workload**. In particular, the use of AMRs to transport sterile instruments and equipment entails a significant physical workload reduction as these deliveries often involve heavy lifting and uncomfortable twists in the body (MiR, 2018). Therefore, AMRs help **alleviate the workload for such physically strenuous tasks**.

On the other hand, as technological advances enable robots to **work alongside humans** instead of in delimited separate spaces such as cages, the **risk of collision with or harm** to the human worker could eventually increase. For this reason, robots include several embedded sensors to avoid any potential harm they could cause to humans. In the case of AMRs, the robots are able to detect objects so that if someone is walking within the robot's path, the robot can instantly stop in less than a second (Holland et al., 2021). The AI-powered software embedded in AMRs also enables them to identify and classify objects they see so as to plan collision-free paths (Fragapane et al., 2020).

The physical implications of the **automation of cognitive tasks** are of a more **indirect nature**. For instance, the automated patient monitoring may result in a reduction in the daily walking distance of workers (EU-OSHA, 2022d). In the long term, this is expected to increase the occurrence of MSK disorders.

5.1.2 Exposure to biological and chemical risks

AI-based systems and complex non-AI-based systems have also helped **improve the overall safety of HeSCare professionals**. For instance, the use of surgical robots for catheter placements and guidewire operating systems of vascular interventions have been found to **protect doctors from X-ray**

radiation (Chen et al., 2023). Moreover, all robotic applications (not only limited to surgical robots) help **reduce the exposure** of healthcare professionals **to infectious diseases** that the patient may have such as COVID-19, HIV, hepatitis B or tuberculosis (Shen et al., 2022).

Existing procedures for the disinfection of healthcare facilities rely on manual application of chemicals that tends to be time-consuming, resource-intensive and prone to high degrees of human error (McGinn et al., 2020). In this respect, the use of robots to complement disinfection tasks has been found to be very effective in reducing the number of bacteria remaining in manually disinfected rooms (Casini et al., 2023). In fact, **disinfection robots** allow to apply **UV irradiation disinfection methods safely** in hospital settings. UV irradiation has also been proven to be a **less laborious and time-consuming method to disinfect rooms** and hospital facilities (Mehta et al., 2023). Hence, the use of robots for disinfection in healthcare facilities **reduces the exposure of workers to bacteria** and related contagious diseases. Moreover, such UV disinfection robots are designed in a way as to **shield bystanders and equipment from UV rays** (McGinn et al., 2020; Perminov et al., 2021).

Similarly, the use of **robots for the collection of test samples** has been proven to **reduce the risk of infection** for workers. In the case of nasal swabbing, used among others to test for COVID-19, a study conducted in Taiwan with 80 participants at two teaching hospitals found that robot collection of such samples **minimised risks of infection** and reduced stress for healthcare providers (Yu et al., 2023).

5.2 Psychosocial implications

The automation of cognitive and physical tasks in the HeSCare sector is expected to change the way clinical care is provided, with direct implications for HeSCare professionals' workload and job characteristics. Such changes in clinical practices are expected to have a psychosocial effect on the workforce, with both positive and negative implications. The extent of the psychosocial effects related to the deployment of advanced technologies may, in turn, depend on the readiness of professionals to interact with such machines. In this context, adequate training is regarded as pivotal to enhance trust and provide workers with the adequate skills to take advantage of the opportunities that advanced technologies promise.

5.2.1 Workload

The healthcare system must continue to improve its productivity and efficiency to respond to an increasing demand for HeSCare services driven by the rising burden of illness, multimorbidity and disability driven by ageing and epidemiological trends (Panch et al., 2018). In this context, AI technologies are regarded as crucial to **help meet the demand for healthcare services while guaranteeing an adequate workload** for the professionals in the sector. Advanced technologies can help **reduce workers' stress and risk of burnout** by providing overall **gains in productivity**. For instance, in the field of oncology, Alabi et al. (2021) found that AI enhances precision medicine and improves clinical decisions, thanks to which oncologists may experience 'emotional satisfaction, reduced depersonalisation and increased professional efficacy' (p. 11). Similarly, in emergency departments, it is considered as physically impossible to keep up with the rising demand (Jiang et al., 2021). To alleviate workers' workload and reduce their risk of burnout, AI technologies have been found helpful to ease a portion of the increasing clinical burden (Boonstra & Laven, 2022).

By **automating physical tasks**, workers can benefit from a **more structured workflow**, streamlining operational processes and reallocating resources more effectively, allowing them to manage their professional responsibilities more efficiently (Zayas-Cabán, 2021). This improved balance can contribute to **reduce stress levels** and increase job quality and satisfaction, thereby **promoting better mental and emotional wellbeing** among employees. For instance, it has been argued that the use of AMRs for hospital logistics alleviates healthcare professionals from many monotonous and sometimes stressful tasks such as the picking up and transportation of objects unrelated to the healthcare profession (Kriegel et al., 2022).

Likewise in the case of **automation of cognitive tasks**, as AI systems **take over** the performance of **routine tasks**, healthcare professionals can focus on more rewarding tasks. For instance, RMP systems can regularly collect patient data so that healthcare workers can spend more time with patients (Ragno et al., 2023). However, the deployment of advanced technologies can also create new tasks, some of which can be monotonous. For instance, healthcare professionals will need to set up or configurate the parameters of the technologies. Moreover, as some of the technologies are still inaccurate and present limitations, healthcare professionals will have to supervise the output given by the technology to guarantee that it is correct.

AI systems are also used to free up workers from administrative tasks that involve repetitive and time-consuming processes that can result in an increase of the workload. A survey collecting responses from nurses working in Canada, Germany and the United States, Canada and Germany found that nurses used around 40% of their working time to conduct non-nursing activities such as delivery and retrieval of food trays, ancillary services or housekeeping services (Yen et al., 2018). With the COVID-19 pandemic, hospital cleaning activities have also increased, bringing an extra workload for healthcare professionals (Aydinocak, 2023). Similarly, the introduction of EHRs has also particularly increased the incidence of administrative burden (Gesner et al., 2019). In this context, AI systems offer a great opportunity to **alleviate some of the administrative burden** of healthcare professionals. In this manner, healthcare professionals **can 'spend more time on tasks that focus on the clinical context** of their patients and attending to their needs' (Hazarika, 2020, p. 2), improving overall job satisfaction and decreasing their risk of burnout.

Whereas the application of AI-based systems has been found to lead to an **intensification of work** in other sectors, the literature focusing on the implications in the HeSCare sector does not mention any implications on work intensity. This might be due to the fact that, given the high and ever-increasing workload of healthcare professionals, the deployment of advanced technology has been regarded through a positive lens so as to alleviate healthcare professionals' workload. Notably, the technology helps healthcare professionals to be more productive, by treating more patients in a shorter amount of time. In this regard, their workload may not decrease but become more bearable with the support of the technological developments.

5.2.2 Mental workload

The use of AI-assisted surgical robots to perform both cognitive and physical tasks has also been found to **reduce healthcare professionals' mental workload**. In general terms, healthcare professionals may deal with mental overload due to the high number of tasks they need to conduct simultaneously. This may in turn affect their psychosocial state and lead to a higher number of operational errors. In this context, it would therefore be desirable to relieve staff from simple and repetitive tasks so they can invest their resources in more demanding tasks (Schäfer et al., 2023). In this respect, in Japan, a government survey on the effectiveness of robots in the healthcare sector found that 42% of workers who had used **monitoring robots** found a **reduction in their psychosocial burden** (Eggleston et al., 2021).

In surgery, AI technologies assist surgeons to take decisions during their operations, which helps them **reduce their levels of stress** when dealing with critical situations (Kazemzadeh et al., 2023). Moreover, AI systems are being integrated into surgical robots with the capability to assess the surgeon's intraoperative workload level so that the robot can provide different levels of assistance (Zhou et al., 2020). This has been found to help **reduce surgeons' mental workload** and improve their performance in high-stress scenarios, such as a haemorrhaging scenario (Yang et al., 2022).

A study conducted in the United Kingdom with 32 surgeons found that self-reported measures of workload and mental effort were significantly lower for robotic-assisted surgeries than for laparoscopic ones (Moore et al., 2015). This information was confirmed by an objective cardiovascular measure of mental effort. However, a systematic review on the impacts of surgical robots on surgeons' physical and mental health covering articles up to December 2019 found mixed results on the physical and mental outcomes of robotic-assisted surgeries (Park et al., 2021). The type of results depended on how mental demand was measured. In that regard, studies using physiological measures showed that **robotic surgeries reduced the mental stress** of surgeons.

On the other hand, AI systems could also **increase workers' mental workload** as healthcare staff need to **familiarise themselves with the technology and learn how to interact with it**. This could represent a barrier for the deployment of AI technologies, as healthcare professionals may be reluctant to engage in such a cumbersome process. Cognitive workload has, in turn, been found in the literature to be related with increased **risk of burnout** (Ehrmann et al., 2022). This is in particular the case for workers who do not have the adequate skills or have not followed the appropriate training to make optimal use of the technologies.

Mental workload may also increase as healthcare professionals may need to undertake additional tasks related to **overseeing the automated systems**. For instance, whereas social robots can automatically interact with humans, a healthcare worker needs to be present to supervise the interaction, to control it or to rectify any malfunction (Coombs et al., 2020). Similarly, AMRs used for the automation of logistic tasks in hospital settings were found to **increase workers' frustration** as they had to correct the errors produced by the robot. In the case of an AMR deployed in a hospital to automatically transport meals to patients, hospital workers found that due to the high instance of errors of the AMR, the workforce had become 'caretakers for the robots despite the robots' (initial) purpose of accomplishing tasks and cooperating with staff' (Tornjberg et al., 2021, p. 10).

5.2.3 Trust

Trust in the performance of AI systems is a pivotal element for safe deployment of the technology. Trust is often associated with **automation bias**, which is defined as the tendency to over rely on the technologies as human workers overvalue machine-provided information over manually derived information (EU-OSHA, 2022d). An **over-reliance on technology** can **increase the exposure to safety risks** as technology can occasionally malfunction (Grissinger, 2019) and result in accidents. In this respect, workers may become less vigilant and proactive in monitoring automated systems, potentially overlooking critical issues that require immediate human intervention.

Over-reliance on technology performance can also contribute to the **loss of certain skills** in the workforce. In particular, automation bias can compromise a **worker's capacity to identify and respond to critical situations** promptly, consequently jeopardising patient safety and overall workplace wellbeing. Likewise, excessive dependence on machines may lead to a potential decrease in workers' proficiency and preparedness to handle unexpected situations (Grissinger, 2019). This, in turn, results in a **greater risk of accidents** in the workplace that can affect both the patient and the healthcare professional.

The challenges related to the over-reliance on AI-based decisions is exacerbated by the **lack of transparency** of AI algorithms. An in-depth field study in a major United States hospital where AI tools were used by diagnostic radiologists for breast and lung cancer found that **professionals experienced increased uncertainty** due to this lack of transparency (Lebovitz et al., 2022). This was particularly the case when the AI tool results diverged from their initial judgement without providing underlying reasoning. To solve related problems, the concept of **explainable AI** was developed through which the AI's outcome was accompanied by explanations on how the system arrived at that decision (Bucinca et al., 2021). However, in the case of AI-based clinical decision support systems, it is quite complex to verify the decision taken by the inherent algorithm (Lyell & Coiera, 2017). Hence, verification complexity could further **increase the risk of cognitive load** for healthcare professionals, potentially leading to more instances of stress and burnout cases among the workforce.

5.2.4 Skills

Technological advances have already transformed the delivery of HeSCare services, and are expected to further revolutionise the sector. As service delivery transforms, it will simultaneously require workers to gain a new set of skills, while leaving other skills obsolete. In this respect, it is as yet unclear whether advanced technologies will have an overall positive or negative effect on **workers' skills**.

On the one hand, advances in AI in the HeSCare sector raise concerns about the **risk of deskilling** of the workforce. As technologies take over certain tasks, healthcare professionals may lose the ability to perform those tasks. According to Aquino et al. (2023), in healthcare, deskilling may result in deterioration of clinical skills, **affecting decision-making** across various stages of the clinical pathway, with potential negative implications on patients' safety. Closely related to the concept of automation bias explained in the previous section, as healthcare professionals rely to a large extent on advanced technologies, they may lose the ability to respond to critical situations, increasing the **risk of accidents** in the workplace.

On the other hand, automation in the HeSCare sector is also expected to enhance human work by replacing human workers in the performance of routine and monotonous tasks so they can focus on more rewarding and complex tasks. As AI-based systems are expected to assist rather than fully replace workers in the delivery of tasks, the use of advanced technologies is likely to optimise care delivery. In this respect, although AI has achieved performance levels comparable to human experts, algorithms still have inaccuracies and lack the capability to incorporate valuable context in their predictions (Agarwal et al., 2023). Hence, AI systems **are not expected to replace healthcare workers but to support their work**. For instance, current evidence supports the assumption that AI-assisted radiologists can achieve better work-related outcomes at a faster rate (Boeken et al., 2023). With a greater focus on specialised responsibilities requiring advanced skills and expertise, workers may experience heightened job satisfaction and a sense of professional fulfilment, contributing to **improved overall wellbeing** (Sypniewska et al., 2023).

As advanced robotics are deployed in the HeSCare sector, workers will need **to learn a new set of skills** in order to make use of the technology. The initial lack of skills to interact with technologies may result in **higher stress levels** and other negative mental health outcomes for workers. For instance, a scoping review on the use of surgical robots found that the training that nurses had received on robotic-assisted surgery was limited with more emphasis being placed on the training of surgeons. This was found to be related with **increased stress levels** among nurses in the perioperative environment (Moloney et al., 2023).

Therefore, establishments must support workers to ensure that they are adequately prepared for the complexities of these specialised roles, thereby **mitigating the risk of occupational stress and burnout**. OSH protocols must be updated to address the potential risks associated with unfamiliar tasks, ensuring that workers have the requisite knowledge and resources to manage diverse challenges without compromising their wellbeing (ILO, 2023).

The lack of adequate skills to take advantage of the opportunities that the deployment of advanced technologies entails has also been associated with the concept of **technostress**. Technostress was first defined by Brod (1984) as the 'inability to adapt or cope with new computer technologies in a healthy manner' (p. 16). Such type of stress can be prompted by several reasons, including the technological demand to work longer and faster, the difficulty in understanding certain tasks, or the uncertainty surrounding AI systems as they constantly update (Rohwer et al., 2022). Technostress has been associated in the overall literature with **increased incidences of burnout** among the workforce. In the case of the healthcare sector, the research on the topic is quite limited. A study analysing survey responses from urologists across German healthcare facilities found that the introduction of advanced technologies and potentially induced technostress was **moderately associated with burnout**, while there was a positive association with job satisfaction and work engagement (Bail et al., 2023). The authors of the study argued that technologies may not act as significant stressors for urologists as the technology is mainly used for administrative-related tasks. Another study collecting the view of nurses via a survey on the introduction of technologies in healthcare establishments found that in fact nurses regarded new technologies as a means to **enhance their work life**, with positive psychosocial implications (Califf et al., 2020). However, nurses were also found to have **increased levels of stress and frustration** as they had to find support from IT technicians when the technology was not working properly. This implied that they had to 'leave the patients' bedside, compromising their time with patients, which may contribute to reduced positive psychological states as well' (Califf et al., 2020, p. 18).

5.2.5 Human interaction

The deployment of technologies may overall reduce the level of human interaction and human touch, which are regarded as very important in the provision of healthcare services. A particular example of the potential loss of human interaction refers to the introduction of robotic devices to help move and lift patients. For instance, caregivers in a residential care facility in Japan reported a reduction in the time they spent with patients as more time had to be dedicated to transport the heavy robotic lifting device across patients' rooms, as well as to configure it to perform the task (Wright, 2023).

Similarly, some healthcare professionals have raised their concerns on the potential dehumanisation of care. Healthcare professionals acknowledge that interpersonal contact is pivotal in the provision of care, as patients need emotional support and encouraging words (Klebbe et al., 2022). Additionally, the use of social robots has also been found in the literature as increasing nurses' concerns for patients' privacy, affecting nurses' experience with their work (Vänni & Salin, 2019).

The automation of care practices may entail that the care workers' responsibilities shift from actively assessing patient needs to responding to alerts and following machine-generated recommendations. This new work arrangement could alienate HeSCare workers as they no longer extend themselves in the decision-making processes (EU-OSHA, 2022d). In this respect, automation may raise concerns about the **potential loss of human judgement and empathy in worker–patient interactions**, which are crucial in quality healthcare services (Morrow et al., 2023).

At the same time, a growing body of literature points out that AI technologies are regarded as great time savers, providing doctors more time to develop **more meaningful and empathetic relationships with**

their patients. However, it is unclear whether doctors will indeed use this saved time to enhance the doctor–patient relationship (Sauerbrei et al., 2023).

5.3 Organisational implications

Overall, technology is also expected to change how workers communicate with each other. **Technological communication**, notifications and alerts can distract employees from the activities they are conducting, leading to **unintentional interruptions in their work** (Orhan et al., 2021). The literature has found that related work delays in some clinical settings, such as intensive care units, **increase work burden and stress levels** among the workforce (McCurdie et al., 2018).

Additionally, the automation of tasks entails an **increased risk** for HeSCare workers to be **victims of cyberattacks**. Health data are regarded as a valuable source of personal information, making them an attractive target for cyberattacks (Clarke & Martin, 2023). Cyberattacks compromise the ability of healthcare institutions to provide adequate care to patients, in some cases leading to serious risks for patients' lives (EU-OSHA, 2022e). In the case of surgical robots, cyberattacks may take the form of attempts to induce failures such as by **manipulating the surgeons' commands** (Ludvigsen & Nagaraja, 2022). Due to automation biases, the decisions and outcomes provided by advanced technologies may be assumed as valid, and therefore lead to the unintentional harm of the patient (Fosch-Villaronga & Mahler, 2021).

This is likely to affect the **mental health** of workers as they are unable to conduct their work for reasons they do not have control over. This leads to **higher stress levels** that may be exacerbated in cases where the healthcare professionals may not have undertaken adequate training to deal with cybersecurity concerns (Kelly et al., 2023). It is therefore crucial to integrate cybersecurity training in healthcare professionals' continuous education.

The introduction of AI-based systems has also extended monitoring and surveillance capabilities, posing new risks in terms of workers' data protection and privacy (Eurofound, 2022). Whereas in other sectors AI technologies have been used to assess workers' performance, it is not expected that in the healthcare sector AI tools will be used to monitor and supervise professionals. In fact, technologies are rather used to monitor patients, or for disease surveillance. The only example on the use of technology to monitor healthcare professionals refers to the use of video-based monitoring of hand hygiene behaviours. A study conducted by McKay et al. (2023) found that the introduction of video-based monitoring resulted in a raise in healthcare professionals' concerns on the use of the system as the basis of criticism or punishments. According to healthcare staff interviewed as part of their study, the use of such monitoring systems could result in professionals feeling more stressed.

As the deployment of AI-based and complex non-AI-based systems transform work practices, the transition to AI-enabled workflows will require careful attention to the potential impact on job roles and responsibilities, emphasising the importance of **providing adequate training and support for workers** to adapt to their evolving roles in the automated environment (Vrontis et al., 2022). In this regard, establishments should introduce timely training programmes to ensure that their workforce know **how to manage these new technologies**. The lack of such trainings may lead to OSH risks such as **high stress levels**. Similarly, as technologies will introduce new roles and tasks, such as those related to the supervision of the AI-based system, it is important to guarantee that this will not represent an unbearable extra workload for healthcare workers. In this respect, it is crucial for employers to **establish clear guidelines** for managing workload distribution and provide sufficient resources and support to prevent burnout and promote a healthy work–life balance. Moreover, fostering a **culture of open communication and collaboration** between workers and technology is essential to effectively integrate automation while maintaining a safe and healthy work environment in the healthcare sector (Llop-Gironés et al., 2021).

6 Relevant automated and automatable tasks in the HeSCare sector

This section provides a more in-depth analysis of a selection of 10 relevant examples of automated tasks or tasks with automation potential carried out by professionals in the HeSCare sector. The selection includes a balanced sample in terms of geographical coverage, sub-sector of activity, type of worker, type of technology, type of task affected and OSH dimension impacted, partly using the taxonomy developed by EU-OSHA (2022b) on AI-based systems and advanced robotics for the automation of tasks.

More specifically, the following examples include the same number of physical and cognitive tasks, with tasks performed by different healthcare professionals (e.g. nurses, surgeons, medical physicists). To the extent possible, we included examples of tasks covering each of the sectors under the scope of this study (i.e. NACE sectors Q86 – human health activities, Q87 – residential care activities, Q88 – social work activities). Based on EU-OSHA's taxonomy, we included examples for each categorisation, with information-, object- and person-related tasks, as well as examples of automation technologies that substitute or assist the worker. We also provided a balanced representation of non-routine and routine tasks, with four cases of the former and six of the latter.

Among the selected examples of automated and automatable tasks, five good practice examples have been identified: three corresponding to the automation of physical tasks, and two to the automation of cognitive tasks. In the literature, the selected good practice examples were identified as relevant to alleviate some of the main OSH implications of the work performed by healthcare professionals. With regard to physical tasks, the physical strain related to manual patient handling, the transport of material and the performance of minimally invasive surgeries have been found in the literature as the leading causes of MSK disorders in healthcare professionals. On the other hand, one of the leading causes of stress and burnout among healthcare professionals refers to the administrative burden. Hence, the introduction of advanced technologies to assist or automate related tasks is expected to be beneficial for professionals.

Table 1 provides an overview of the main characteristics of the selected examples of automated and automatable tasks that will be covered in this section.

Table 1: Information on examples of automated and automatable tasks

Task	Type of task	Type of technology	Reference paper	Geographical coverage	Level of widespread use	Sector of activity (NACE)	Sub-sector of activity	Type of worker	OSH dimension impacted	Task characteristics			Good practice
Tissue manipulation during surgery interventions	Physical Cognitive	Cable driven surgery robot	Pedram et al. (2021), Cao et al. (2020)	EU	Potential for automation	Q86	Q86.1	Surgeons	Physical Psychosocial	Person-related	Non-routine	Assistance	✓
Lifting and moving patients	Physical	Robotic arms, exoskeletons	Greenhalgh et al. (2022), Kulich et al. (2023)	EU	Piloting phase	Q87, Q88	Q87.1, Q87.2, Q87.3, Q88.1	Caregivers Nurses	Physical Organisational	Person-related	Routine	Assistance	✓
Transport of sterile instruments	Physical	Autonomous Mobile Robot	Fragapane et al. (2023)	EU	Piloting phase	Q86, Q87	Q86.1, Q86.2, Q87.1	Doctors Nurses	Physical organisational	Object-related	Routine	Substitution	✓
Blood sample collection	Physical	AI-based robotics	Leipheimer, et al. (2019), Chen et al. (2020)	EU	Potential for automation	Q86	Q86.1, Q86.2	Nurses	Physical, Organisational	Person-related	Routine	Assistance	
Post-stroke rehabilitation of upper limb mobility	Physical	Robotic arm	Li, Pan et al. (2022), Pignolo et al. (2022)	EU	Piloting phase	Q86, Q88	Q86.1, Q88.1	Caregivers	Physical Organisational	Person-related	Non-routine	Substitution	
Triage of patients	Cognitive	AI software embedded in computers	Boonstra & Laven (2022), Fernandes et al. (2020)	EU	Already automated	Q86	Q86.1, Q86.2	Nurses	Cognitive Organisational	Information-related	Routine	Assistance	✓
Medical reporting	Cognitive	AI software embedded in computers	Eshel et al. (2023), Ghatnekar et al. (2021)	Non -EU	Potential for automation	Q86	Q86.1, Q86.2	Doctors Nurses	Cognitive Organisational	Information-related	Routine	Assistance	✓
Diagnosis generation	Cognitive	AI software embedded in computers	Oren et al. (2020), Chen et al. (2021)	EU	Already automated	Q86	Q86.1, Q86.2	Doctors	Cognitive Organisational	Information-related	Non-routine	Assistance	
Remote patient monitoring	Cognitive	AI-software in wearables, computers and IoT	Shaik et al. (2023), Palmieri Serrano et al. (2023)	EU	Already automated	Q86, Q87	Q86.1, Q86.2, Q87.1, Q87.2	Nurses Caregivers	Cognitive Organisational	Information-related	Routine	Substitution	
Detection of precancerous lesions	Cognitive	AI software embedded in computers	Combalia et al. (2022), Goyal et al. (2022)	EU	Potential for automation	Q86	Q86.1, Q86.2	Doctors	Cognitive	Information-related	Non-routine	Assistance	

6.1 Automation of physical tasks

Tissue manipulation during surgery interventions

Tissue manipulation is a task performed within the sector of hospital activities (Q86.1) by surgeons during several surgical procedures such as closing incisions or suturing, knot-tying and tissue retraction. As part of robot-assisted minimally invasive surgeries, recent technological developments have tried to automate tissue manipulation tasks. For instance, Pedram et al. (2021) developed two robotic arms, with the needle-inserting arm including an embedded camera, and the extracting one, which can be incorporated into standard surgical robots (e.g. Raven IV) to automatically perform suturing tasks. The robot has a needle path planning algorithm integrated that, based on the vision system, can accurately assess the optimal motion of the needle inside the tissue. To do so, the surgical robot takes into account the wound width, the tissue angle, the desired needle entry point and the desired needle exit point, along with clinical criteria (e.g. entering the tissue perpendicularly, reaching specific suture depth). Similarly, Cao et al. (2020) developed a surgical robot that is able within endoscopies to suture defects without opening up the patient's body. The cable driven robot is composed of a needle driver and a grasper that are controlled by the surgeon through a console in a robotic workstation. According to the authors, 'the needle driver ensures efficient and reliable needle manipulation, and the grasper assists by handling tissue and suture threads' (Cao et al., 2020, p. 9).

The automation of tissue manipulation is expected to have physical as well as psychosocial OSH implications for surgeons. As a matter of fact, tissue manipulation has been identified as a highly complex task, in particular as part of minimally invasive surgeries in which surgeons have reduced access, visibility and flexibility to operate on the patient's body (Marciano et al., 2022). Minimally invasive surgeries entail that surgeons need to adopt a prolonged static posture that is uncomfortable for the neck and shoulder muscles. Surgeons conducting minimally invasive surgeries have therefore been found to have higher odds of experiencing neck and shoulder pain (Tetteh et al., 2023). The use of surgical robots has been therefore found to help alleviate surgeons' physical strain. Moreover, surgeons need to apply the adequate amount of force to the tissue in a precise manner to avoid any harm to the tissue, an ability that is learnt after years of experience (Golahmadi et al., 2021). Surgeons may experience high stress levels associated with conducting this task. Hence, the use of surgical robots to automate the task is expected to improve workers' mental wellbeing.

Lifting and moving patients

As part of residential care activities (sector Q87), caregivers and nurses lift and move patients several times a day, for example to move them from the bed to the wheelchair, to reposition them, to turn them to change diapers or sheets, or to perform daily hygiene tasks. In recent years there have been many technological advances to help in the performance of patient manual handling tasks. First, mechanical aids were introduced such as transfer boards, slides and slings, as well as mechanical lifts (Sivakanthan et al., 2021). Later on, robotic devices were developed to assist in patient transfer. An example of robotic systems to assist in patient transfer is the Strong Arm, which consists of a robotic arm that can be attached to a user's wheelchair (Greenhalgh et al., 2022). The Strong Arm has an onboard computer that allows the robotic arm to be programmed by the user or the caregiver, while the computer can also receive input from various integrated sensors (Sivaprakasam et al., 2017).

Another example is the AgileLife Transfer and Mobility System developed by Next Health LLC that enables the lifting and transfer of the patient between the wheelchair and the bed with no need for human intervention (Kulich et al., 2023). The patient transfer system is composed of a hospital bed at the foot of which there is a docking station where the caregiver can place the wheelchair. Through a user interface, the caregiver can activate the automated transfer by pressing the 'Transfer to bed' button. Then 'the seat of the wheelchair rotates backward as the bed begins to lower and flatten and a conveyer gently pulls the person onto the bed. The system stops upon sensing that the person's feet have passed the foot of the bed' (Kulich et al., 2023, p. 3). The transfer from the bed to the wheelchair follows the inverse order. Such robotic systems have been found effective in reducing the physical burden of caregivers and nurses, resulting in a lower incidence of MSK disorders.

Transport of sterile instruments

A wide range of sterile instruments are circulated across hospital facilities several times a day between the place of use and the departments that sterilise the instruments (Fragapane et al., 2023). Hence, several different healthcare workers, and in particular nurses, need to spend a significant amount of their working time in transporting such instruments through hospital facilities. Recent technological advances in the logistics sector are promising for the automation of such processes in hospitals. Notably, AMRs are robotic applications that incorporate motion planning features that enable them to calculate a collision-free path to move around a predefined area (Fragapane et al., 2021). These embedded motion planning features have facilitated the introduction of AMRs in the hospital activities sector (Q86.1). A study conducted by Fragapane et al. (2023) measured the benefits of AMRs for the transport of sterile instruments in three different hospital settings. Their findings showed that AMR is an affordable material handling system that can perform optimally for forward and return logistics such as those concerning the closed loop of sterile instrument transportation.

Nevertheless, the use of AMRs in hospital facilities to transport other types of objects (e.g. food trays, linen) has also been found to have negative OSH implications. In particular, healthcare workers may experience frustration and stress if they need to correct the many errors that the robot makes. A study conducted by Tornbjerg et al. (2021) in a medium-sized Danish hospital researched the perceptions of workers on the use of AMRs in the hospital's basement to automate the transport of service carts with cutlery, glasses and dishes. The results of the study showed that the healthcare professionals' workload had not been reduced but had changed. Notably, the hospital staff felt they had to act as caretakers for the robots, while they showed limited knowledge on the processes that the robot had to execute to perform the task. The introduction of the AMRs indeed translated to staff spending 'a great amount of time helping the robots fulfil tasks' (Tornbjerg et al., 2021, p. 8).

Blood sample collection

A common task conducted in the initial phase of patients' care refers to the obtention of blood samples to help diagnose the patient. Nurses tend to perform this routine task several times a day within the hospital activities sector (Q86.1). Blood sample collection requires interaction between a patient who may potentially be infected and healthcare professionals, therefore increasing the risk of disease spread (Di Lallo et al., 2021). The COVID-19 pandemic has stressed the importance of introducing mitigation strategies to reduce the spread of a disease. In this context, there have been several recent advances to automate the collection of samples for testing, including blood sampling. Leipheimer et al. (2019) developed a robot that through ultrasound technology is able to locate the vein in a patient's forearm and then insert a needle after calculating the adequate alignment of the needle trajectory with the vessel depth. After the blood draw, the robot retracts and dispenses the needle. A similar robotic application was developed by Chen et al. (2020) that also incorporates some safety features such as the ability 'to electromagnetically release the needle when sudden motions or excessive insertion forces are detected' (p. 7). Despite the incorporation of safety features, it is still possible that the technology malfunctions, potentially causing harm to the patient or the healthcare professional. This therefore increases healthcare professionals' exposure to physical risks.

The automation of blood sample collection reduces healthcare professionals' exposure to infectious diseases as well as potential contaminated materials. It also holds the potential to alleviate healthcare professionals' workload, in particular in emergency departments. In fact, the literature has pointed out that 90% of diagnostic procedures conducted in emergency rooms and intensive care units require vascular access, to among other tasks draw blood samples (Chen et al., 2020). Hence, the introduction of robots for blood sampling is likely to improve workflows and therefore reduce workers' stress levels. Additionally, blood collection is related to high levels of human errors depending on the healthcare professionals' experience and patients' physiology (Leipheimer et al., 2019). Hence, automation can help reduce the number of errors made (e.g. failed access attempts, first-stick success rates). This arguably can improve workers' level of wellbeing as they fear less to make such errors.

Post-stroke rehabilitation of upper limb mobility

Rehabilitation is an essential part of care for patients who have suffered a stroke. As a matter of fact, two out of three stroke patients have to some extent a residual disability that limits their mobility and their day-to-day activities (Li et al., 2021). Therefore, these stroke survivors need to engage in rehabilitation therapy for a full recovery. This rehabilitation consists of the multiple repetition of exercises that can be 'labour intensive and time consuming for treating therapists' (Li et al., 2021, p. 1). Several upper limb rehabilitation robots have been developed in the past two decades to substitute therapy professionals in conducting rehabilitation tasks. For instance, the Automatic Recovery Arm Motility Integrated System, or ARAMIS, is composed of 'two computer-controlled, symmetric, and interacting exoskeletons' (Pignolo et al., 2022, p. 3). The stroke survivor sits in a chair and places each of their arms inside the exoskeleton structure. Thanks to the exoskeleton the patient is able to replicate the movement of their healthy arm with the slightly paralysed one in a synchronous manner. In this way, the patient can autonomously conduct a conventional rehabilitation session. The automation of post-stroke rehabilitation exercises is also expected to have a positive OSH impact on therapists as they will not need to engage in repetitive exercises that entail performing the same movements multiple times in a row (Li et al., 2021). Therapists will therefore feel less physical discomfort.

Due to the usually limited mobility of stroke survivors, rehabilitation is often conducted at home or in residential facilities (sectors Q88 and Q87). The automation of rehabilitation procedures therefore implies that therapy professionals will spare a significant amount of their working time as they won't need to commute to different patients' residencies. Nevertheless, initial research on the introduction of such exoskeletons found that qualified staff were still needed to prescribe and set up the robot, and to oversee and control the progression of the patient (Li et al., 2021). Additionally, such exoskeletons take up a significant amount of space and are costly, which hinders their deployment in home and residential settings (Li, Fu et al., 2022). At the same time, stroke is one of the leading causes of disability worldwide (Pignolo et al., 2022). Amid the trend in population ageing, the number of patients needing post-stroke rehabilitation is forecasted to considerably increase in the coming years. To cope with the rising demand while guaranteeing that the therapists' stress levels do not increase, the deployment of such automation technologies might be regarded as necessary.

6.2 Automation of cognitive tasks

Triage of patients

In the sector of hospital activities (Q86.1), healthcare workers need to manage the influx of patients arriving at hospital facilities. The overall increase in the demand for healthcare services has resulted in overcrowded emergency departments to the point that it has been considered physically impossible for clinicians to keep up with the rising demand (Boonstra & Laven, 2022). In this context, AI-based systems offer the opportunity to help improve the efficiency of patient management in hospital facilities. For instance, Jianq et al. (2021) developed an AI model that can triage patients with potential cardiovascular diseases using data available at the triage stage (e.g. blood pressure, pulse rate, oxygen saturation). The results of their study found that their model can optimally differentiate between low-risk and high-risk patients. Similarly, Klug et al. (2020) developed an AI-based predictive mortality model to help classify the urgency in the treatment of patients arriving at emergency departments. The model calculated mortality based on data such as age, arrival mode and vital signs. It should be noted that AI-based triage tools are designed to assist physicians rather than to replace them. Advances in such tools are at an early stage, with implemented triage systems found hitherto to be efficient in specific patient populations (Boonstra & Laven, 2022).

The use of AI systems to assist in the triage of patients is expected to have positive OSH implications for healthcare workers at emergency departments. Notably, such systems can alleviate the workload of hospital workers. The reduction in their workload, in turn, is expected to improve overall wellbeing of workers by reducing stress levels and thus their risk of burnout (Boonstra & Laven, 2022). Additionally, the use of AI systems for the triage of patients is expected to reduce the waiting times for patients to be attended to. In turn, this can reduce patients' potential frustration, stress or anger that could be expressed in the form of violence or verbal abuse towards the medical staff.

Medical reporting

Professionals in the human health sector (Q86) spend a considerable amount of their working time carrying out administrative tasks such as writing patients' medical reports or updating EHRs. The increased administrative burden has been found to be one of the leading causes of clinicians' burnout (Van Buchem et al., 2021). In this context, recent advances in NLP methods have been promising to help alleviate the administrative burden of healthcare professionals.

A systematic literature review conducted by Li, Pan et al. (2022) identifies several of the novel uses of NLP related to medical reporting. A particular application they include refers to automated text generation. A central component of NLP is natural language generation (NLG), which refers to the creation of new text from existing documents, images or videos. In the medical field, some pilot applications of NLG have tried to automate the writing of medical reports based on the analysis of medical images. For instance, radiology reports normally contain the same type of information (i.e. patient's history, symptoms and image medical interpretation) and are divided into pre-established sections (i.e. comparison, indication, findings and impressions) (Monshi et al., 2020). Novel applications of NLP have therefore been able to develop comprehensible and clinically valid radiology reports based on the analysis of X-ray images (Nguyen et al., 2021).

Another relevant use of NLP for medical reporting relates to the introduction of the so-called digital scribes. As described by Van Buchem et al. (2021), a digital scribe normally includes a microphone that records the conversation between the physician and the patient that is then transcribed thanks to an automated speech recognition system. In a second step, the digital scribe by applying NLP models can extract relevant information from the conversation and provide a report to the physician.

The automation of medical reporting has the potential to help alleviate the administrative burden of healthcare professionals, reducing related stress levels and improving their overall wellbeing at work. Additionally, this will free up time for radiologists to conduct more rewarding tasks such as direct patient treatment or even to use the generated reports to contribute to medical research for better treatment options (Pang et al., 2023).

Diagnosis generation via interpretation of medical images

Interpretation of medical images such as X-rays and CT scans is a fundamental procedure in the diagnosis of patients. The increasing demand on radiology departments coupled with the shortage of radiologists has placed hope in the deployment of AI applications as a potential solution (Chen et al., 2021). Research in the field has demonstrated the advantages that AI-based diagnosis generation tools entail compared to human discretion. Broadly speaking, as AI technologies have the ability to learn from millions of image samples, they have been found to detect, with high levels of accuracy, image abnormalities that the human eye may not be able to detect (Oren et al., 2020).

A particularly promising field of application refers to mammography interpretation to detect breast cancer. The use of AI-based diagnostic support software for breast cancer detection has been found to improve the accuracy of radiologists either by providing interpretative assistance (Yoon et al., 2023) or as a stand-alone tool (McKinney et al., 2020). As AI-based tools still incur errors, they are expected to complement rather than substitute clinicians' diagnostics. However, the extent to which clinicians can augment their skills thanks to AI diagnostic systems depends on the levels of accuracy of the tool. In this respect, the use of such tools may translate to automation bias, by which individuals overvalue machine-provided information over manually derived information (EU-OSHA, 2022d). This can pose a risk as clinicians may over rely on the diagnosis provided by the machine, disregarding their own skills that they may eventually unlearn.

The deployment of AI-based diagnostic support software in the hospital activities sector (Q86.1) is expected to improve radiologists' overall wellbeing at work. Notably, the introduction of such support tools will alleviate the increasing workload of these professionals. A study conducted by Raya-Povedano et al. (2021) found that the introduction of AI-based diagnostic tools could reduce up to 70% of the workload of healthcare professionals without reducing the levels of accurate cancer detection in different screening settings. Additionally, a survey conducted with healthcare professionals from breast screening units of five health institutions in England found that one of the main drivers for adoption of such technologies refers to workforce shortages, reflecting respondents' 'shared experience of work pressure in radiology departments' (Chen et al., 2021, p. 4). Hence, the use of AI-based diagnostic tools to assist healthcare professionals could help improve workflows in hospital facilities.

Remote patient monitoring

A routine task performed by nurses and other healthcare professionals on a daily basis refers to patient monitoring, that is the measure of vital signs and other physiological parameters to assist in clinical judgments or treatment plans (Shaik et al., 2023). Recent technological advances (e.g. wearables) have enabled the remote monitoring of patients. Historically, RPM has been used in remote or rural areas, or for home-based chronically ill patients. They can therefore be deployed across sectors: hospital activities (sector Q86.1), residential nursing care activities (Q87.1), and social work activities without accommodation (Q88). Thanks to embedded AI technologies, RPM systems are able to collect data from patients and, in a second step, analyse the data for a variety of purposes such as identifying any abnormalities, predicting health conditions and to classify patients' data (Shaik et al., 2023).

A literature review conducted by Palmieri Serrano et al. (2023) provided an overview on the benefits of RPM for healthcare professionals. According to the review, the majority of healthcare professionals regarded such technologies as 'increasingly relevant and advantageous for their practice' (p. 7). Notably, they stated that RPM technologies could help them identify deterioration in patients' health easier and thus to provide adequate timely care. This, in turn, helped avoid unnecessary clinic visits for the patients. Overall, this is expected to improve workflows at clinical institutions, and thus alleviate the work of healthcare professionals. In this respect, a study conducted in the United States found that the introduction of RPM considerably decreased nurses' workload (Zubrinic et al., 2023). In particular, during a two-year period, the number of unnecessary nurse visits to the bedside of patients decreased significantly. This implied that nurses reduced the distance they had to walk every day, overall improving their physical condition. The reduction in walking distance could translate to higher levels of sedentarism, but as nurses still need to move to perform several tasks, it is not expected that the effect on sedentarism will be considerable. Additionally, RPM and in particular home-based patient monitoring were found to reduce caregivers' stress levels, as they knew that patients were automatically being monitored (Klemets et al., 2019).

However, there are still some challenges that hinder the widespread deployment of RPM technologies in the healthcare sector. According to Shaik et al. (2023), barriers mainly relate to privacy concerns on the use of patients' data, noise and variability in real-world situations that may affect the accuracy of measurement systems, and the transparency about the way the algorithms analysing patients' data work. These limitations arguably affect healthcare professionals' trust in the technology, and could increase their stress levels as they are concerned about how RPMs could negatively affect patients' timely and optimal care. Additionally, RPM systems are also expected to reduce human interaction between healthcare professionals and their patients. It is widely admitted that interaction with the patient is an important and rewarding part of the work conducted by healthcare professionals, giving them a feeling of fulfilment. If AI-based systems reduce the contact with patients, it is expected that workers may feel less motivated, negatively impacting their mental health at work.

Furthermore, whereas RPM systems were expected to alleviate the workload of healthcare professionals, there is evidence that the introduction of such systems can increase perceived workload. In particular, a study assessing the introduction of RPM systems to telemonitor COVID-19 patients in 12 healthcare organisations in Belgium found that healthcare professionals had to engage in comprehensive RPM follow-up on top of their routine care (Van Grootven et al., 2023). Healthcare professionals who were asked about their experience with RPM systems mentioned that this was due to the fact that no additional human resources were incorporated to support the telemonitoring, resulting in an increased work burden.

Detection of precancerous lesions via assessment of dermoscopic images

Whereas melanoma represents the deadliest type of skin cancer in Europe, the timely diagnosis of melanoma is jeopardised by the global shortage of dermatologists. Furthermore, the levels of diagnosis accuracy are lower than for other types of cancer. According to Combalia et al. (2022), the accuracy of diagnosis is '71% for naked-eye inspection and 90% using a dermatoscope' (p. 1). Against this background, there have been many research efforts to facilitate the diagnosis of skin lesions via AI technologies in the human health activities sector (Q86). Recent developments in imaging techniques have allowed to collect high-quality data on skin lesions from patients across the world, which has helped in the development of AI solutions to distinguish malignant from benign skin lesions (Goyal et al., 2020). Some examples of such systems are the medical imaging systems Dermascan and Moleanalyzer pro. These AI-based software are able to analyse traces of hyperpigmentation in the image of a skin surface to identify and diagnose any existing lesions (Li, Fu et al., 2022).

An extensive body of literature found that such systems have accuracy levels on par with dermatologists' ones for the identification of skin cancer lesions (Baker et al., 2023; Goyal et al., 2020). However, such diagnostic tools still have some limitations and therefore still cannot fully replace dermatologists but assist them in diagnosing patients. One such limitation refers to the fact that such diagnostic tools do not take into account patients' clinical history, ethnicity or skin colour (Goyal et al., 2020). This has overall positive OSH implications as clinicians' skills will not become obsolete, meaning that they will not fear losing their job. At the same time, clinicians may face the problem of automation bias, by which they over rely on the information provided by the technology. This means that clinicians may incur errors or that they may fail to respond to critical situations when they arise. In the long term, this could have a negative psychosocial effect on them as they feel frustrated or resentful of the actions they took based on the output provided by AI-based systems.

Given the current shortage of dermatologists worldwide, the introduction of AI-based diagnosis tools for skin cancer is expected to alleviate dermatologists' growing workload. Earlier diagnosis is also expected to help apply adequate treatment to patients already at an early stage, improving recovery times or extending their life. Hence, research has pointed to the clinical benefit of integrating AI-based diagnostic tools for skin cancer 'within clinical workflows to minimize the burden on care teams' (Beltrami et al., 2022, p. 3). Hence, AI-based imaging software has the potential to improve care workflows, reducing dermatologists' workload and associated stress levels.

6.3 Good practice examples

Based on the list of relevant automated and automatable tasks in the HeSCare sector, five good practice examples were selected, including three physical tasks and two cognitive ones performed by different healthcare professionals. We found evidence that the reported good practice examples improved working conditions in general, and were effective in promoting health, safety and efficiency in the workplace. Furthermore, there was a reduction in OSH risks for HeSCare professionals. The selected good practice examples also tackle some of the most critical OSH challenges of the HeSCare sector, namely the intense workload and significant administrative burden, as well as working conditions related to MSK disorders.

6.3.1 Tissue manipulation during surgery interventions

- **Drivers for deployment**

Tissue manipulation, and in particular suturing tasks, is a highly complex task, only mastered by surgeons after years of experience (Tang et al., 2020). In robot-assisted surgeries, this task is even more difficult as surgeons need to apply the adequate level of force to the tissue without any haptic feedback. As surgeons fear that they will not perform this task correctly, their levels of stress may increase. In turn, frequent exposure to stress has been found to have a negative effect on surgeons' performance, which in the long term has led to higher rates of burnout among surgeons compared to non-surgical physicians (Budden et al., 2023). As surgical robots can assist and replace human surgeons in performing such tasks, it is expected that surgeons are less exposed to intraoperative stressors.

Furthermore, minimally invasive surgeries entail that surgeons have reduced access to operate on the patient's body. Hence, conducting tissue manipulation tasks has been found to result in higher pain prevalence (e.g. back, neck, and arm or shoulder pain), fatigue and muscular numbness in surgeons (Stucky et al., 2018). In this respect, surgical robots can help reduce such MSK disorders by taking over or assisting in the performance of tissue manipulation tasks in minimally invasive surgeries.

- **Impact on OSH, working conditions and job content**

A large body of literature has identified the MSK benefits that robot-assisted surgeries have compared to conventional ones. Notably, the absence of a surgical gown in robot-assisted surgeries facilitates the sitting position and repositioning of the surgeon during surgical interventions, reducing discomfort in the neck, shoulders and back (Mendes et al., 2020). However, it is worth mentioning that surgeons still report considerable levels of physical strain, in particular in the neck and trapezius due to their prolonged posture when working with the surgical robots' console (Wee et al., 2020). Given the admitted theoretical benefits of surgical robots, the persisting discomfort has been associated with poor compliance with positioning recommendations, and with the suboptimal design of the robotic console and the table height for varying physical attributes (Wee et al., 2020).

A systematic review conducted by Budden et al. (2023) gathered evidence on differences in surgeons' stress levels between robotic-assisted surgeries and conventional laparoscopic surgeries. The evidence collected shows mixed results, although the majority of reported studies found that the average heart rate in conventional surgeries was higher than in robotic-assisted ones. The authors conclude that there is low-quality evidence available on surgeons' stressors during surgeries, emphasising the need for more research to understand intraoperative stressors. Altogether, the evidence collected points out that the automation of such tasks can be a solution to reduce stress levels among surgeons. In fact, recent advances in surgical robots have embedded force feedback mechanisms that can warn the surgeon when applying excessive force, or limiting the force that can be applied (Golahmadi et al., 2021). This will facilitate the surgeons' task, and thus reduce related stress levels.

At the same time, the automation of tissue manipulation tasks may entail that surgeons lose the skills to perform such tasks. However, research on the topic has found that the use of surgical robots with inbuilt force feedback mechanisms can facilitate surgeons' understanding on when they are exerting excessive force to the tissue (Golahmadi et al., 2021). In this regard, surgeons can take advantage of the technology to improve their skills.

- **Workers' experience and involvement**

The deployment of surgical robots with embedded force feedback mechanisms has been found to improve surgical performance in terms of decreased tissue damage (Golahmadi et al., 2021). Moreover, surgical robots can measure the force exerted and provide feedback to surgeons, thus flattening their learning curve. Surgical trainees have therefore shown their interest in having more access to robotic-assisted surgery within their surgical training (Fleming et al., 2021).

Surgeons' experience with the use of surgical robots to assist in the performance of certain surgical tasks depends on their physical characteristics. Notably, surgeons of smaller stature and glove size tend to have more ergonomic problems when using surgical robots (Hislop et al., 2023). This, in turn, affects their performance as well as their incidence of MSK disorders. In that regard, research has found that female surgeons, who tend to be of smaller stature and glove size, reported to take significantly longer to complete suturing tasks with surgical robots than their male counterparts (Hislop et al., 2023). Likewise, they reported a higher number of complaints with regard to neck and shoulder pain. Hence, while there is evidence on the MSK benefits of using surgical robots to assist in tissue manipulation tasks, these benefits may be lost due to a suboptimal design of the robotic equipment.

- **Strategies for safe and healthy implementation**

Evidence on the use of surgical robots to assist or automate certain tasks within surgical interventions found that workers' experience depends on their physical attributes. This highlights the importance of having a tailored approach for the optimal design of surgical equipment. Hence, an adaptative design of the surgical equipment is pivotal to guarantee that the introduction of surgical robots to perform tissue manipulation tasks is ergonomically optimal.

Additionally, it is important to develop guidelines and trainings to learn how to employ the correct postures and equipment set-up in robot-assisted surgeries. Based on a systematic review on surgical ergonomics, Tetteh et al. (2023) developed guidelines on optimal postures and equipment set-up as part of robotic-assisted surgeries. The guidelines provide adjustment measures to place the console, the chair or the table so as to guarantee the most convenient posture for the surgeon. For instance, the robotic console should be adjusted to achieve the most neutral neck angle, while the chair should be placed so that feet touch the floor and knees are at a 90-degree angle. The development and dissemination of such types of guidelines is fundamental to facilitate that surgeons take advantage of the ergonomic benefits of robotic-assisted surgeries.

Similarly, robotic surgery is seldom included as part of the training curricula of surgeons. This may be due to the cost of conducting robot surgical training, and the already quite burdensome curricula of surgeon residents (Shaw et al., 2022). To guarantee a timely and optimal incorporation of robot training into surgical training, European health professionals' associations have developed and proposed structured training programmes for robotic-assisted surgeries. For instance, the European Academy of Robotic Colorectal Surgery developed a formal, optional training scheme for the use of surgical robots in colorectal interventions.[9] The advancements of standardised and structured training programmes will help in the automation of surgical tasks such as tissue manipulation while addressing any OSH implications.

6.3.2 Lifting and moving patients

- **Drivers for deployment**

Manual patient handling presents several OSH challenges as it often involves postures with deep bending, twisting or kneeling, which have to be repeated several times a day. Lifting and moving patients can therefore result in physical injuries, and has in fact been found in the literature as one of the main causes of physical burden and MSK disorders in caregivers (Brinkmann et al., 2022). In addition, patient manual handling always entails a risk of accidents, which can result in falls, strains and injuries, both for the patient and the caregiver.

To avoid physical pain and MSK disorders, a variety of solutions have been implemented in the HeSCare sector. Firstly, many guidelines have been developed on how caregivers and nurses should manually handle patients to avoid uncomfortable positions. Whereas such ergonomic positions can alleviate caregivers' physical burden, caregivers still take on a significant physical load. Moreover, it is difficult to ensure that caregivers and nurses fully comply with such guidelines. Secondly, there have been technological advances such as transfer boards, slides or slings, as well as mechanical lifts that facilitate patient manual handling (Sivakanthan et al., 2021). Nevertheless, such devices still present some operational disadvantages that have negative MSK implications for healthcare professionals. In the case of transfer boards, slides and slings, such devices still require significant human effort to operate, translating to a minimal reduction in medical staff's physical load on the back, shoulders and neck (Sivakanthan et al., 2021). Likewise, mechanical lifts 'still require awkward manipulations and significant human effort to operate' (Sivakanthan et al., 2021, p. 4).

- **Impact on OSH, working conditions and job content**

The use of robotic devices to lift and move patients has been found in the literature to reduce the physical burden of nurses and caregivers. For instance, a study conducted by Brinkmann et al. (2022) compared physical strain of caregivers using conventional, ergonomic and robotic-assisted patient transfer systems. Ergonomic transfers referred to patient transfers following ergonomic guidelines. Robotic-assisted patient transfer was found to reduce force exertion compared to conventional and ergonomic lifting techniques. Conversely, more than half of the participants in the study could not reduce their force exertion when using ergonomic techniques. Hence, robotic-assisted transfer seemed to be the sole optimal solution to alleviate caregivers' physical strain when lifting and moving patients.

Robotic-assisted lifting devices have also been found to present comparative advantages with respect to other existing devices helping in patient transfer, such as mechanical lifts. A study conducted by Greenhalgh et al. (2022) compared the robotic-assisted lifting device (i.e. Strong Arm) with a mechanical lifting device (i.e. Hoyer Advanced). Their results found that the former led to reduced muscle activation in the back, as well as better posture (e.g. lower range of back flexion, bending and rotation). Hence, robot devices assisting in patient lifting and moving have been found as the most helpful to reduce the risk of MSK disorders.

- **Workers' experience and involvement**

Healthcare professionals present mixed views regarding the use of robots to assist them in moving or lifting patients. Whereas they admit that the use of robotic devices helps them in reducing the physical demands related to lifting activities, they still have some concerns on the potential 'dehumanisation' of care (Klebbe et al., 2022). A survey conducted by Parviainen et al. (2019) with nurses and other healthcare professionals in Finland investigated their perceptions on the use of care robots. Their results point out that workers found robotic devices beneficial when assisting in physically demanding tasks such as the lifting of patients as long as the nurse–patient interaction remained intact with the use of the robotic device. Therefore, healthcare professionals' acceptance of robot-assistive devices was found to be related to the preservation of human interaction in care provision. Klebbe et al. (2022) found similar

[9] For more information, please refer to: https://www.escp.eu.com/education/european-school-of-coloproctology/robotic-training-programme (last accessed 12 December 2023).

evidence via semi-structured interviews with healthcare professionals on the use of care robots. Interviewees mentioned that robot lifting devices should be designed to be 'skin-friendly, provide a certain degree of flexibility, and be suitable to be warmed up to body temperature' (Klebbe et al., 2022, p. 13). Hence, participants in their study also highlighted the importance of humanising robots to be acceptable for care use.

In 2018, the Hampshire County in the United Kingdom pioneered a pilot programme for the use of cobots to help caregivers in patient manual handling (Local Government Association, 2021). The cobot consisted of an exoskeleton placed around the workers' lower back and hip with embedded sensors analysing the workers' movements to nudge them to adopt an ergonomic posture to move the patient. The carers who participated in the pilot programme showed high levels of satisfaction using the technology, reporting lower fatigue and physical pain after their work shift (Local Government Association, 2021). Moreover, carers mentioned that the technology helped them be more aware of their posture, and thus be more careful in adopting an ergonomic position to handle patients.

A study gathering the views of healthcare professionals working in a residential care facility in Japan where a lifting device had been introduced (i.e. Hug) found that workers who used the robotic device had to shorten their interaction with the patient, as more time was dedicated to moving the lifting device across the residential care facility (Wright, 2023). This provides evidence on some new monotonous tasks that may arise with the introduction of such types of technologies. In this respect, healthcare professionals will also need to learn how to configure the device and its parameters. Nevertheless, an initial period of learning when adopting a new device is inevitable, while the benefits of its introduction are expected to surpass the initial costs.

- **Strategies for safe and healthy implementation**

HeSCare professionals' acceptance of robotic devices to assist in the lifting and moving of patients is pivotal to guarantee an optimal implementation. In this respect, to win over caregivers and nurses who are still expressing some concerns on the potential loss of human interaction due to robots, it is important to **involve the HeSCare professionals** who are going to interact with the robotic device so they can share their recommendations with the technology developers in terms of design and functionalities.

Another aspect that is important to gain HeSCare professionals' acceptance refers to the **safety of the robotic device**. HeSCare professionals need to trust that the device will work properly with minimal errors, otherwise they will be stressed about the uncertainties of its use. In fact, any malfunctioning of the device can result in serious injuries to the patient, and the HeSCare professionals themselves. For this reason, such robotic devices have incorporated safety features to guarantee their safe use, such as force and speed limits, or selected keep-out zones or loading limits (Sivaprakasam et al., 2017).

Hence, to take advantage of the reduction in MSK disorders that robot lifting devices promise, it is important that their design and implementation take into consideration the concerns and the needs of HeSCare professionals. The insights collected from pilot studies on the deployment of such devices demonstrate that it is important to guarantee that human interaction remains unchanged.

6.3.3 Transport of sterile instruments

- **Drivers for deployment**

According to Fragapane et al. (2023), hospitals tend to 'struggle to manage an efficient sterile instrument logistics system' (p. 1). In particular, it is difficult to maintain a timely flow of instruments, both sterilised and to be sterilised, between the point of use and the departments for sterile processing. This is in particular the case as the demand of sterile instruments can vary considerably due to unexpected events, such as the need for emergency surgery (Fragapane et al., 2023). In turn, the unavailability of sterile instruments has been found as a significant cause in delays in surgical interventions (Fragapane et al., 2023). This can hinder the provision of timely care and increase healthcare professionals' stress.

To optimise the flow of sterile instruments across hospital facilities, several solutions have been developed in recent years. An alternative is the manual transportation using dedicated clean and soiled elevators that connect directly with the decontamination area of sterilisation departments. However, such models still require continuous work from a porter who transports the instruments (Fragapane et al., 2023). Another solution refers to the use of automated guided vehicles (AGVs) to transport sterile instruments. Yet, AGVs have some limitations in their use, as they follow pre-established paths, and can only pick up and deliver material in specific points within hospital facilities (Fragapane et al., 2023).

- **Impact on OSH, working conditions and job content**

Fragapane et al. (2023) conducted case studies in three hospitals located in Denmark and Norway to compare the transport of sterile instruments via manual transport with dedicated lifts, AGVs and AMRs. Their results show that AMRs enabled for sterile instruments to be timely delivered and rapidly returned to the sterilisation department. This helped sterilisation departments to 'distribute duties more evenly across the workday while avoiding bottlenecks during washing' of the equipment (p. 13). According to the authors, AMRs offer a competitive advantage with respect to AGVs as the smaller dimensions of AMRs and flexibility to adapt their path facilitate their implementation in busy environments. For instance, if the pick-up or delivery points of AGVs were to be changed, hospitals would need to 'implement (new) physical reference points, set up new readers for the wagons, establish the new infrastructure information and adapt the guide-path of the AGV's controls' (Fragapane et al., 2023, p. 9). On the other hand, AMRs digitally establish new routes and delivery points, meaning that installation is considerably quicker.

A practical case example refers to the Zealand University Hospital in Denmark that in 2018 introduced the Mobile Industrial Robot (MiR) to autonomously manage deliveries from the hospital's sterilisation centre (MiR, 2018). The robot travelled more than 10 km per week, therefore reducing the distance that staff had to walk during a week, having a positive physical implication for them. The transportation of sterile instruments was described by the operations manager at the hospital to consist of monotonous and repetitive tasks (MiR, 2018). Therefore, the automation of sterile instruments could alleviate the monotonous work burden of healthcare professionals, freeing up time they can then use for more rewarding tasks related to their profession. However, it should also be mentioned that the use of AMRs will also imply that healthcare professionals will need to perform monotonous tasks such as setting up the device and controlling the parameters. The introduction of AMRs to transport sterile instruments also reduced healthcare professionals' exposure to biological risks, in particular their exposure to contaminated material and potential pathogens.

- **Workers' experience and involvement**

Whereas some research has provided evidence on the additional workload that the introduction of AMRs may incur for hospital staff (Tornbjerg et al., 2021), the deployment of an AMR in the Zealand University Hospital for the transport of sterile instruments was found to be well accepted by workers and to improve workflows in general (MiR, 2018). Furthermore, healthcare professionals at the hospital referred to the AMR as a colleague rather than a machine (MiR, 2018). This exemplified the quick acceptance of the hospital's staff with the introduction of the technology.

The involvement of workers who were going to interact and use the AMR was important to guarantee an optimal deployment. According to the company deploying the technology, workers were involved in the process of deployment of the AMR, providing inputs to guarantee a safe and smooth implementation of the technologies (Gain & Co, 2017). For instance, workers recommended for the AMR to include a functionality by which it would politely warn individuals when approaching them. Additionally, based on professionals' recommendations, a sign was placed on the front of the AMR to indicate the robot's direction for people around it.

- **Strategies for safe and healthy implementation**

The enterprise in charge of the deployment of the robots stated that for the optimal implementation of AMRs for the transport of sterile instruments, several years of careful planning were required beforehand (Gain & Co, 2017). It can be therefore inferred that the optimal introduction of AI-based technologies in the workplace requires **thorough prior planning**. Additionally, the **involvement of healthcare professionals** who were going to benefit from the AMR was also regarded as important to gain acceptability and trust in the device. Similar conclusions were reported by the VTT Technical Research Centre of Finland that studied the deployment of two AMRs at the Seinäjoki Central Hospital for the delivery of supplies across the hospital (Melanson, 2017). According to their study, joint planning that involved various occupational groups and stakeholders was a key contributor to the success of the implementation and to achieve the objectives sought.

6.3.4 *Triage of patients*

- **Drivers for deployment**

The growing demand for care will also translate to a higher influx of patients into emergency departments. This may put hospitals and staff under operational pressure when their capacity cannot meet the demand. In emergency departments, healthcare professionals need to assign priority levels to patients arriving at emergency rooms based on their urgency of treatment. Consistent approaches for the assessment of patient prioritisation have been developed such as the Manchester Triage System (MTS) and the Patient Acuity Tool (PAT), by which healthcare professionals score patients based on acuity. However, some symptoms are not easily recognisable, meaning 'that patients may need to wait for a long time for a medical observation, resulting in an increased risk of morbidity' (Fernandes et al., 2020, p. 2). Hospitals are therefore looking for solutions to help them more efficiently manage an increasing number of patients. Against this background, clinical decision support systems hold the potential to assist clinicians in the triage of patients.

- **Impact on OSH, working conditions and job content**

A scoping review conducted by Fernandes et al. (2020) on the use of AI-based systems to inform emergency departments' triage of patients found that such systems were successful in predicting the acuity of patients (e.g. cardiac arrest, heart failure, presence of acute infectious disease). Similarly, several triage systems were able to identify patients with high probability of hospital admission. AI-based triage of patients was therefore found in a significant number of studies to alleviate the workload of healthcare professionals in emergency departments (Fernandes et al., 2020). In this respect, AI-based triage systems can help reduce diagnostic errors, by for example recognising abnormalities that might be difficult for the clinician to initially detect. The use of such systems also reduces the exposure of healthcare professionals to patients with infectious diseases.

Additionally, as the demand for care increases, the mental workload of clinicians is expected to increase in parallel, with negative psychological implications for them. In this regard, some AI-based tools supporting triage decisions have been found to alleviate clinicians' mental workload so that they can concentrate primarily on the provision of care (Boonstra & Laven, 2022). Furthermore, such tools help healthcare professionals make a rational assessment of a patient's conditions in a stressful environment (Falavigna et al., 2019). In this respect, an AI-based patient triage system developed by researchers at Amiens Picardy University Hospital in France was able 'to classify patients more rapidly, and more patients in parallel' (Arnaud et al., 2022, p. 8). This was argued to help free up time for physicians that they could use for direct patient care. In this respect, physicians acted as flow managers in emergency departments since the final decision on the patient is always on them (Arnaud et al., 2022).

AI-based triage systems are not conceived to substitute clinical judgement but to support it. Notably, some of the studies included in the scoping review conducted by Boonstra and Laven (2022) stated that the developed tools can only partially replace an expert physician, and are therefore 'helpful for hospitals that do not have a specific type of specialist available to make informed clinical decisions' (p. 7). In fact, according to Boonstra and Laven (2022), despite the evidence collected on effective triage supportive tools, implementing AI in emergency care is not straightforward. This is partly due to the 'inherent complexity and uncertainty of clinical information' (Jiang et al., 2021, p. 2). Hence, clinicians may not fear that such systems will take over their jobs, or that their skills are likely to become obsolete in the near future.

On the other hand, a related problem refers to over-reliance of clinicians on the information provided by the AI-based systems. This might represent a problem as physicians solely rely on the information provided by the AI tool, and stop making use of their decision-making abilities, with also a consequent loss or obsolescence of skills. Nevertheless, as such tools are envisaged to support rather than replace healthcare professionals, it is unlikely that their role in emergency departments will be significantly altered. In fact, some of these tools are designed to be customised by physicians according to their decision-making process (Falavigna et al., 2019).

- **Workers' experience and involvement**

Given the growing workload of healthcare professionals in emergency departments, the development and introduction of AI-based triage systems has been welcomed by professionals with an overall positive attitude. For instance, Cao et al. (2024) conducted a survey in China with 677 medical staff to assess their preference between AI-based and manual triage in emergency departments. Their results showed an overall acceptance rate of AI triage of 77.1%, while almost half of respondents preferred to use AI-based triage exclusively. This reflects the extent to which healthcare professionals considered as relevant the adoption of automated processes in overcrowded and overburdened healthcare facilities. Moreover, prior understanding and experience using AI-based triage systems was found to help reduce healthcare professionals' uncertainty about the risks of the system, improving overall acceptance levels (Cao et al., 2024).

- **Strategies for safe and healthy implementation**

The majority of examples of AI-based triage systems deployed in emergency departments are located in Asian countries and the United States, with only a few examples of pilot case studies being conducted in EU Member States (Boonstra & Laven, 2022). This may be due to the fact that, in general terms, AI-based triage systems are still at an initial phase of development as it is difficult to have a single model to predict disease severity due to the heterogeneity in patients' characteristics (Lee et al., 2021).

A particular concern for the deployment of AI-based triage systems is the potential discrimination bias of the algorithms enabling these systems due to issues at the programming phase. For this reason, it is important to guarantee that training data are held to a high standard, to avoid any undetected bias. However, there is a limited availability of training data for AI-based triage models due to the highly technical nature of the inherent data, making it difficult to ensure bias-free training data (EU-OSHA, 2023). Hence, as an alternative to guarantee that discrimination does not occur, monitoring the correct functioning of the triage systems (and therefore of the algorithms that enable its functioning) is pivotal to gain healthcare professionals and patients' trust. For instance, in 2022, the University of Montreal Hospital in Canada deployed an AI-based system to facilitate the triage of patients. According to the hospital managers who were involved in the deployment, it was important to guarantee that the functioning of the system was continuously monitored to avoid any biases (Serebrin, 2022). Moreover, the hospital management team explained that the AI-based system would be used to improve hospital management rather than for direct patient care. For this reason, it is important to involve healthcare professionals in the design of the system, as the AI-based system will be a tool supporting the decision-making processes of healthcare professionals (Falavigna et al., 2019). Similarly, a group of researchers from Amiens Picardy University Hospital in France developed a triage model for the emergency department that was able to highlight the most important words or phrases that contributed to prediction. This was helpful for healthcare professionals as they could better understand the algorithmic process and identify potential biases (Arnaud et al., 2023).

6.3.5 Medical reporting (digital scribes)

- **Drivers for deployment**

Healthcare professionals dedicate a considerable amount of their working time to conduct administrative tasks, such as updating EHRs. A study conducted in Germany and the United States found that physicians in emergency departments spent 29.4% of their time performing documentation activities (Schneider et al., 2021). Likewise, a study estimating the time spent per year on administrative tasks by healthcare professionals in the Netherlands found that this could be translated into over 100,000 full-time positions (Maas et al., 2020). The huge administrative workload exacerbates the overall work burden healthcare professionals face given the increasing demand for care. This is even more concerning as healthcare professionals who spend more time updating EHRs, in particular in irregular working hours, were found to be at higher risk of burnout (Van Buchem et al., 2021). To deal with the administrative burden, hospitals started hiring medical scribes defined as individuals who manage administrative tasks such as summarising a patient consultation. Despite overall reductions in work burden for clinicians, many issues were found with medical scribes mainly relating to the high costs of employing them (Ghatnekar et al., 2021). Moreover, the use of medical scribes was not found to alleviate the administrative burden but to shift it to other healthcare personnel (Van Buchem et al., 2021).

Although in its infancy, recent developments in large language models (LLMs) have been regarded as a potential solution to decrease the administrative burden of healthcare professionals. In general terms, LLMs are capable of rapidly adapting, summarising and rephrasing information; while the availability of large volumes of free-text information to train LLMs is argued to enhance the development and deployment of LLM-based technologies in the healthcare field (Arora & Arora, 2023).

- **Impact on OSH, working conditions and job content**

A pilot study comparing the use of digital scribes versus manual note-taking in the emergency department of a United States hospital showed that both notes were similar in terms of quality (assessed with the Physician Documentation Quality Instrument) (Eshel et al., 2023). Whereas the quality of the automatically drafted reports could be at par with that of clinicians' themselves, clinicians would still need to revise the documents to ensure their accuracy. In this respect, the use of AI-based systems is not at a stage that it can replace the work of clinicians but it can optimise the quality and speed of note creation (Eshel et al., 2023). Notably, digital scribes have been found to be 2.17 times faster than manually typing the information and approximately 3.12 times faster than dictating notes (Wang et al., 2021).

It is important to highlight, however, that medical notes also include conclusions drawn by clinicians from observing or physically examining the patient that may not be communicated verbally (as in the presence of the patient) (Quiroz et al., 2019). Digital scribes can therefore act as a tool to prepare very advanced drafts for which clinicians will only need to revise and do minor changes. The use of such AI-based systems therefore still alleviates considerably the administrative burden of healthcare professionals.

A challenge on the use of digital scribes refers to the over-reliance on the technology, with clinicians assuming that the notes taken by the scribe are accurate. Clinicians therefore may find that they diagnosed or recommended a treatment based on a flawed document, which could arguably increase their stress, anger or frustration when making use of digital scribes. However, it is expected that clinicians will still need to revise the documents created by the digital scribes, acknowledging the limitations the technology has. In this regard, digital scribes need to be seen as effective note-takers and transcribers, instead of tools to automate medical reporting. In fact, the accuracy of some of the most prominent digital scribes in the United States is still contested (Walker, 2023).

Additionally, the use of digital scribes can also help improve the clinician–patient relationship as the clinician could focus fully on the patient, instead of having to turn to their computer to simultaneously report the information provided (Quiroz et al., 2019). In fact, this can create a feeling that the clinical visit was 'impersonal and formulaic' (Ghatnekar et al., 2021, p. 805). The use of digital scribes therefore helps build a more meaningful human interaction between the healthcare professional and the patient that was highlighted in the literature as of particular importance for healthcare professionals.

- **Workers' experience and involvement**

Research on the attitude of physicians towards automated transcription shows an overall interest in the use of such AI-based technologies as they are expected to considerably alleviate their administrative burden (Fraile Navarro et al., 2023). The use of medical scribes to optimise medical reporting has been identified in the literature as very useful to alleviate the administrative burden of healthcare professionals (Shah et al., 2021). Physicians also mentioned that scribes were very beneficial as they enabled them to provide undivided attention to the patient. A study analysing the implementation of digital scribes in the Moffitt Cancer Centre in the United States found that physicians reported to have more time to dedicate to updating EHRs (Nguyen et al., 2023). In other words, digital scribes were identified as helpful in making the administrative burden more bearable. This arguably improved the mental wellbeing of healthcare professionals, although the study by Nguyen et al. (2023) did not find a significant improvement in healthcare professionals' mental health in terms of burnout.

- **Strategies for safe and healthy implementation**

AI-based digital scribes have demonstrated to be effective in taking notes and transcribing conversations between patients and clinicians, while research found that they have adequate levels of accuracy. To guarantee that the benefits of the technology are fully exploited, it is important that **adequate legal frameworks (i.e. GDPR in the EU) are enforced** to ensure the respect of patients' privacy. Moreover, whereas the field of NLP has been making huge advances in recent times, digital scribes are still likely to incur many errors. This is due to the fact that to accurately write medical notes, the NLP model needs to account for the differences between spoken and written language, as well as between lay and expert terminology (Quiroz et al., 2019). It is therefore important that the **clinician oversees and reviews the clinical notes produced** and corrects any misinformation.

Additionally, the introduction of digital scribes implies that healthcare professionals will need to follow a **training programme** to understand how the technology works. According to Ghatnekar et al. (2021), there are several types of training available that can ensure an effective implementation of digital scribes, such as role-based training or process-based training.

7 Conclusions: what have we learnt?

The sustainability of the HeSCare sector is at stake given the trend in the ageing of the population that will significantly increase the demand for HeSCare services. In parallel, current shortages in the HeSCare workforce are expected to continue increasing as a substantial part of the workforce is approaching retirement age. Furthermore, poor working conditions and several OSH challenges related to the nature of HeSCare work are expected to exacerbate workforce shortages. In this respect, the majority of reported OSH implications refer to mental health issues due to excessive workloads, and MSK disorders due to the repetitive and physically strenuous tasks that need to be conducted.

In this context, AI and robotics hold the potential to address the challenges of the HeSCare sector. However, they also raise other potential negative OSH implications. In this report, we have provided evidence on the current state of automation of cognitive and physical tasks in the HeSCare sector, with an extensive number of examples of automated tasks or tasks with the potential for automation. A comparative analysis of the examples presented above allows to identify some takeaways on the automation of tasks in the HeSCare sector, which can be summarised as follows:

- **More bearable workload for HeSCare professionals:** advanced technologies were found to help HeSCare professionals to be more productive, by treating more patients in a shorter amount of time. This improved their ability to manage increasing workloads, which had been associated with a growing number of burnout cases.
- **Significant reduction in MSK risks and exposure to biological and chemical risks:** as advanced technologies take over the performance of physically strenuous tasks related to repetitive and uncomfortable positions and movements, the incidence of MSK disorders was found to decrease considerably. Likewise, the automation of physical tasks also reduced professionals' exposure to contaminated areas and infectious diseases.
- **Supporting the job of HeSCare professionals rather than substituting them:** automation systems still present some limitations that require the involvement of HeSCare professionals. Hence, the output provided by the technologies is still monitored and checked by the professionals. This implies that HeSCare professionals will need to take over other tasks related to the supervision of the technology, which might be considered as monotonous and burdensome. At the same time, these limitations imply that HeSCare professionals are not likely to incur automation bias by which they over rely on the output provided by the technology over their human judgement.
- **Concerns on the potential loss of human interaction:** as advanced technologies take over the performance of certain tasks, the contact with the patient, which is of utmost importance in the HeSCare sector, is expected to be reduced. Moreover, while the technologies are expected to alleviate the workload of HeSCare professionals so they can dedicate more time to direct patient care, there is no evidence that workers will dedicate this time to it.
- **Relevance of providing adequate training to professionals:** training is pivotal to guaranteeing that HeSCare professionals take full advantage of the technology, and to help them easily overcome the initial increase in mental workload as they learn how to interact with the technology. In the case of some already widespread technologies, such as surgical robots, several European-level associations have developed structured training programmes to facilitate a safe, healthy and efficient implementation across hospital facilities in different European locations.

- **Importance of involving HeSCare professionals in the design and deployment of the technologies:** the examples we provided showed instances where the design of the technology had not been optimally adapted to all types of physical attributes (e.g. height, glove size, etc.), which led to a higher number of complaints about physical pain. In other cases, HeSCare professionals' experience with the technology was directly dependent on whether they had been involved in determining the best configuration of the tool so they could take full advantage of it.
- **Building trust is pivotal for widespread deployment of automation systems:** trust can be enhanced if automated systems show high levels of accuracy, or if they include adequate explanations and monitoring systems to identify any inaccuracies. In this respect, algorithmic transparency plays a crucial role so professionals can understand the output provided by the AI-based systems. Additionally, the enforcement of data protection legislation (i.e. GDPR) is of utmost importance to guarantee the protection of patients and workers' data, and thus their trust and acceptance of the technologies.

Based on these findings, some recommendations to ensure adequate OSH when introducing AI-based systems and advanced robotics in the HeSCare sector have been formulated:

- **Establishment of design standards:** to guarantee a proper use of the automated systems, on top of required safety features, considering MSK health factors such as user interface design and equipment ergonomics is helpful to minimise the incidence of physical strain and to ensure a wider acceptance and use of the technology by HeSCare professionals. Furthermore, to ensure that HeSCare professionals make use of the technology, it is important to adapt the technology's features so as to assist the medical staff according to their needs. This is in particular the case as automated systems still present limitations, making monitoring by HeSCare professionals necessary.
- **Implementation of training programmes:** with the objective of guaranteeing a proper use and maintenance of the automated system, while facilitating professionals' acceptance of the technology. Trainings should be developed involving all relevant stakeholders, and in particular HeSCare professionals. The training should also help workers to be aware of the limitations as well as potential inherent biases in the systems or the data they use for their functioning. Similarly, the training programmes could be accompanied with a set of guidelines, such as those developed to guide HeSCare professionals in moving patients so as to avoid MSK risks.
- **Set up mechanisms for continuous monitoring of AI-based systems:** trust and acceptance of the technology by both HeSCare professionals and patients is important to guarantee its widespread use. In this respect, an optimal strategy relates to setting up a monitoring system to: (i) monitor the functioning of the algorithm and AI-based systems; and (ii) maintain human oversight of the output to avoid bias and errors. An adequate level of resources should be allocated to the optimal implementation of such monitoring systems.

8 References

Agarwal, N., Moehring, A., Rajpurkar, P., & Salz, T. (2023). Combining human expertise with artificial intelligence: Experimental evidence from radiology. *NBER — National Bureau of Economic Research, Working Paper 31422*.

Alabi, R. O., Hietanen, P., Elmusrati, M., Youssef, P., Almangush, A., & Mäkitie, A. A. (2021). Mitigating burnout in an oncological unit: A scoping review. *Frontiers in Public Health, 9*.

Alser, O., Dorken-Gallastegi, A., Proaño-Zamudio, J. A., Nederpelt, C., Mokhtari, A. V., Mashbari, H., et al. (2023). Using the Field Artificial Intelligence Triage (FAIT) tool to predict hospital critical care resource utilization in patients with truncal gunshot wounds. *The American Journal of Surgery, 226*(2), 245-250.

Aquino, Y. S., Rogers, W. A., Braunack-Mayer, A., Frazer, H., Win, K. T., Houssami, N., et al. (2023). Utopia versus dystopia: Professional perspectives on the impact of healthcare artificial intelligence on clinical roles and skills. *International Journal of Medical Informatics, 169*, 104903.

Arana-Landín, G., Laskurain-Iturbe, I., Iturrate, M., & Landeta-Manzano, B. (2023). Assessing the influence of industry 4.0 technologies on occupational health and safety. *Heliyon, 9*, e13720.

Arnaud, E., Elbattah, M., Ammirati, C., Dequen, G., & Ghazali, D. A. (2022). Use of artificial intelligence to manage patient flow in emergency departments during the COVID-19 pandemic: A prospective, single-center study. *International Journal of Environmental Research and Public Health,* 19/15.

Arnaud, E., Elbattah, M., Moreno-Sánchez, P. A., Dequen, G., & Ghazali, D. A. (2023). Explainable NLP model for predicting adminissions at emergency department using triage notes. *IEEE International Conference on Big Data (BigData)*, 4843-4847.

Arora, A., & Arora, A. (2023). The promise of large language models in health care. *The Lancet, 401*(10377), 641. https://doi.org/10.1016/S0140-6736(23)00216-7

Aslam, I., Davis, S. A., Feldman, S. R., & Martin, W. E. (2015). A review of patient lifting interventions to reduce health care worker injuries. *Workplace Health & Safety, 63*(6), 267-275.

Aydinocak, E. U. (2023). Robotic systems and healthcare logistics. In I. Iyigün, & Ö. F. Görçün (Eds), *Health 4.0 and medical supply chain* (pp. 79-96). Springer.

Bail, C., Harth, V., & Mache, S. (2023). Digitalization in urology – A multimethod study of the relationships between physicians' technostress, burnout, work engagement and job satisfaction. *Healthcare, 11*, 2255.

Baker, K. A., Roberts, E., Harman, K., Mullarkey, D., & Kalsi, D. (2023). BT06 Using artificial intelligence to triage skin cancer referrals: Outcomes from a pilot study. *British Journal of Dermatology, 188*(4).

Baltazar, A. R., Petry, M. R., Silva, M. F., & Moreira, A. P. (2021). Autonomous wheelchair for patient's transportation on healthcare institutions. *SN Applied Sciences, 3*, 354.

Barrio Lopez, I., Benzakour, A., Mavrogenis, A., Benzakour, T., Ahmad, A., & Lemée, J.-M. (2023). Robotics in spine surgery: Systematic review of literature. *International Orthopaedics, 47*, 447-456.

Beltrami, E. J., Brown, A. C., Salmon, P. J. M., Leffell, D. J., Ko, J. M., & Grant-Kels, J. M. (2022). Artificial intelligence in the detection of skin cancer. *Journal of the American Academy of Dermatology, 87*(6), 1336–1342.

Bernal, D., Campos-Serna, J., Tobias, A., Vargas-Prada, S., Benavides, F. G., & Serra, C. (2015). Work-related psychosocial risk factors and musculoskeletal disorders in hospital nurses and nursing aides: A systematic review and meta-analysis. *International Journal of Nursing Studies, 52*(2), 635-648.

Blanco-Gonzalez, A., Cabezon, A., Seco-Gonzalez, A., Conde-Torres, D., Antelo-Riveiro, P., Pineiro, A., & Garcia-Fandino, R. (2023). The role of AI in drug discovery: Challenges, opportunities, and strategies. *Pharmaceuticals, 16*(6), 891.

Boehm, F., Graesslin, R., Theodoraki, M.-N., Schild, L., Greve, J., Hoffmann, T. K., & Schuler, P. J. (2021). Current advances in robotics for head and neck surgery—A systematic review. *Cancers, 13*(6), 1398.

Boeken, T., Feydy, J., Lecler, A., Soyer, P., Feydy, A., Barat, M., & Duron, L. (2023). Artificial intelligence in diagnostic and interventional radiology: Where are we now? *Diagnostic and Interventional Imaging, 104*(1), 1-5.

Bohr, A., & Memarzadeh, K. (2020). The rise of artificial intelligence in healthcare applications. In A. Bohr, & K. Memarzadeh (Eds), *Artificial intelligence in healthcare* (pp. 25-60). Academic Press.

Bonzini, M., Comotti, A., Fattori, A., Serra, D., Laurino, M., Mastorci, F., Bufano, P., Ciocan, C., Ferrari, L., Bollati, V., & Di Tecco, V. (2023). Promoting health and productivity among ageing workers: A longitudinal study on work ability, biological and cognitive age in modern workplaces (PROAGEING study). *BMC Public Health, 23*, 1115.

Boonstra, A., & Laven, M. (2022). Influence of artificial intelligence on the work design of emergency department clinicians a systematic literature review. *BMC Health Services Research, 22*.

Brinkmann, A., Fifelski-von Böhlen, C., Kowalski, C., Laura, S., Meyer, O., Diekmann, R., & Hein, A. (2022). Providing physical relief for nurses by collaborative robots. *Scientific Reports, 12*, 8644.

Brod, C. (1984). *Technostress: The human cost of the computer revolution*. Addison-Wesley.

Bucinca, Z., Malaya, M. B., & Gajos, K. Z. (2021). To trust or to think: Cognitive forcing functions can reduce overreliance on AI in AI-assisted decision-making. *Proceedings of the ACM on Human-Computer Interaction, 5*, 1-21.

Budden, A., Song, S., Henry, A., Wakefield, C. E., & Abbott, J. (2023). A systematic review of biological changes in surgeons' acute stress levels during surgery. *Surgery in Practice and Science, 13*, 100174.

Califf, C. B., Sarker, S., & Sarker, S. (2020). The bright and dark sides of technostress: A mixed-methods study involving healthcare IT. *MIS Quarterly, 44*, 809-856.

Cao, B., Huang, S., & Tang, W. (2024). AI triage or manual triage? Exploring medical staffs' preference for AI triage in China. *Patient Education and Counseling, 119*, 108076.

Cao, L., Li, X., Phan, P. T., Tiong, A. M. H., Kaan, H. L., Liu, J., Lai, W., Huang, Y., Le, H. M., Miyasaka, M., Ho, K. Y., Chiu, P. W. Y., & Phee, S. J. (2020). Sewing up the wounds: A robotic suturing system for flexible endoscopy. *IEEE Robotics & Automation Magazine, 27*(3), 45-54.

Casey, A., Davidson, E., Poon, M., Hong, H., Duma, D., Grivas, A., et al. (2021). A systematic review of natural language processing applied to radiology reports. *BMC Medical Informatics and Decision Making, 21*, 179.

Casini, B., Tuvo, B., Scarpaci, M., Totaro, M., Badalucco, F., Briani, S. L., et al. (2023). Implementation of an environmental cleaning protocol in hospital critical areas using a UV-C disinfection robot. *International Journal of Environmental Research Public Health, 20*(5), 4284.

Cattaneo, U., & Pozzan, E. (2020, 7 April). *Women health workers: Working relentlessly in hospitals and at home*. International Labour Organization (ILO).

Chen, A. I., Balter, M. L., Maguire, T. J., & Yarmush, M. L. (2020). Deep learning robotic guidance for autonomous vascular access. *Nature Machine Intelligence, 2*(2), 104-115.

Chen, Y., Stavropoulou, C., Narasinkan, R., Baker, A., & Scarbrough, H. (2021). Professionals' responses to the introduction of AI innovations in radiology and their implications for future adoption: A qualitative study. *BMC Health Services Research, 21*(1), 813.

Chen, P., Wang, Y., Tian, Y., Guo, Y., & Xu, K. (2023). The catheter and guidewire operating systems of vascular interventional surgical robots: A systematic review. *IEEE Transactions on Medical Robotics and Bionics, 5*(2), 180-195.

Choi, I., Ko, K., Song, H., Jung, B.-J., Hwang, J.-H., Moon, H., & Yang, G.-H. (2023). A meal-assistance robot system for Asian food and its food acquisition point estimation and user interface based on face recognition. *Applied Sciences, 13*(5), 3216.

Christoforou, E. G., Avgousti, S., Ramdani, N., Novales, C., & Panayides, A. S. (2020). The upcoming role for nursing and assistive robotics: Opportunities and challenges ahead. *Frontiers in Digital Health, 2*.

Clarke, M., & Martin, K. (2023). Managing cybersecurity risk in healthcare settings. *Healthcare Management Forum*, 1-4.

Combalia, M., Codella, N., Rotemberg, V., Carrera, C., Dusza, S., Gutman, D., Helba, B., Kittler, H., Kurtansky, N. R., Liopyris, K., Marchetti, M. A., Podlipnik, S., Puig, S., Rinner, C., Tschandl, P., Weber, J., Halpern, A., & Malvehy, J. (2022). Validation of artificial intelligence prediction models for skin cancer diagnosis using dermoscopy images: The 2019 International Skin Imaging Collaboration Grand Challenge. *The Lancet Digital Health, 4*(5), e330-e339.

Coombs, C., Hislop, D., Taneva, S. K., & Barnard, S. (2020). The strategic impacts of intelligent automation for knowledge and service work: An interdisciplinary review. *The Journal of Strategic Information Systems, 29*(4), 101600.

Dalsgaard, T., Jensen, M., Hartwell, D., Mosgaard, B. J., Jørgensen, A., & Jensen, B. R. (2020). Robotic surgery is less physically demanding than laparoscopic surgery. *Annals of Surgery, 271*(1), 106-113.

Diab-El Schahawi, M., & Zingg, W. (2021). Ultraviolet disinfection robots to improve hospital cleaning: Real promise or just a gimmick? *Antimicrobial Resistance & Infection Control, 10*(33).

Di Lallo, A., Murphy, R., Krieger, A., Zhu, J., Taylor, R. H., & Su, H. (2021). Medical robots for infectious diseases: Lessons and challenges from the COVID-19 pandemic. *IEEE Robotics & Automation Magazine, 28*(1), 18-27.

Doyle, O. M., Leavitt, N., & Rigg, J. A. (2020). Finding undiagnosed patients with hepatitis C infection: An application of artificial intelligence to patient claims data. *Scientific Reports, 10*, 10521.

EFPIA (2019). *Unleashing the potential of data to improve cancer care.* European Federation of Pharmaceutical Industries and Associations (EFPIA).

Eggleston, K., Suk Lee, Y., & Iizuka, T. (2021). Robots and labor in the service sector: Evidence from nursing homes. *NBER Working Paper 28322*.

Ehrmann, D. E., Gallant, S. N., Nagaraj, S., Goodfellow, S. D., Eytan, D., Goldenberg, A., & Mazwi, M. L. (2022). Evaluating and reducing cognitive load should be a priority for machine learning in healthcare. *Nature Medicine, 28*, 1331-1333.

Eshel, R., Bellolio, F., Boggust, A., Shapiro, N. I., Mullan, A. F., Heaton, H. A., Madsen, B. E., Homme, J. L., Iliff, B. W., Sunga, K. L., Wangsgard, C. R., Vanmeter, D., & Cabrera, D. (2023). Comparison of clinical note quality between an automated digital intake tool and the standard note in the emergency department. *The American Journal of Emergency Medicine, 63*, 79-85.

EU-OSHA – European Union Agency for Safety and Health at Work, *European Survey of Enterprises on New and Emerging Risks (ESENER)*, 2019. Available at: https://osha.europa.eu/en/facts-and-figures/esener

EU-OSHA – European Union Agency for Safety and Health at Work, *Human health and social work activities – evidence from the European Survey of Enterprises on New and Emerging Risks (ESENER)*, 2022a. Available at: https://osha.europa.eu/en/publications/human-health-and-social-work-activities-evidence-european-survey-enterprises-new-and-emerging-risks-esener

EU-OSHA – European Union Agency for Safety and Health at Work, *Advanced robotics, artificial intelligence and the automation of tasks: definitions, uses, policies and strategies and Occupational Safety and Health*, 2022b. Available at: https://osha.europa.eu/en/publications/advanced-robotics-artificial-intelligence-and-automation-tasks-definitions-uses-policies-and-strategies-and-occupational-safety-and-health

EU-OSHA – European Union Agency for Safety and Health at Work, *Advanced robotics and automation: implications for occupational safety and health*, 2022c. Available at: https://osha.europa.eu/sites/default/files/2022-06/Advanced_robotics_automation_implications.pdf

EU-OSHA – European Union Agency for Safety and Health at Work, *Cognitive automation: implications for occupational safety and health*, 2022d. Available at: https://osha.europa.eu/en/publications/summary-cognitive-automation-implications-occupational-safety-and-health-0

EU-OSHA – European Union Agency for Safety and Health at Work, *Incorporating occupational safety and health in the assessment of cybersecurity risks*, 2022e. Available at: https://osha.europa.eu/en/publications/incorporating-occupational-safety-and-health-assessment-cybersecurity-risks

EU-OSHA – European Union Agency for Safety and Health at Work, *Advanced robotic automation: comparative case study report*, 2023. Available at: https://osha.europa.eu/en/publications/summary-advanced-robotic-automation-comparative-case-study-reports

Eurofound. (2020). *Long-term care workforce: Employment and working conditions*. Publications Office of the European Union.

Eurofound. (2021). *European Working Conditions Survey (EWCS) 2021*. https://www.eurofound.europa.eu/en/surveys/european-working-conditions-surveys-ewcs

Eurofound. (2022). *Ethics in the digital workplace*. Publications Office of the European Union.

European Commission. (2018). *Inequalities in access to healthcare. A study of national policies 2018*. https://ec.europa.eu/social/BlobServlet?docId=20339&langId=en

European Commission. (2023a). *The impact of demographic change – in a changing environment*. Commission Staff Working Document SWD(2023) 21 final. European Commission.

European Commission. (2023b). *Employment and Social Developments in Europe 2023: Addressing labour shortages and skills gaps in the EU*. European Commission.

Falavigna, G., Costantino, G., Furlan, R., Quinn, J. V., Ungar, A., & Ippoliti, R. (2019). Artificial neural networks and risk stratification in emergency departments. *Internal and Emergency Medicine, 14*(2), 291-299.

Fernandes, M., Vieira, S. M., Leite, F., Palos, C., Finkelstein, S., & Sousa, J. M. (2020). Clinical decision support systems for triage in the emergency. *Artificial Intelligence in Medicine, 19*.

Fleming, C. A., Ali, O., Clements, J. M., Hirniak, J., King, M., Mohan, H. M., Nally, D. M., Burke, J., & The Association of Surgeons in Training (ASIT). (2021). Surgical trainee experience and opinion of robotic surgery in surgical training and vision for the future: A snapshot study of pan-specialty surgical trainees. *Journal of Robotic Surgery, 16*(5), 1073-1082.

Fosch-Villaronga, E., & Mahler, T. (2021). Cybersecurity, safety and robots: Strengthening the link between cybersecurity and safety in the context of care robots. *Computer Law & Security Review, 41*, 105528.

Fragapane, G., Hvolby, H.-H., Sgarbossa, F., & Strandhagen, J. O. (2020). Autonomous mobile robots in hospital logistics. In B. Lalic, V. Majstorovic, U. Marjanovic, G. von Cieminski, & D. Romero (Eds), *Advances in production management systems* (pp. 672-679). Springer.

Fragapane, G., Hvolby, H.-H., Sgarbossa, F., & Strandhagen, J. O. (2023). Autonomous mobile robots in sterile instrument logistics: An evaluation of the material handling system for a strategic fit framework. *Production, Planning & Control, 34*(1), 53-67.

Fraile Navarro, D., Kocaballi, A. B., Dras, M., & Berkovsky, S. (2023). Collaboration, not confrontation: Understanding general practitioners' attitudes towards natural language and text automation in clinical practice. *ACM Transactions on Computer-Human Interaction, 30*(2).

Füszl, A., Zatorska, B., Van den Nest, M., Ebner, J., Presterl, E., & Diab-Elschahawi, M. (2021). The use of a UV-C disinfection robot in the routine cleaning process: A field study in an Academic hospital. *Antimicrobial Resistance & Infection Control, 10*(84).

Gain & Co. (2017, 10 March). Gain & Co concludes largest hospital tender for self-driving robots in Denmark. *Gain & Co Insights*. https://gainco.dk/gain-co-concludes-largest-hospital-tender-for-self-driving-robots-in-denmark/

Garcia Valencia, O. A., Thongprayoon, C., Jadlowiec, C. C., Mao, S. A., Miao, J., & Cheungpasitporn, W. (2023). Enhancing kidney transplant care through the integration of chatbot. *Healthcare, 11*, 2518.

Garety, P., Edwards, C. J., Ward, T., Emsley, E., Huckvale, M., McCrone, P., et al. (2021). Optimising AVATAR therapy for people who hear distressing voices: Study protocol for the AVATAR2 multi-centre randomised controlled trial. *Trials, 22*, 366.

George, E. I., Brand, T. C., LaPorta, A., Marescaux, J., & Satava, R. M. (2018). Origins of robotic surgery: From skepticism to standard of care. *Journal of The Society of Laparoscopic & Robotic Surgeons, 22*(4).

Gerke, S., Minssen, T., & Cohen, I. G. (2020). Ethical and legal challenges of artificial intelligence-driven healthcare. In Bohr & Memarzadeh (Eds), *Artificial intelligence in healthcare* (pp. 295-336). Elsevier.

Gesner, E., Gazarian, P., & Dykes, P. (2019). The burden and burnout in documenting patient care: An integrative literature review. *Studies in Health Technology and Informatics, 21*(264), 1194-1998.

Ghatnekar, S., Faletsky, A., & Nambudiri, V. E. (2021). Digital scribe utility and barriers to implementation in clinical practice: A scoping review. *Health and Technology, 11*(4), 803-809.

Goh, E. Z., & Ali, T. (2022). Robotic surgery: An evolution in practice. *Journal of Surgical Protocols and Research Methodologies, 2022*(1), snac003.

Golahmadi, A. K., Khan, D. Z., Mylonas, G. P., & Marcus, H. J. (2021). Tool-tissue forces in surgery: A systematic review. *Annals of Medicine & Surgery, 65*.

Goryakin, Y., Thiébaut, S. P., Cortaredona, S., Lerouge, M. A., Cecchini, M., Feigl, A. B., & Ventelou, B. (2020). Assessing the future medical cost burden for the European health systems under alternative exposure-to-risk scenarios. *PLOS ONE, 15*(9), e0238565.

Goyal, M., Knackstedt, T., Yan, S., & Hassanpour, S. (2020). Artificial intelligence-based image classification methods for diagnosis of skin cancer: Challenges and opportunities. *Computers in Biology and Medicine, 127*, 104065.

Grant, K., McParland, A., Mehta, S., & Ackery, A. D. (2020). Artificial intelligence in emergency medicine: Surmountable barriers with revolutionary potential. *Annals of Emergency Medicine, 75*(6), 721-726.

Greenberg, N., Docherty, M., Gnanapragasam, S., & Wessely, S. (2020). Managing mental health challenges faced by healthcare workers during COVID-19 pandemic. *BMJ, 368*.

Greenhalgh, M., Blaauw, E., Deepak, N., St Laurent, M., Cooper, R., Bendixen, R., Grindle, G. G., Koontz, A. M., & Cooper, R. A. (2022). Clinical and ergonomic comparison between a robotic assisted transfer device and a mobile floor lift during caregiver-assisted wheelchair transfers. *American Journal of Physical Medicine & Rehabilitation, 101*(6), 561-568.

Grissinger, M. (2019). Understanding human over-reliance on technology. *Pharmacy and Therapeutics, 44*(6), 320.

Gruijthuijsen, C., Garcia-Peraza-Herrera, L. C., Borghesan, G., Reynaerts, D., Deprest, J., Ourselin, S., et al. (2022). Robotic endoscope control via autonomous instrument tracking. *Frontiers in Robotics, 9*.

Grundy, E. M., & Murphy, M. (2017). Population ageing in Europe. In J.-P. Michel, B. L. Beattie, F. C. Martin, & J. Walston (Eds), *Oxford textbook of geriatric medicine* (3rd ed.) (pp. 11-18). Oxford Academic.

Hashimoto, D. A., Rosman, G., Rus, D., & Meireles, O. R. (2018). Artificial intelligence in surgery: Promises and perils. *Annals of Surgery, 268*(1), 70-76.

Hazarika, I. (2020). Artificial intelligence: Opportunities and implications for the health workforce. *International Health, 12*(4), 241-245.

Hentout, A., Aouache, M., Maoudj, A., & Akli, I. (2019). Human-robot interaction in industrial collaborative robotics: A literature review of the decade 2008-2017. *Advanced Robotics, 22*(15-16), 764-799.

Hislop, J., Orth, D., Tirosh, O., Isaksson, M., Hensman, C., & McCormick, J. (2023). Does surgeon sex and anthropometry matter for tool usability in traditional laparoscopic surgery? A systematic review and meta-analysis. *Surgical Endoscopy, 37*(9), 6640-6659.

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

Holland, J., Kingston, L., McCarthy, C., Armstrong, E., O'Dwyer, P., Merz, F., & McConnell, M. (2021). Service robots in the healthcare sector. *Robotics, 10*(1), 47.

Honavar, S. G. (2020). Electronic medical records–The good, the bad and the ugly. *Indian Journal of Ophthalmology, 68*(3), 417.

Hou, X., Shen, G., Zhou, L., Li, Y., Wang, T., & Ma, X. (2022). Artificial intelligence in cervical cancer screening and diagnosis. *Frontiers in Oncology, 12*.

Hunter, B., Hindocha, S., & Lee, R. W. (2022). The role of artificial intelligence in early cancer diagnosis. *Cancers, 14*(6), 1524.

ILO. (2023). *How can occupational safety and health be managed?* International Labour Organization (ILO). https://www.ilo.org/global/topics/labour-administration-inspection/resources-library/publications/guide-for-labour-inspectors/how-can-osh-be-managed/lang—en/index.htm

Irfan, B., Céspedes, N., Casas, J., Senft, E., Gutiérrez, L. F., Rincon-Roncanio, M., et al. (2023). Personalised socially assistive robot for cardiac rehabilitation: Critical reflections on long-term interactions in the real world. *User Modeling and User-Adapted Interaction, 33*(2), 497-544.

Jiang, H., Mao, H., Lu, H., Lin, P., Garry, W., Lu, H., et al. (2021). Machine learning-based models to support decision-making in emergency department triage for patients with suspected cardiovascular disease. *International Journal of Medical Informatics, 145*, 104326.

Kaiser, M. S., Al Mamun, S., Mahmud, M., & Hoque Tania, M. (2021). Healthcare robots to combat COVID-19. In K. Santosh, & A. Joshi (Eds), *COVID-19: Prediction, decision-making, and its impacts. Lecture notes on data engineering and communications technologies* (pp. 83-97). Springer.

Kazemzadeh, K., Akhlaghdoust, M., & Zali, A. (2023). Advances in artificial intelligence, robotics, augmented and virtual reality in neurosurgery. *Frontiers in Surgery, 10*, 1241923.

Kelly, B., Quinn, C., Lawlor, A., Killeen, R., & Burrell, J. (2023). Cybersecurity in healthcare. In H. Sakly, K. Yeom, S. Halabi, M. Said, J. Seekins, & M. Tagina (Eds), *Trends of artificial intelligence and big data for e-health* (pp. 213-231). Springer.

Kennion, O., Maitland, S., & Brady, R. (2022). Machine learning as a new horizon for colorectal cancer risk prediction? A systematic review. *Health Sciences Review, 4*, 100041.

Kester, L., & Kirschner, P. A. (2012). Cognitive tasks and learning. In *Encyclopedia of the Sciences of Learning* (pp. 619-622). Springer.

Kim, J., de Mathelin, M., Ikuta, K., & Kwon, D.-S. (2022). Advancement of flexible robot technologies for endoluminal surgeries. *Proceedings of the IEEE, 110*(7), 909-931.

Kim, H. K., Jeong, H., Park, J., Park, J., Kim, W.-S., & Kim, N. (2022). Development of a comprehensive design guideline to evaluate the user experiences of meal-assistance robots considering human-machine social interactions. *International Journal of Human-Computer Interaction, 38*(17), 1687-1700.

Klemets, J., Määttälä, J., & Hakala, I. (2019). Integration of an in-home monitoring system into home care nurses' workflow: A case study. *International Journal of Medical Informatics, 123*, 29-36.

Klug, M., Barash, Y., Bechler, S., Resheff, Y. S., Tron, T., Ironi, A., Soffer, S., Zimlichman, E., & Klang, E. (2020). A gradient boosting machine learning model for predicting early mortality in the emergency department triage: Devising a nine-point triage score. *Journal of General Internal Medicine, 35*(1), 220-227.

Kong, Y.-K., Choi, K.-H., Park, S.-S., Shim, J.-W., & Shim, H.-H. (2023). Evaluation of the efficacy of a lift-assist device regarding caregiver posture and muscle load for transferring tasks. *International Journal of Environmental Research and Public Health, 20*(2).

Konle-Seidl, R., & Danesi, S. (2022). *Digitalisation and the changes in the world of work*. European Parliament – Study requested by the EMPL Committee.

Kriegel, J., Rissbacher, C., Reckwitz, L., & Tuttle-Weidinger, L. (2022). The requirements and applications of autonomous mobile robotics (AMR) in hospitals from the perspective of nursing officers. *International Journal of Healthcare Management, 15*(3), 204-210.

Kulich, H. R., Wei, L., Crytzer, T. M., Cooper, R. A., & Koontz, A. M. (2023). Preliminary evaluation of an automated robotic transfer assist device in the home setting. *Disability and Rehabilitation: Assistive Technology, 18*(5), 511-518.

Lavoie-Tremblay, M., Gélinas, C., Aubé, T., Tchouaket, E., Tremblay, D., Gagnon, M.-P., & Côté, J. (2022). Influence of caring for COVID-19 patients on nurses's turnover, work satisfaction and quality of care. *Journal of Nursing Management, 30*(1), 33-43.

Lebovitz, S., Lifshitz-Assaf, H., & Levina, N. (2022). To engage or not to engage with AI for critical judgments: How professionals deal with opacity when using AI for medical diagnosis. *Organization Science, 33*.

Lee, J.-T., Hsieh, C.-C., Lin, C.-H., Lin, Y.-J., & Kao, C.-Y. (2021). Prediction of hospitalization using artificial intelligence for urgent patients in the emergency department. *Scientific Reports, 11*(1), 19472.

Leibig, C., Brehmer, M., Bunk, S., Byng, D., Pinker, K., & Umutlu, L. (2022). Combining the strengths of radiologists and AI for breast cancer screening: a retrospective analysis. *The Lancet Digital Health, 4*(7), 507-519.

Leipheimer, J. M., Balter, M. L., Chen, A. I., Pantin, E. J., Davidovich, A. E., Labazzo, K. S., & Yarmush, M. L. (2019). First-in-human evaluation of a hand-held automated venipuncture device for rapid venous blood draws. *Technology, 7*(3), 98-107.

Li, L. (2022). Reskilling and upskilling the future-ready workforce for industry 4.0 and beyond. *Information Systems Frontiers*, 1-16.

Li, L., Fu, Q., Tyson, S., Preston, N., & Weightman, A. (2022). A scoping review of design requirements for a home-based upper limb rehabilitation robot for stroke. *Topics in Stroke Rehabilitation, 29*(6), 449-463.

Li, I., Pan, J., Goldwasser, J., Verma, N., Wong, W. P., Nuzumlalı, M. Y., Rosand, B., Li, Y., Zhang, M., Chang, D., Taylor, R. A., Krumholz, H. M., & Radev, D. (2022). Neural natural language processing for unstructured data in electronic health records: A review. *Computer Science Review, 46*, 100511.

Li, L., Tyson, S., & Weightman, A. (2021). Professionals' views and experiences of using rehabilitation robotics with stroke survivors: A mixed methods survey. *Frontiers in Medical Technology, 3*, 780090.

Llop-Gironés, A., Vračar, A., Llop-Gironés, G., Benach, J., Angeli-Silva, L., Jaimez, L., et al. (2021). Employment and working conditions of nurses: Where and how health inequalities have increased during the COVID-19 pandemic? *Human Resources for Health, 19*(1), 1-11.

Local Government Association. (2021, 30 March). *Taking the strain with cobots in care*. https://www.local.gov.uk/case-studies/taking-strain-cobots-care

Longmore, S. K., Naik, G., & Gargiulo, G. D. (2020). Laparoscopic robotic surgery: Current perspective and future directions. *Robotics, 9*(2), 42.

Ludvigsen, K. R., & Nagaraja, S. (2022). Dissecting liabilities in adversarial surgical robot failures: A national (Danish) and EU law perspective. *Computer Law & Security Review, 44*.

Lundberg, C. L., Sevil, H. E., Behan, D., & Popa, D. O. (2022). Robotic nursing assistant applications and human subject tests through patient sitter and patient walker tasks. *Robotics, 11*(3), 63.

Lyell, D., & Coiera, D. (2017). Automation bias and verification complexity: A systematic review. *Journal of the American Medical Informatics Association, 24*(2), 423-431.

Maas, L., Geurtsen, M., Nouwt, F., Schouten, S., van de Water, R., et al. (2020). The Care2Report System: Automated medical reporting as an integrated solution to reduce administrative burden in healthcare. Proceedings of the 53rd Hawaii International Conference on System Sciences.

Magistri, P., Tarantino, G., Assirati, G., Olivieri, T., & Catellani, B. (2019). Robotic liver resection for hepatocellular carcinoma: A systematic review. *The International Journal of Medical Robotics and Computer Assisted Surgery, 15*(4), e2004.

Marciano, F., Mattogno, P. P., Codenotti, A., Cocca, P., Fontanella, M. M., & Doglietto, F. (2022). Work-related musculoskeletal disorders among endoscopic transsphenoidal surgeons: A systematic review of prevalence and ergonomic interventions. *International Journal of Occupational Safety and Ergonomics, 28*(1), 459-468.

Marešová, P., Mohelská, H., & Kuča, K. (2015). Economics aspects of ageing population. *Procedia Economics and Finance, 23*, 534-538.

Mayor, N., Coppola, A. S., & Challacombe, B. (2022). Past, present and future of surgical robotics. *Trends in Urology & Men's Health, 13*(1), 7-10.

McCurdie, T., Sanderson, P., & Aitken, L. M. (2018). Applying social network analysis to the examination of interruptions in healthcare. *Applied Ergonomics, 67*, 50-60.

McGinn, C., Scott, R., Donnelly, N., Roberts, K., Bogue, M., Kiernan, C., & Beckett, M. (2020). Exploring the applicability of robot-assisted UV disinfection in radiology. *Frontiers in Robotics and AI, 7*.

McKay, K. J., Li, C., Sotomayor-Castillo, C., Ferguson, P. E., Wyer, M., & Shaban, R. Z. (2023). Health care workers' experiences of video-based monitoring of hand hygiene behaviors: A qualitative study. *American Journal of Infection Control, 51*(1), 83-88.

McKinney, S. M., Sieniek, M., Godbole, V., et al. (2020). International evaluation of an AI system for breast cancer screening. *Nature, 577*, 89-94.

Mehta, I., Hsueh, H.-Y., Taghipour, S., Li, W., & Saeedi, S. (2023). UV disinfection robots: A review. *Robotics and Autonomous Systems, 161*, 104332.

Melanson, A. (2017, 27 September). *Study affirms benefits of robotics in care services.* Aethon news blog. https://aethon.com/study-affirms-benefits-of-robotics-in-care-services/

Mendes, V., Bruyere, F., Escoffre, J. M., Binet, A., Lardy, H., Marret, H., Marchal, F., & Hebert, T. (2020). Experience implication in subjective surgical ergonomics comparison between laparoscopic and robot-assisted surgeries. *Journal of Robotic Surgery, 14*(1), 115-121.

MiR. (2018). *Mobile robot transports sterile goods in hospital.* Mobile Industrial Robots (MiR case studies). Mobile Industrial Robots.

Moloney, R., Coffey, A., Coffey, J. C., & O'Brien, B. (2023). Nurses' perceptions and experiences of robotic assisted surgery (RAS): An integrative review. *Nurse Education in Practice, 71*.

Monshi, M. M. A., Poon, J., & Chung, V. (2020). Deep learning in generating radiology reports: A survey. *Artificial Intelligence in Medicine, 106*, 101878.

Moore, L. J., Wilson, M. R., McGrath, J. S., Waine, E., Masters, R. S., & Vine, S. J. (2015). Surgeons' display reduced mental effort and workload while performing robotically assisted surgical tasks, when compared to conventional laparoscopy. *Surgical Endoscopy, 29*, 2553-2560.

Morrow, E., Zidaru, T., Ross, F., Mason, C., Patel, K. D., Ream, M., & Stockley, R. (2023). Artificial intelligence technologies and compassion in healthcare: A systematic scoping review. *Frontiers in Psychology, 13*, 971044.

Mousa, M., Boyle, J., Skouteris, H., Mullins, A. K., Currie, G., Riach, K., & Teede, H. J. (2021). Advancing women in healthcare leadership: A systematic review and meta-synthesis of multi-sector evidence on organisational interventions. *eClinicalMedicine, 39*, 101084.

Muralidhar, D., Sirasala, S. J., Spiller, M., Sühn, T., Illanes, A., Boese, A., & Friebe, M. (2021). Collaborative robot as scrub nurse. *Current Directions in Biomedical Engineering, 7*(1).

Murphy, A. (2020, 1 July). *Autonomous robots check patients in at Belgium hospitals*. Innovation Origins. https://innovationorigins.com/en/autonomous-robots-check-patients-in-at-belgium-hospitals/ (last accessed 2 May 2023).

Na, E., Jung, Y., & Kim, S. (2023). How do care service managers and workers perceive care robot adoption in elderly care facilities? *Technological Forecasting and Social Change, 187*, 122250.

Nguyen, L. H., Drew, D. A., Graham, M. S., Joshi, A. D., Guo, C. G., Ma, W., et al. (2020). Risk of COVID-19 among front-line health-care workers and the general community: A prospective cohort study. *The Lancet Public Health, 5*(9), e475-e483.

Nguyen, H. T. N., Nie, D., Badamdorj, T., Liu, Y., Zhu, Y., Truong, J., & Cheng, L. (2021). *Automated generation of accurate \& fluent medical X-ray reports* (arXiv:2108.12126). arXiv.

OECD. (2021). *Health expenditure in relation to GDP*. Organisation for Economic Cooperation and Development (OECD). https://www.oecd-ilibrary.org/sites/e26f669c-en/index.html?itemId=/content/component/e26f669c-en

OECD. (2022). *Health at a glance: Europe 2022. State of Health in the EU Cycle*. OECD Publishing.

OECD. (2023a). *Health at a glance 2023: OECD indicators*. OECD Publishing.

OECD. (2023b). *Recommendation of the Council on Artificial Intelligence, OECD/LEGAL/0449*. OECD Publishing.

Oren, O., Gersh, B. J., & Bhatt, D. L. (2020). Artificial intelligence in medical imaging: Switching from radiographic pathological data to clinically meaningful endpoints. *The Lancet Digital Health, 2*(9), e486-e488.

Orhan, M. A., Castellano, S., Khelladi, I., Marinelli, L., & Monge, F. (2021). Technology distraction at work. Impacts on self-regulation and work engagement. *Journal of Business Research, 126*, 341-349.

Panch, T., Pearson-Stuttard, J., Greaves, F., & Atun, R. (2019). Artificial intelligence: Opportunities and risks for public health. *The Lancet – Digital Health, 1*(1), 13-14.

Panch, T., Szolovits, P., & Atun, R. (2018). Artificial intelligence, machine learning, and health systems. *Journal of Global Health, 8*(2), 020303.

Pang, T., Li, P., & Zhao, L. (2023). A survey on automatic generation of medical imaging reports based on deep learning. *BioMedical Engineering OnLine, 22*(1), 48.

Pappa, S., Ntella, V., Giannakas, T., Giannakoulis, V. G., Papoutsi, E., & Katsaounou, P. (2020). Prevalence of depression, anxiety, and insomnia among healthcare workers during the COVID-19 pandemic: A systematic review and meta-analysis. *Brain, Behavior, and Immunity, 88*, 901-907.

Park, K. S., Pan, F., Steffens, D., Young, J., & Hong, J. (2021). Are surgeons working smarter or harder? A systematic review comparing the physical and mental demands of robotic and laparoscopic or open surgery. *World Journal of Surgery, 45*, 2066-2080.

Parviainen, J., Turja, T., & Van Aerschot, L. (2019). Social robots and human touch in care: The perceived usefulness of robot assistance among healthcare professionals. In O. Korn (Ed.), *Social robots: Technological, societal and ethical aspects of human-robot interaction* (pp. 187-204). Springer International Publishing.

Patel, E., Saikali, S., Mascarenhas, A., Moschovas, M. C., & Patel, V. (2023). Muscle fatigue and physical discomfort reported by surgeons performing robotic-assisted surgery: A multinational survey. *Journal of Robotic Surgery, 17*, 2009-2018.

Pedram, S. A., Shin, C., Ferguson, P. W., Ma, J., Dutson, E. P., & Rosen, J. (2021). Autonomous suturing framework and quantification using a cable-driven surgical robot. *IEEE Transactions on Robotics, 37*(2), 404-417.

Perminov, S., Mikhailovskiy, N., Sedunin, A., Okunevich, I., Kalinov, I., Kurenkov, M., & Tsetserukou, D. (2021). *UltraBot: Autonomous mobile robot for indoor UV-C disinfection*. International Conference on Automation Science and Engineering, CASE.

Persson, M., Redmalm, D., & Iversen, C. (2022). Caregivers' use of robots and their effect on work environment – A scoping review. *Journal of Technology in Human Services, 40*(3), 251-277.

Pham, K. T., Nabizadeh, A., & Selek, S. (2022). Artificial intelligence and chatbots in psychiatry. *Psychiatric Quarterly, 93*, 249-253.

Philip, P., Micoulaud-Franchi, J.-A., Sagaspe, P., De Sevin, E., Olive, J., Bioulac, S., & Sauteraud, A. (2017). Virtual human as a new diagnostic tool, a proof of concept study in the field of major depressive disorders. *Scientific Reports, 7*, 42656.

Pignolo, L., Tonin, P., Nicotera, P., Bagetta, G., & Scuteri, D. (2022). ROBOCOP (ROBOtic Care of Poststroke Pain): Study protocol for a randomized trial to assess robot-assisted functional and motor recovery and impact on poststroke pain development. *Frontiers in Neurology, 13*, 813282.

Price, K., Peine, J., Dupont, E., & Chitalia, Y. (2023). Using robotics to move a neurosurgeon's hands to the tip of their endoscope. *Science Robotics, 82*(8).

Prochaska, J., Vogel, E., Chieng, A., Kendra, M., Baiocchi, M., Pajarito, S., et al. (2021). A therapeutic relational agent for reducing problematic substance use (Woebot): Development and usability study. *Journal of Medical Internet Research, 23*(3).

Quiroz, J. C., Laranjo, L., Kocaballi, A. B., Berkovsky, S., Rezazadegan, D., & Coiera, E. (2019). Challenges of developing a digital scribe to reduce clinical documentation burden. *Npj Digital Medicine, 2*(1), 114.

Ragno, L., Borboni, A., Vannetti, F., Amici, C., & Cusano, N. (2023). Application of social robots in healthcare: Review on characteristics, requirements, technical solutions. *Sensors, 23*(15), 6820.

Rajkomar, A., Kannan, A., Chen, K., Vardoulakis, L., Chou, K., Cui, C., & Dean, J. (2019). Automatically charting symptoms from patient-physician conversations using machine learning. *JAMA Internal Medicine, 179*(6), 836-838.

Rawaf, S., Allen, L. N., Stigler, F. L., Kringos, D., Quezada Yamamoto, H., & van Weel, C. (2020). Lessons on the COVID-19 pandemic, for and by primary care professionals worldwide. *European Journal of General Practice, 26*(1), 129-133.

Raya-Povedano, J. L., Romero-Martín, S., Elías-Cabot, E., Gubern-Mérida, A., Rodríguez-Ruiz, A., & Álvarez-Benito, M. (2021). AI-based strategies to reduce workload in breast cancer screening with mammography and tomosynthesis: A retrospective evaluation. *Radiology, 300*(1), 57-65.

Reverberi, C., Rigon, T., Solari, A., Hassan, C., Cherubini, P., Group, G. G., & Cherubini, A. (2022). Experimental evidence of effective human–AI collaboration in medical decision-making. *Scientific Reports, 12*, 14952.

Rohwer, E., Flöther, J.-C., Harth, V., & Mache, S. (2022). Overcoming the “Dark Side” of technology—A scoping review on preventing and coping with work-related technostress. *International Journal of Environmental Research in Public Health, 19*, 3625.

Saetra, H. K., & Fosch-Villaronga, E. (2021). Healthcare digitalisation and the changing nature of work and society. *Healthcare, 9*(8), 1007.

Sahni, N., Stein, G., Zemmel, R., & Cutler, D. (2023). The potential impact of artificial intelligence on healthcare spending. *NBER Working Paper 30857*.

Sauerbrei, A., Kerasidou, A., Lucivero, F., & Hallowell, N. (2023). The impact of artificial intelligence on the person-centred, doctor-patient relationship: Some problems and solutions. *BMC Medical Informatics and Decision Making, 23*.

Schäfer, M. B., Friedrich, J. H., Hotz, J., Worbs, L., Weiland, S., & Pott, P. P. (2023). Robotic scrub nurse: Surgical instrument handling with a granular jamming gripper. *Current Directions in Biomedical Engineering, 1*(174-177), 9.

Schneider, A., Williams, D. J., Kalynych, C., Wehler, M., & Weigl, M. (2021). Physicians’ and nurses’ work time allocation and workflow interruptions in emergency departments: A comparative time-motion study across two countries. *Emergency Medicine Journal, 38*, 263-268.

Schwaner, K. L., Dall’Alba, D., Jensen, P. T., Fiorini, P., & Savarimuth, T. R. (2021). *Autonomous needle manipulation for robotic surgical suturing based on skills learned from demonstration*. IEEE International Conference on Automation Science and Engineering (CASE).

Secinaro, S., Calandra, D., Secinaro, A., Muthurangu, V., & Biancone, P. (2021). The role of artificial intelligence in healthcare: A structured literature review. *BMC Medical Informatics and Decision Making, 25*, 125.

Serebrin, J. (2022, 30 December). *L’intelligence artificielle au service des urgences.* La Presse Canadienne. https://www.lapresse.ca/actualites/sante/2022-12-30/l-intelligence-artificielle-au-service-des-urgences.php#:~:text=Le%20Centre%20hospitalier%20de%20l,l'admission%20de%20certains%20patients.

Serrano, L. P., Maita, K. C., Avila, F. R., Torres-Guzman, R. A., Garcia, J. P., Eldaly, A. S., Haider, C. R., Felton, C. L., Paulson, M. R., Maniaci, M. J., & Forte, A. J. (2023). Benefits and challenges of remote patient monitoring as perceived by health care practitioners: A systematic review. *The Permanente Journal, 27*(4), 100-111.

Shah, L. M., Borycki, E. M., Shah, K. A., Kushniruk, A. W. (2021). Effects of medical scribes on patients, physicians, and safety: A scoping review. *Knowledge Management & E-Learning, 13*(4), 559-629.

Shahkoo, A. A., & Abin, A. A. (2023). Deep reinforcement learning in continuous action space for autonomous robotic surgery. *International Journal of Computer Assisted Radiology and Surgery, 18*, 423-431.

Shaik, T., Tao, X., Higgins, N., Li, L., Gururajan, R., Zhou, X., & Acharya, U. R. (2023). Remote patient monitoring using artificial intelligence: Current state, applications, and challenges. *WIREs Data Mining and Knowledge Discovery, 13*(2), e1485.

Shanafelt, T. D., Dyrbye, L. N., Sinsky, C., Hasan, O., Satele, D., Sloan, J., & West, C. P. (2016). Relationship between clerical burden and characteristics of the electronic environment with physician burnout and professional satisfaction. *Mayo Clinic Proceedings, 91*(7), 836-848.

Shaw, R. D., Eid, M. A., Bleicher, J., Broecker, J., Caesar, B., Chin, R., Meyer, C., Mitsakos, A., Stolarksi, A. E., Theiss, L., Smith, B. K., & Ivatury, S. J. (2022). Current barriers in robotic surgery training for general surgery residents. *Journal of Surgical Education, 79*(3), 606-613.

Shen, Y., Ge, R., & Qian, X. (2022). Robotic “Zero Contact” surgery for occupational protection against infectious disease. *Frontiers in Public Health, 10*.

Shin, C., Ferguson, P. W., Pedram, S. A., Ma, J., Dutson, E. P., & Rosen, J. (2019). *Autonomous tissue manipulation via surgical robot using learning based model predictive control*. Montreal: 2019 International Conference on Robotics and Automation (ICRA).

Shortliffe, E. H., & Sepúlveda, M. J. (2018). Clinical decision support in the era of artificial intelligence. *Journal of the American Medical Association, 320*(21), 2199-2200.

Singh, R., Wang, K., Qureshi, M. B., & Rangerl, I. C. (2022). Robotics in neurosurgery: Current prevalence and future directions. *Surgical Neurology International, 13*, 373.

Sinsky, C., Colligan, L., Li, L., et al. (2016). Allocation of physician time in ambulatory practice: A time and motion study in 4 specialties. *Ann Intern Med. 165*(11), 753-760.

Sivakanthan, S., Blaauw, E., Greenhalgh, M., Koontz, A. M., Vegter, R., & Cooper, R. A. (2019). Person transfer assist systems: A literature review. *Disability and Rehabilitation: Assistive Technology, 16*(3), 270-279.

Sivaprakasam, A., Wang, H., Cooper, R. A., & Koontz, A. M. (2017). Innovation in transfer assist technologies for persons with severe disabilities and their caregivers. *IEEE Potentials, 36*(1), 34-41.

Smirnova, V., Khamatnurova, R., Kharin, N., Yaikova, E., Baltina, T., & Sachenkov, O. (2022). The automatization of the gait analysis by the Vicon Video System: A pilot study. *Sensors, 22*(19), 7178.

Soltan, A. S., Yang, J., Pattanshetty, R., Novak, A., Yang, Y., Rohanian, O., et al. (2022). Real-world evaluation of rapid and laboratory-free COVID-19 triage for emergency care: External validation and pilot deployment of artificial intelligence driven screening. *Lancet Digital Health, 4*, e266-e278.

Sowa-Kofta, A., Rodrigues, R., Lamura, G., Sopadzhiyan, A., Wittenberg, R., Bauer, G., Doetter, L. F., Ilinca, S., Marczak, J., Piersinaru, A., & Rothgang, H. (2019). Long-term care and migrant care work: Addressing workforce shortages while raising questions for European countries. *Eurohealth Observer, 25*(4).

Stucky, C.-C. H., Cromwell, K. D., Voss, R. K., Chiang, Y.-J., Woodman, K., Lee, J. E., & Cormier, J. N. (2018). Surgeon symptoms, strain, and selections: Systematic review and meta-analysis of surgical ergonomics. *Annals of Medicine and Surgery, 27*, 1-8.

Sypniewska, B., Baran, M., & Kłos, M. (2023). Work engagement and employee satisfaction in the practice of sustainable human resource management–Based on the study of Polish employees. *International Entrepreneurship and Management Journal*, 1-32.

Takase, T., Masumoto, N., Shibatani, N., Matsuoka, Y., Tanaka, F., Hirabatake, M., et al. (2022). Evaluating the safety and efficiency of robotic dispensing systems. *Journal of Pharmaceutical Health Care and Sciences, 8*(1), 24.

Tang, X. (2020). The role of artificial intelligence in medical imaging research. *BJR Open, 2*(1), 20190031.

Tang, B., Zhang, L., & Alijani, A. (2020). Evidence to support the early introduction of laparoscopic suturing skills into the surgical training curriculum. *BMC Medical Education, 20*(1), 70.

Tetteh, E., Wang, T., Kim, J. Y., Smith, T., Norasi, H., Van Straaten, M. G., Lal, G., Chrouser, K. L., Shao, J. M., & Hallbeck, M. S. (2023). Optimizing ergonomics during open, laparoscopic, and robotic-assisted surgery: A review of surgical ergonomics literature and development of educational illustrations. *The American Journal of Surgery*, S0002961023005895.

Tornbjerg, K., Kanstrup, A. M., Skov, M. B., & Rehm, M. (2021). Investigating human-robot cooperation in a hospital environment: Scrutinising visions and actual realisation of mobile robots in service work. In *Proceedings of the 2021 ACM Designing Interactive Systems Conference* (pp. 381-391).

Van Buchem, M. M., Boosman, H., Bauer, M. P., Kant, I. M. J., Cammel, S. A., & Steyerberg, E. W. (2021). The digital scribe in clinical practice: A scoping review and research agenda. *Npj Digital Medicine, 4*(1), 57.

VandeWeerd, C., Yalcin, A., Aden-Buie, A. G, Wang, Y., Roberts, M., Mahser, N., Fnu, C., & Fabiano, D. (2020). HomeSense: Design of an ambient home health and wellness monitoring platform for older adults. *Health and Technology, 10*, 1291-1309.

Van Grootven, B., Alvarez Irusta, L., Christiaens, W., Mistiaen, P., De Meester, C., Cornelis, J., Dierckx de Casterlé, B., Van Durme, T., & van Achterberg, T. (2023). Experiences with the implementation of remote monitoring in patients with COVID-19: A qualitative study with patients and healthcare professionals. *Journal Nursing Scholarship, 55*(1), 67-78.

Vänni, K. J., & Salin, S. E. (2019). Attitudes of professionals toward the need for assistive and social robots in the healthcare sector. In O. Korn (Ed.), *Social robots: Technological, societal and ethical aspects of human-robot interaction* (pp. 205-236). Springer.

van Smeden, M., Reitsma, J. B., Riley, R. D., Collins, G. S., & Moons, K. G. (2021). Clinical prediction models: Diagnosis versus prognosis. *Journal of Clinical Epidemiology, 132*, 142-145.

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies, and human resource management: A systematic review. *The International Journal of Human Resource Management, 33*(6), 1237-1266.

Walker, J. (2023, 23 July). *At startup that says its AI writes medical records, humans do a lot of the work.* The Wall Street Journal. https://www.wsj.com/articles/at-startup-that-says-its-ai-writes-medical-records-humans-do-a-lot-of-the-work-794be22e

Wang, J., Lavender, M., Hoque, E., Brophy, P., & Kautz, H. (2021). A patient-centered digital scribe for automatic medical documentation. *JAMIA Open, 4*(1), ooab003.

Wang, X., Li, Z., & Fan, H. (2022). The design of outpatient blood collection based on collaboration robots. Guilin: Proceedings Volume 12244, 2nd International Conference on Mechanical, Electronics, and Electrical and Automation Control (METMS 2022).

Wee, I. J., Kuo, L.-J., & Ngu, C.-Y. J. (2020). A systematic review of the true benefit of robotic surgery: Ergonomics. *The International Journal of Medical Robotics and Compared Assisted Surgery, 16*(4), e2113.

WHO. (2023). *Occupational hazards in the health sector*. World Health Organization (WHO). https://www.who.int/tools/occupational-hazards-in-health-sector (last accessed 30 November 2023).

Wiljer, D., & Hakim, Z. (2019). Developing an artificial intelligence–enabled health care practice: Rewiring health care professions for better care. *Journal of Medical Imaging and Radiation Sciences, 50*(4), 8-14.

Wright, J. (2018). Tactile care, mechanical Hugs: Japanese caregivers and robotic lifting devices. *Asian Anthropology, 17*(1), 24-39.

Wright, J. (2023, 9 January). *Inside Japan's long experiment in automating elder care*. MIT Technology Review. https://www.technologyreview.com/2023/01/09/1065135/japan-automating-eldercare-robots/

Yang, J., Barragan, J. A., Farrow, J. S., Sundaram, C. P., Wachs, J. P., & Yu, D. (2022). An adaptive human-robotic interaction architecture for augmenting surgery performance using real-time workload sensing—Demonstration of a semi-autonomous suction tool. *Human Factors, 11*.

Yang, H. Y., & Seon, J. K. (2023). The landscape of surgical robotics in orthopedics surgery. *Biomedical Engineering Letters, 13*, 537-542.

Yen, P.-Y., Kellye, M., Lopetegui, M., Saha, A., Loversidge, J., Chipps, E. M., et al. (2018). Nurses' time allocation and multistaking of nursing activities: A time motion study (pp. *1137-1146*). AMIA Annual Symposium Proceedings Archive.

Yoon, J. H., Han, K., Suh, H. J., Youk, J. H., Lee, S. E., & Kim, E.-K. (2023). Artificial intelligence-based computer-assisted detection/diagnosis (AI-CAD) for screening mammography: Outcomes of AI-CAD in the mammographic interpretation workflow. *European Journal of Radiology Open, 11*, 100509.

Yu, J.-H., Hsieh, S.-H., Chen, C.-H., & Huang, W.-K. (2023). Comparison of the safety, effectiveness, and usability of swab robot vs. manual nasopharyngeal specimen collection. *Heliyon, 9*(10), e20757.

Zayas-Cabán, T., Haque, S. N., & Kemper, N. (2021). Identifying opportunities for workflow automation in health care: Lessons learned from other industries. *Applied Clinical Informatics, 12*(03), 686-697.

Zemmar, A., Lozano, A. M., & Nelson, B. J. (2020). The rise of robots in surgical environments during COVID-19. *Nature Machine Intelligence, 2*, 566-672.

Zhang, P.-I., Hsu, C.-C., Kao, Y., Chen, C.-J., Kuo, Y.-W., Hsu, S.-L., et al. (2020). Real-time AI prediction for major adverse cardiac events in emergency department patients with chest pain. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine, 28*, 93.

Zhou, T., Cha, J. S., Gonzalez, G., Wachs, J. P., Sundaram, C. P., & Yu, D. (2020). Multimodal physiological signals for workload prediction in robot-assisted surgery. *ACM Transactions on Human-Robot Interaction, 9*(2), 1-26.

Zubrinic, M., Vrbanic, L., & Keshavjee, S. (2023). Remote telemonitoring is associated with improved patient safety and decreased workload of nurses. *JTCVS Open, 16*, 493-497.

TE-02-24-537-EN-N

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

European Agency
for Safety and Health at Work
Santiago de Compostela 12
48003 Bilbao, Spain
E-mail: information@osha.europa.eu

https://osha.europa.eu

Publications Office
of the European Union