4. THE ROLE OF DIGITAL TECHNOLOGY IN HEALTH AND LONG-TERM CARE SECTORS

Emilio Gómez-González, Emilia Gómez, Songül Tolan, Fernando Martínez-Plumed, Annarosa Pesole, Enrique Fernández-Macías, José Hernández-Orallo, Emilia Gómez, Alessandra Conte, Sara Grubanov Boskovic

The role of digital technologies in health and long-term care sectors has been manifold. Digital technologies have, amongst others, transformed the delivery of health and care services and generated new type of professional roles and skillsets, therefore affecting both the demand for and the supply of healthcare workers. However, the full implementation of digital technologies – and its potential effect on health and care workforce – remain closely related to numerous ethical, social and labour market aspects.

Given the broad scope of the topic, this chapter focuses on **three specific thematic areas.**

The **first contribution** aims to provide an overview of the main applications brought to the healthcare sector by Artificial Intelligence (AI), together with their benefits and challenges.

KEY MESSAGES

Currently, the spectrum of AI applications in healthcare is extremely broad: it ranges from applications with high technology availability value, such as algorithms for computer-aided diagnosis or imaging tools, to applications that are still immature, such as mind reading or whole-brain simulation.

Three groups of ethical and social aspects related to AI in the healthcare sector can be distinguished: 1) issues such as data privacy, fairness or human oversight which have been broadly discussed in the context of general AI; 2) issues of particular relevance in medicine and healthcare, but also common in other domains, e.g. transparency, the required updates in evaluation, benchmarking and legislation; 3) controversial aspects not yet considered in other fields, e.g. ethical guidelines related to self-experimentation medicine.

COVID-19 has emphasised both the opportunities and ethical challenges of the use of AI in medicine, bringing an increased interest for the public. Given the strong implications of health data-related AI systems and the overlap with public health policies, an analysis of opportunities and risks has to be carried out before systems are fully deployed.

The **second contribution** aims to assess the impact of AI progress on four specific health-related occupations: medical doctors; nursing and midwifery professionals; paramedical practitioners; and medical and pharmaceutical technicians.

KEY MESSAGES

Overall, the findings on AI research intensity suggest high activity in AI areas that contribute to abilities *dealing with things* and ideas and low activity for abilities *dealing with people.*

In particular, medical doctors are the category most exposed to AI. The majority of AI exposure is driven by its impact on tasks that require abilities dealing with ideas (e.g. comprehension, attention and search as well as conceptualisation). On other hand, little AI exposure can be expected through basic processing abilities (e.g. visual processing or auditory processing) or through abilities that deal with people (e.g. modelling and social interaction or communication).

AI could also play a novel role in the context of technology-driven labour market polarisation, depending on whether AI exposure is labour-replacing or labour-enhancing. In the labour-replacement scenario, it could lead to unpolarising effects and a reduction in income inequality; whereas in the labour-enhancing scenario, it could imply an expansion of productivity for high-skilled occupations, potentially leading to occupational upgrading effects and an expansion of income inequality.

The **third thematic contribution** aims to analyse how the divide in internet access and digital skills within elderly Europeans poses a barrier to the implementation of telemedicine.

KEY MESSAGES

Digital technologies, such as telemedicine, have great potential to improve the population's access to health and LTC. However, the digital divide within certain socio-demographic groups remains considerable in the EU to the point of becoming a barrier to the implementation of telemedicine.
The findings show that strengthening the potential of telemedicine among elderly people requires additional efforts in promoting digital inclusion, especially for elderly people living alone in their homes, the elderly with a low level of education and those living in rural and remote areas. Moreover, particular attention should

also be paid to bridging the digital divide between elderly men and women, the latter group having lower percentages of internet use and digital skills than men.

Internet access is also a social and economic affordability issue. For example, only one third of the EU's population aged 80+ who lives in rural and remote areas owns a computer. At the same time, almost all households in the EU own a telephone, which opens up the possibility of strengthening the mobile healthcare practices among the EU's elderly.

4.1 ARTIFICIAL INTELLIGENCE IN MEDICINE AND HEALTHCARE: SOCIAL IMPACTS AND CHALLENGES

Artificial intelligence (AI) has become a technological domain of strategic importance and a key driver of economic development in all sectors. In the domain of medicine and healthcare, AI is giving rise to new applications, paradigms – even defying the traditional roles of doctors and patients – and risks. Here we present a brief overview of the main applications brought to medicine and healthcare by AI, together with their benefits and challenges. We then introduce these issues in the context of the COVID-19 health emergency. Lastly, we illustrate some specific, very recent examples of AI systems in medicine and healthcare related to demography and migration, and, from the questions that arise: the risk of data bias and the dual potential of communication and conversational platforms and of systems for border control.

AI IN MEDICINE AND HEALTHCARE: BENEFITS AND CHALLENGES

Gómez-González & Gómez (2020) provide an updated review of the current and future applications of AI in the area of medicine and healthcare based on an analysis of state-of-the-art research and technology, including software, personal monitoring devices, genetic tests and editing tools, personalised digital models, online platforms, augmented reality devices and surgical and companion robotics.

Figure 24 presents a 'visual overview' of the Gómez-González & Gómez (2020) review, including well-established applications such as the use of algorithms to support medical diagnosis, robots in surgery or conversational platforms ('chatbots') for patient assistance. In Figure 24, the different applications are assigned a Technology Availability Level (TAL) scale, presented in Table 5. The TAL provides a qualitative description of the degree of availability of a technology in a numerical scale in 10 steps (levels), ranging from 0 (unknown status, not considered feasible) to 9 (available for the general public).

We observe in Figure 24 that applications such as algorithms for computer-aided diagnosis or imaging tools have a high TAL value, while others such as mind reading or whole-brain simulation are still immature according to this scale. The TAL scale is similar in format (and related) to the standard 'Technology Readiness Level' (TRL) scale commonly used to assess research and development figures, but it is based on published references (in scientific and academic literature, industrial or corporate reports, and in general media citing sources considered to be reliable according to standards). These kinds of scales are useful for conveying practical information about the proximity to the market of any given technology.

The technological realm expands to the social and ethical aspects associated with the use of medical AI systems. Beyond their technology availability level, AI systems offer extraordinary opportunities – e.g. derived from greater efficiency – in medical and clinical areas of deep social interest such as oncology, genetics and neurosciences, but also present possible risks and ethical questions raised by their implementation. This balance between benefits and risk is represented by the 'controversy level' in Figure 24. This level ranges from (commonly assumed) 'positive' or beneficial applications of AI (e.g. software for decision support to improve diagnostic efficiency) to (commonly considered) 'negative' or harmful areas (e.g. new tools for bioterrorism or the possibility of engineering biologic weapons targeted against certain populations), crossing through many intermediate domains where a balance between the potential benefits and associated risks needs to be carefully sought.

There are different types of controversial issues. Some of them show a clear potential duality, such as the possibility of preventing diseases through genetic editing and the use of neural interfaces and neurostimulation for controlling advanced prosthesis, or for unwanted registration of brain signals ('thought reading') and interference with neural signals to impose limits on human free will. Other questionable topics refer to autonomous systems which may make vital decisions for people, and the use of AI-mediated genetic research to challenge fundamental boundaries and the very basic definitions of life (e.g. 'engineered, enhanced humans', human-animal hybrids) (Gómez-González & Gómez, 2020).

TABLE 5. The Technology Availability Level (TAL) scale defined in Gómez-González and Gómez (2020)

TAL Score	Status of viability of the technology
TAL 0	Unknown status. Not considered feasible according to references.
TAL 1	Unknown status. Considered feasible according to related, indirect references.
TAL 2	General/basic idea publicly proposed.
TAL 3	Calls for public funding of research and development (R&D) open.
TAL 4	Results of academic/partial projects disclosed.
TAL 5	Early design of product disclosed.
TAL 6	Operational prototype/'first case' disclosed.
TAL 7	Products disclosed but not available.
TAL 8	Available products for restricted (e.g. professional) users.
TAL 9	Available for the public.

FIGURE 24. - A visual overview of the classification of AI and AI-mediated technologies in medicine and healthcare according to their ethical and social impact. SW: software, AR: augmented reality, VR: virtual reality, IoT: internet of things, TAL: Technology Availability Level
Note: reproduced with permission from Gómez-González & Gómez (2020)

AI and AI-mediated technologies	Specific implementations.	TAL	Social Impact
Algorithms for computer-aided diagnosis.	SW for decision support in (most) clinical areas.	8, 9	Positive
Structured reports, eHealth.	SW for improved workflow, efficiency.	8, 9	
AR/VR, advanced imaging tools.	Tools for information visualization and navigation.	6, 7, 9	
	Image-guided surgery. Teleoperation.	4, 6, 9	
Digital pathology, 'virtopsy'.	SW for automated, extensive analysis.	4-9	
Personalized, precision medicine.	Tailored treatments. Prediction of response.	4-9	
	'In-silico' modeling and testing. The 'digital twin'.	4-8	
	Drug design.	4, 8	
Apps, chatbots, dashboards, online platforms.	The 'digital doctor' (assistance for professionals and for patients).	8, 9	
Companion and social robots.	For hospitalized persons, children & the elderly.	4-9	
Big Data collection and analysis.	Epidemiology, prevention and monitoring of disease outbreaks.	2-9	
	Fraud detection. Quality control, monitoring of physicians and treatments.	4-9	
IoT, wearables, mHealth.	Automated clinical/health surveillance in any environment/institution.	7, 8	
	Monitoring, automated drug delivery.	7-9	
Gene editing.	Disease treatment, prevention.	7, 8	
Merging of medical and social data. 'Social' engineering.	Prevention of episodes with clinical relevance (e.g. suicide attempts).	6, 8	Controversial
	Tailored marketing (e.g. related to female cycles).	6, 8	
Reading and decoding brain signals. Interaction with neural processes.	Treatment of diseases. Restoring damaged functions.	3-8	
	Brain-machine interfaces.	5-8	
	Control of prostheses, exoskeletons. 'Cyborgs'.	2-7	
	Neurostimulation. Neuromodulation.	4-8	
	Neuroprostheses (for the central nervous system).	2-5	
	Mind 'reading' and 'manipulation'.	1-3	
Genetic tests. Population screening.	Disease tests. Direct-to-consumer tests.	4-9	
Personalized, precision medicine.	Individual profiling. Personalized molecules (for treatment) at 'impossible' prices.	3-8	
Gene editing.	'Engineered' humans.	2, 6	
	Gene-enhanced 'superhumans'.	2	
	Self-experimentation medicine. Biohacking.	2, 6	
Fully autonomous AI systems.	The 'digital doctor'.	2-5	
	'Robotic surgeon'.	2, 4	
Human-animal embryos.	Organs for transplants.	2, 4, 5	
	Hybrid beings ('chimera').	2, 4	
The quest for immortality.	Whole-brain emulation / 'transplant'.	1, 2	
The search for artificial life forms.	'Living machines' ('biological robots', 'biobots')	4, 6	
	Military.	2, 3	
Evil biohacking.	Targeting specific individuals or groups.	1, 2	
Weaponization.	From 'small labs' to military labs.	1, 2	
Bioterrorism.	From 'small labs'.	1, 2	Negative

These controversial aspects are being dealt with at different levels. We can distinguish three groups of ethical and social aspects related to AI in medicine, according to how they are considered in comparison to other application domains (Gómez-González & Gómez, 2020). The first group includes issues which are common to other areas of the application of AI systems, namely social networks, electronic commerce, automation of manufacturing processes and autonomous vehicles. These are topics such as data privacy, fairness or human oversight, and have been broadly discussed in the context of general AI ethical frameworks (EU, 2019b). The second group comprises topics also common in other application domains but of particular relevance in medicine and healthcare such as transparency, the trust in the relationship between doctors and patients or the required updates in evaluation, benchmarking and legislation. Lastly, a third group refers to controversial aspects not yet considered in other fields. Among them, ethical guidelines related to self-experimentation medicine (including gene editing) or the generation of artificial life forms.

From the previous analysis, we can emphasise three novel emerging paradigms. Firstly, we observe a division of medicine into three main streams, all of them having AI as a supporting tool: (1) 'fake-based medicine', based on (unfounded, unconfirmed) rumours and presenting 'ancient, natural knowledge' as opposed to scientific, evidence-based medicine, supposedly under malicious control by academia, institutions and governments; (2) 'patient-generated medicine', derived from the growing online availability of the many (correct and unsupervised, unreliable) sources of medical information; and (3) 'scientifically tailored medicine', evolved from the most advanced scientific research into extended personalised and precision medicine (Gómez-González & Gómez, 2020). The second emerging effect is the increase in social differences and inequalities in the access to AI systems in medicine and healthcare, due to the technical complexities and high costs associated with these systems, e.g. personalised drug design or (genetically) tailored treatments (Gómez-González & Gómez, 2020). Lastly, this analysis also warns about new forms of 'digital health scammers', bio-hacking and bioterrorism, arguing how a disorderly development of technology – without analysis and debate about ethical and societal impact – may bring strong conflicts with fundamental rights and principles of our free, democratic, particularly European, societies.

A SOCIAL DEBATE

A public debate has already started around some of the issues presented above. Most of them relate to the human perception of AI-based diagnostics, the (un) trust generated by increasingly autonomous systems and the well-known concerns about the privacy and security of personal data.
In addition, there is a growing number of voices (including highly qualified scientists, physicians and entrepreneurs) who demand for open and truthful information on the actual results of AI-based medicine, particularly in areas of high social interest (e.g. cancer and neuroscience). They also ask for preventive regulations, especially on

the most dangerous and controversial topics – before it's 'too late' – and advocate a clear focus on human-centred AI development in medicine and healthcare. Most of these concerns are also explicitly included in the 'urgent priorities for the next decade' defined by the World Health Organization in early 2020 (WHO, 2020).

However, to date, there are still no European or international references to a coordinated overview and analysis of the ethical aspects and social impact of AI in the medical field and related areas. Nor are there any specific regulations on many of the most conflictive issues mentioned below.

THE COVID-19 PANDEMIC: CONSEQUENCES AND AN ENHANCED ROLE FOR AI

Since early 2020, the unexpected Severe Acute Respiratory Syndrome Coronavirus (SARS-CoV-2) outbreak and the corresponding COVID-19 disease have had strong consequences for individuals and societies all over the world. In many areas, including the most industrialised, the effectiveness of the mechanisms of transmission and contagion of the virus has caused an overflow of patients and the immediate scarcity of health resources – from supplies to professionals and hospital facilities – leading to severe societal effects and very high death tolls.

The many unknowns about the disease and the lack of vaccine or effective treatment have prompted many harsh measurements of compulsory population confinement, prohibition of travel and economic lockdown at a very fast pace and with many uncertainties about their duration and future evolution. In this extraordinarily difficult context, there has been an explosion of research in all related scientific fields in which AI-mediated technologies have proven to be essential tools for the common goals of controlling the spread, preventing the contagion and curing the many sick people. Machine learning techniques are being exploited to support COVID-19 diagnosis, to develop potential vaccines and drugs and to build epidemiological models of transmission and spread. AI is also exploited in online information platforms – including the fight against fake information – robotics and telemedicine, and data-driven models are exploited for individual contact tracing and social distancing, as well as quarantine and population confinement control (Nigris et al., 2020).
In these extraordinary circumstances, some of the ethical questions mentioned in the previous section become more relevant, bringing a sudden interest for the public. They include conceptual reflections on how to prioritise health attention (Ahuja, 2020) and assign reduced resources (e.g. who should be attended to? How should an automated system assist the triage of incoming patients? (Walsh, 2020)); concerns of massive (including genetic) data collection (Wee, 2020) and population monitoring (Schechner et al., 2020); the opposition of the industry to additional regulations about data control and the training of systems which – in their view – would slow down the ability to respond to crises such as COVID-19 (Chee, 2020); and the possibility of deleting personal information after the pandemic can be considered as 'controlled' – as in Norway (Klesty & Macfie, 2020).

In addition, AI-mediated technologies are being used for different levels of social monitoring, from aerial drones to enforce the confinement of the population (Linder, 2020a) to the control of interpersonal distancing in public spaces (Linder, 2020b). However, devices with an original 'healthcare orientation' (e.g. hand washing (Kelly et al., 2020)) can be easily employed to monitor the individual behaviour – even in private environments – and send the information to third parties.

DEMOGRAPHY AND DATA BIAS IN AI SYSTEMS

One important factor influencing the performance of AI systems in general (and machine learning models in particular) is the 'quantity' and 'quality' of the data used to train them. This has been a subject of extensive analysis since the early days of AI that becomes a particularly complex question for health-related data since they are commonly fragmented and potentially biased with respect to the many demographic features (e.g. age, gender, ethnicity, body mass and others) accounting for the variability of the population in which they will be exploited (Panch et al., 2019).

Systems trained with non-representative, biased datasets will not only produce 'operational' (strictly technical) errors if applied to individuals for which they have not been suited, but the resulting outputs may be completely wrong, with very serious consequences and the corresponding – yet unsolved – questions about liability and responsibility. In another area – security monitoring – an initial example of this new type of errors was recently brought into the headlines as the incorrect identification by a facial – possibly racially biased – recognition system led to the arrest of an innocent person (Hill, 2020).

AI algorithms require representative numbers of cases to 'learn' and it may not be easy to provide them with enough, well-balanced sets to achieve an appropriate representation of the different human groups for generalised medical applications. This is a particularly high risk for under-represented populations.

PERSONAL CROSS-LANGUAGE COMMUNICATION AND 'PSYCHOLOGICAL HACKING'

Of particular interest is the development of AI-mediated devices to enhance interpersonal communication. In the context of the COVID-19 pandemic, they are potentially useful for overcoming the limitations in physical contact required to fight the disease.

New technological designs include conversational assistants (e.g. 'chatbots') that can also work in a cross-language setting, incorporating, for instance, devices or 'connected' face masks capable of performing real-time translations (Kelly & Tomoshige, 2020). These types of systems evolve from an extensive research literature on natural language processing and automatic translation. With an obvious potential 'for good', they are exploited to facilitate medical assistance, interactive translations, cross-language communication (e.g. the integration of migrants), cross-language telemedicine and to fight loneliness in quarantine periods or in certain remote, isolated environments.

Nevertheless, automated (autonomous) conversational platforms may also result in the development of psychological, emotional links between people and machines. This has been a topic of extensive analysis since the early days of AI which has come to the interest of the general public in the context of the current COVID-19 pandemic. During prolonged periods of social isolation – with available online platforms – some users declare that they 'feel very connected' to the AI systems they use (Metz, 2020). Questions arise as to whether such platforms are used by vulnerable populations – children, the elderly and people with mental ailments – which may develop trust in and affection for them. There may be beneficial applications of affective computing, for example to support certain therapies linked to neurological or psychiatric disorders (e.g. dementia), but the risk of manipulation is high.

A recent report[68] shows that malicious interference ('hacking') of a wearable can (relatively easily) generate fake signals for the user to take medicines or other actions, with the obvious risks of inducing severely damaging consequences (e.g. overdose). As pointed out in Gómez-González & Gómez (2020), health data present a worrying vulnerability to illicit 'manipulation', since alterations of data would be extremely difficult to track and identify. It seems that the (evil design of) conversational chatbots may open a window to new forms of interference in people (particularly for those more vulnerable). This can be considered as 'psychological hacking' ('psycho-hacking'), and calls for its further analysis.

HEALTH AND AI SYSTEMS FOR BORDER CONTROL

One of the areas in which AI systems are beginning to be exploited is that of border control. This is a very sensitive application with many different aspects to consider, from the strictly logistic ones (many hundreds of millions of people enter the European Union each year) to governmental requirements to fight crime and terrorism, the need for user-friendly procedures and the requirement for the robust protection of the human rights of citizens, migrants and asylum-seekers. Automated systems for screening at borders, with conversational capabilities in particular, are of great interest (Accenture, 2017), even the subject of EU-funded projects,[69] and some countries are in different stages of testing (Kendrick, 2019). In 2018, a detailed analysis of the use of automated systems at the Canadian border warned how they may have a strong, negative impact from the point of view of human rights and exacerbate disparities with the more vulnerable, under-resourced communities (Molnar & Gill, 2018).

In the current international situation established by the COVID-19 pandemic, health information related to the disease is an additional requirement for entering Europe and virtually any country in the world. Many of the issues commented come to the front line. What would happen if health data were merged with other types of individual information at a border? (Beduschi, 2020; Molnar & Gill, 2018) Will access to Europe, or to a particular country, be granted if a person has 'proper' (COVID-19) antibodies? We should develop automated systems, as in other context, in a trustworthy way (EU, 2019b).

CONCLUSIONS: ADDRESSING NEW CHALLENGES

Given the strong implications of health data-related AI systems and the overlap with public health policies required to address the exceptional circumstances of the COVID-19 pandemic, an analysis of opportunities and risks should be carried out before systems are fully deployed.

AI advances in medicine and healthcare result from research, development and innovation with considerable public funding. However, society and citizens are not fully aware of the extent to which the use of these technologies has expanded in the medical and healthcare field, or of the ethical and social implications that they may have. There is a need for a multidisciplinary analysis covering not only the clinical and scientific perspectives on AI systems in the medical and healthcare sectors, but their humanistic, ethical – even philosophical – views as well. Moreover, new policy challenges clearly arise.

The European Union has the extended, experienced and trustworthy resources to lead this debate based on an open, international environment, and to define any ethical and social guidelines – even setting limits if necessary – with the required legislative and regulatory actions.

4.2 THE IMPACT OF AI ON HEALTH-RELATED OCCUPATIONS: TASKS, COGNITIVE ABILITIES AND AI BENCHMARKS

'We should stop training radiologists now. It's just completely obvious that within five years, deep learning is going to do better than radiologists.'[70] This is what Geoffrey Hinton, one of the pioneers and global leading researchers in artificial intelligence (AI) said in November 2016. Many other top AI researchers share this opinion. So, Andrew Ng, too wondered whether 'radiologists should be worried about their job'.[71] It is the opinions of AI experts, who have led Frey & Osborne (2017) to conclude that 47% of all US jobs are at high risk of being automated. This alarmist study triggered waves of concern about the future of work: if half of all existing jobs will disappear as a result of automation, will there be sufficient replacement jobs and where will they come from? However, as of July 2020 (four years after Hinton's 5-year-prediction), there is no radiologist who has been replaced by AI.

Clearly, predicting future developments of work is not a trivial task. There are many aspects to consider when determining if and when machines could substitute humans in an entire occupation. One reason for why radiologists have not been replaced is that the stakes of decisions in radiology are extremely high (human lives depend on them) and we still need humans accountable in high-stakes decision-making (Reardon, 2019). Another reason is that radiologists have to perform in their occupation many other relevant tasks in addition to interpreting medical images. In fact, most jobs involve many tasks and not all of them may be visible when researchers determine their potential for automation. In most cases, AI may only have the capabilities to perform parts of an occupation, in such a way that the introduction of AI only leads to a reorganisation of a job. Nevertheless, in order to predict which occupations will be affected by AI, we need to have adequate measures for the contents of occupations and the capabilities of AI.

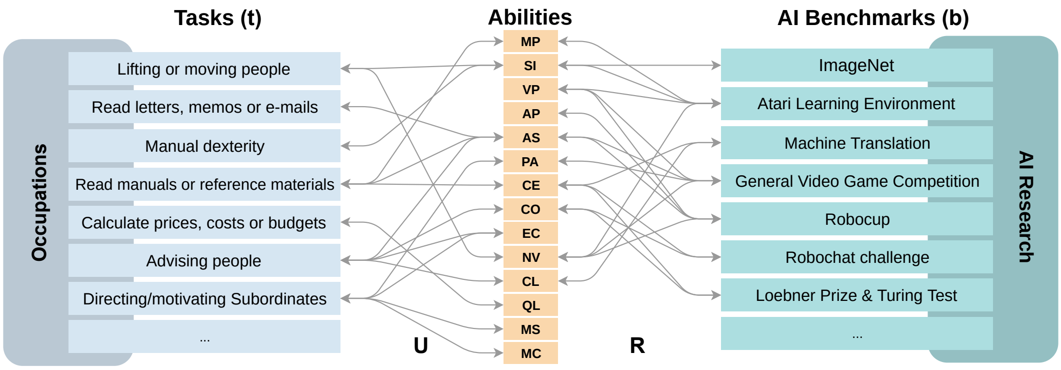
In this thematic contribution, we present a framework, developed in Tolan et al. (2020), that allows for the analysis of the occupational impact of AI progress. The section focuses on medical occupations. In this framework, we measure occupations as bundles of tasks and we measure AI progress as the result of research activity that is made observable through performance metrics or benchmarks. In order to connect AI benchmarks with tasks, we introduce an intermediate layer of cognitive abilities. Thus, the framework links tasks to cognitive abilities, and these to indicators that measure performance in different AI fields (Figure 25).

The intermediate layer of cognitive abilities allows us to distinguish machines that, through AI, are empowered with the abilities to perform a range of several tasks using machines that are explicitly constructed or programmed to perform specific tasks. For instance, the ability to understand the human language (Manning & Schütze, 1999) can be applied to a variety of tasks (such as reading or writing emails or advising patients). We derive the following 14 cognitive abilities from the cognitive science literature (Hernandez-Orallo, 2017):

- Memory processing (MP)
- Sensorimotor interaction (SI)
- Visual processing (VP)
- Auditory processing (AP)
- Attention and search (AS)
- Planning, sequential decision-making and acting (PA)
- Comprehension and expression (CE)
- Communication (CO)
- Emotion and self-control (EC)
- Navigation (NV)
- Conceptualisation, learning and abstraction (CL)
- Quantitative and logical reasoning (QL)
- Mind modelling and social interaction (MS)
- Metacognition and confidence assessment (MC)

We combine multiple data sources to develop the framework. The task information is based on a combination of the European Working Conditions Survey (EWCS) worker surveys and the Survey of Adult Skills (PIAAC) as well as the occupational database O*Net. The list of 328 AI computational tasks is obtained from

FIGURE 25. Bidirectional and indirect mapping between occupations and AI
Source: Tolan et al. (2020)



benchmarking initiatives, challenges, competitions and scientific literature as metrics indicating progress in AI techniques. Furthermore, we obtain information on wage percentiles of occupations from the Structure of Earnings Survey 2014.[72]

For a comprehensive measure of work contents, we use the task-based approach from Fernández-Macías & Bisello (2020). An occupational task can be understood as a specific act of transformation on an object. On the basis of the type of object being transformed and the type of transformation, we can create a taxonomy of different types of tasks. At the highest level, this classification differentiates between tasks that operate on material things (physical tasks), tasks that operate on ideas or information (intellectual tasks) and tasks that operate on social relations (social tasks). From those, a nested taxonomy with increasing levels of detail unfolds. The parts of that taxonomy relevant to this chapter are listed in Table 6.

The framework allows us to present the work content of occupations in terms of task requirements. When applying the framework to the data, we obtain information on the relevance of each task for each occupation, where the relevance of a task is composed of time spent on that task and the workers' subjective evaluation of the importance of that task to the occupation.

We present in Figure 26 the task requirements for the following selected medical occupations:[73]

- **medical doctors**: medical doctors (physicians) study, diagnose, treat and prevent illness, disease, injury and other physical and mental impairments in humans through the application of the principles and procedures of modern medicine. They plan, supervise and evaluate the implementation of care and treatment plans by other healthcare providers, and conduct medical education and research activities;
- **nursing and midwifery professionals**: nursing and midwifery professionals provide treatment and care services for people who are physically or mentally

TABLE 6. Tasks: nested structure of work content
Source: Fernández-Macías & Bisello (2020).

Physical tasks	Intellectual tasks	Social tasks
a) Strength b) Dexterity	a) Information processing: i. Literacy: a. Business b. Technical c. Humanities ii. Numeracy: a. Accounting b. Analytic b) Problem solving: i. Information gathering and evaluation ii .Creativity and resolution	a) Serving/attending b) Teaching/training/coaching c) Selling/influencing d) Managing/coordinating

ill, disabled or infirm, and others in need of care due to potential risks to health including before, during and after childbirth. They assume responsibility for the planning, management and evaluation of the care of patients, including the supervision of other healthcare workers, working autonomously or in teams with medical doctors and others in the practical application of preventive and curative measures;

- **paramedical practitioners**: paramedical practitioners provide advisory, diagnostic, curative and preventive medical services more limited in scope and complexity than those carried out by medical doctors. They work autonomously or with the limited supervision of medical doctors, and apply advanced clinical procedures for treating and preventing diseases, injuries and other physical or mental impairments common to specific communities;
- **medical and pharmaceutical technicians**: medical and pharmaceutical technicians perform technical tasks to assist in the diagnosis and treatment of illness, disease, injuries and impairments.

Figure 26 shows that, for nurses and paramedicals, physical tasks (strength and dexterity) are more relevant than for medical doctors or medical technicians, while social tasks (serving, teaching, selling and managing) are equally relevant for nurses and medical doctors. The greatest differences are prevalent among the intellectual tasks. Here, medical doctors exhibit the highest relevance, in literacy and problem-solving tasks specifically, where creativity and resolution tasks have the highest relevance for medical doctors. In contrast, accounting tasks are most relevant for medical technicians. All in all the task-based approach provides an appropriate measure of work contents.

When mapping tasks to cognitive abilities, we maintain the threefold division. We thereby need to consider that cognitive abilities do not exhibit physical properties per se but that they are active when performing tasks on physical objects. Therefore, we translate the high level categorisation of work tasks to cognitive abilities by sorting each ability according to the objects that they operate on into one of the following three categories: (1) dealing with **people**; (2) dealing with **ideas** or information; and 3) dealing with (physical or virtual) objects or **things**.

For a detailed view of the relevance of different cognitive abilities within occupations, we present in Figure 27 the required abilities for each occupation relative to the total required cognitive abilities in each occupation. All four medical occupations clearly show very similar relevance profiles. For all selected occupations, abilities related to things are on average less relevant than abilities related to people or ideas. For all four occupations, human language comprehension (CE), communication (CO), attention and search (AS) and conceptualisation (CL) are the most relevant cognitive abilities. Not surprisingly, for nurses and paramedicals, people-related abilities and sensorimotor interaction (SI) are more relevant than for medical doctors and medical and pharmaceutical technicians. Equivalently, memory processing (MP) and quantitative reasoning (QL) are more relevant for doctors and medical technicians than for nurses or paramedical practitioners. Overall, considering the nature of these occupations, we can say that task requirements are adequately mapped to cognitive ability requirements.

Figure 28 shows the computed AI research intensity for each cognitive ability for benchmarking initiatives taking place in every two-year period from 2008 to 2018.

FIGURE 26. Relevance of tasks for selected medical occupations
Source: JRC CAS – HUMAINT.

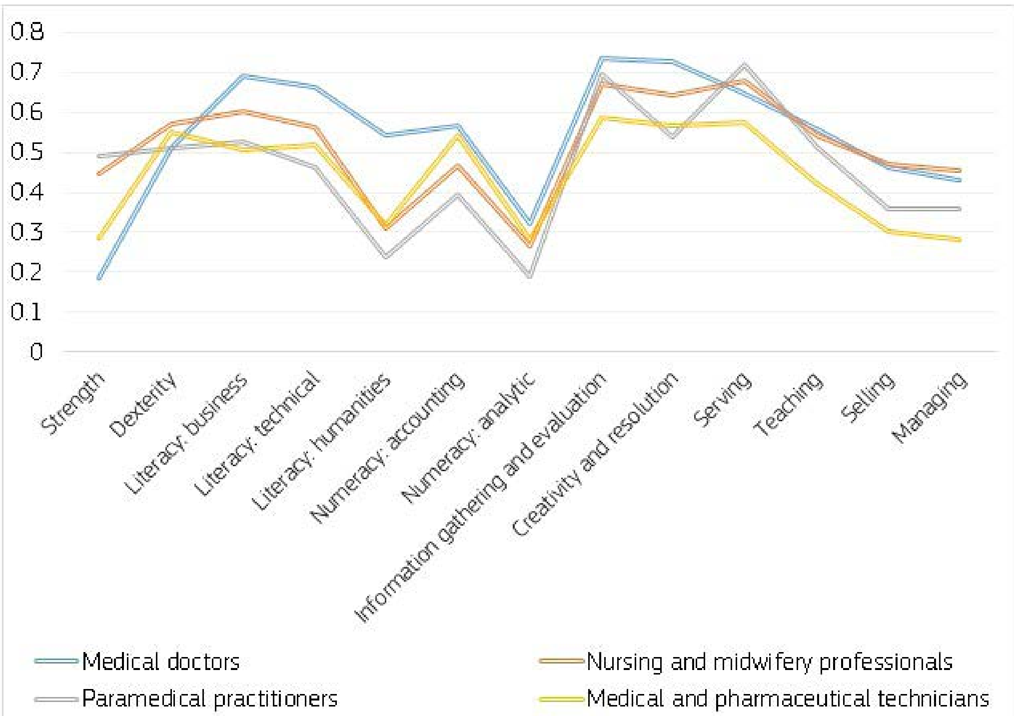
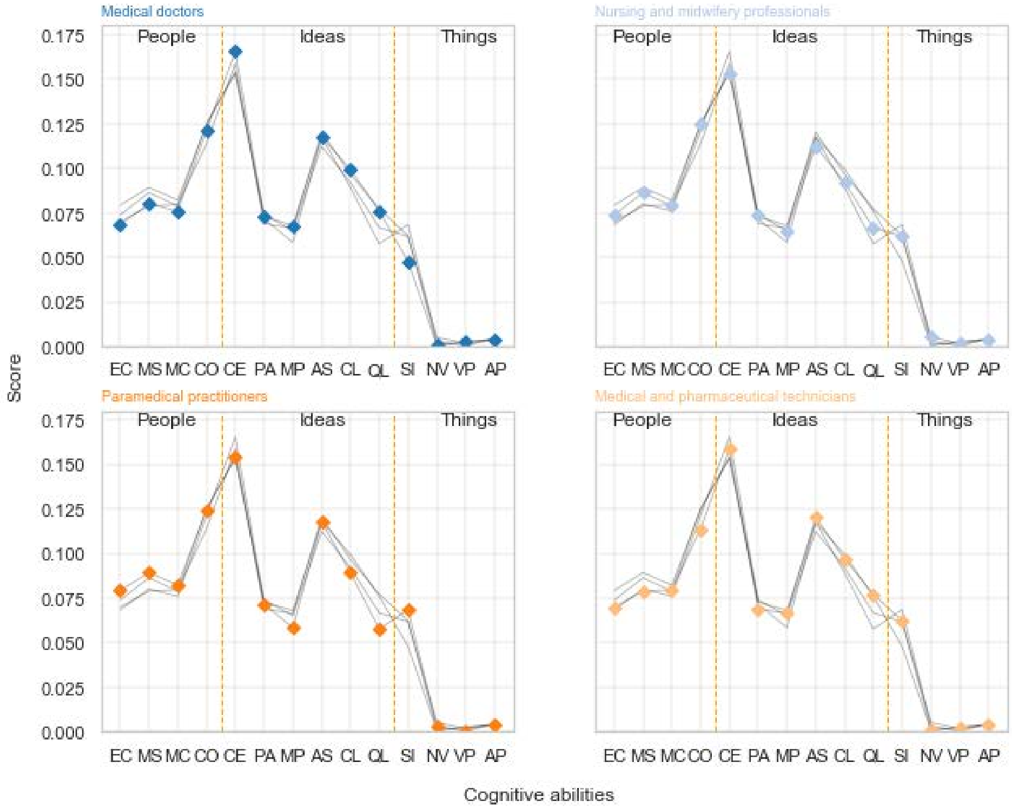


FIGURE 27. Relevance of cognitive abilities for selected medical occupations
Source: JRC CAS – HUMAINT.



AI research intensity measures activity in terms of documents created in research and development related to the list of AI benchmarks. We relate AI benchmarks to the cognitive abilities that they address, e.g. we link the benchmark 'imageNet initiative' to visual processing (VP). We see that most AI research activity can be attributed to visual processing (VP), attention and search (AS), comprehension, compositional expression (CE), conceptualisation, learning and abstraction (CL) and quantitative and logical reasoning (QL). We see almost no research intensity on people-related social interaction (MS) and metacognition (MC). This may be due to the lack of suitable benchmarks to evaluate the interactions of agents (human and virtual) in social contexts, as well as the challenge (today) of developing agents able to properly perform in social contexts with other agents having beliefs, desires and intentions, coordination, leadership, etc. as well as being aware of their own capacities and limits. Note that Figure 28 also shows trends over the years for each cognitive ability. There is a clear 'increasing' trend in visual processing (VP) and attention and search (AS), while other abilities remain more or less constant (MP, SI, AP, CO, CL and MS) or have a small progressive decline (PA, CE, EC and QL). Note that these values are relative. For instance, PA, CE or QL have decreased in proportion to the rest. In absolute numbers, with an investment in AI research that is doubling every 1-2 years (Shoham et al., 2018), all of them are actually growing. Thus, the figure shows that imbalances in AI research activity are increasing.

FIGURE 28. AI research activity per cognitive ability weighted by average intensity per period
Source: JRC CAS – HUMAINT.

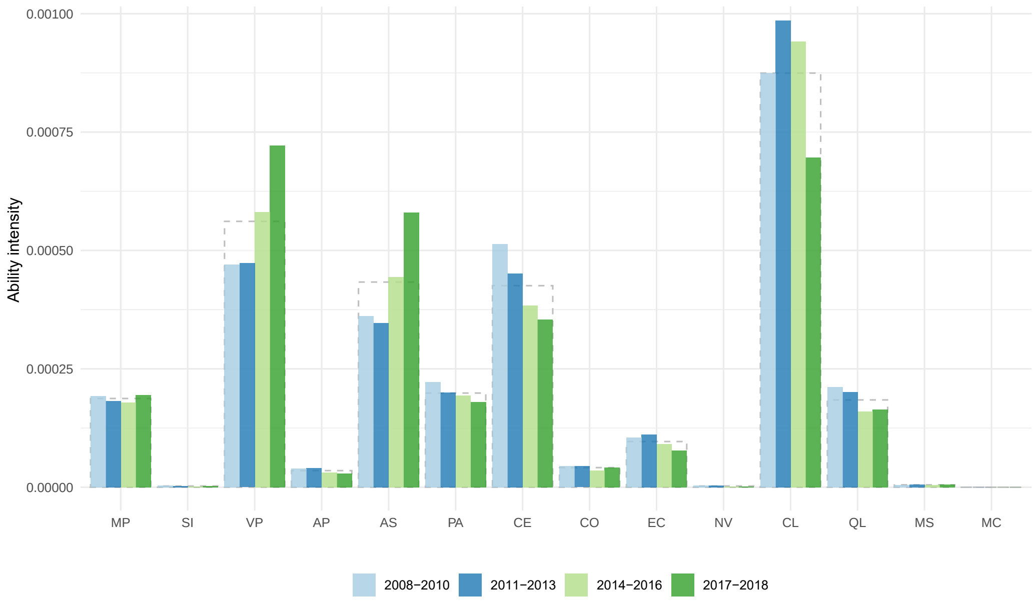


Figure 29 depicts the computed AI exposure score differentiated by cognitive abilities. We obtain the AI exposure score by mapping AI progress to work contents through the layer of cognitive abilities for the four medical occupations selected. Firstly, the figure shows that out of this group of occupations, medical doctors are most exposed to AI. Secondly, Figure 29 clearly shows that most AI exposure is driven by its impact on tasks that require abilities that deal with ideas, such as comprehension (CE), attention and search (AS) as well as conceptualisation (CL). This is not because we assign more cognitive abilities (six) to the ideas category than to the other categories (four each), since the smallest exposure score from the ideas abilities (in most cases quantitative reasoning (QL)) is still always greater than the highest exposure score from the people category. Compared to this, the exposure scores in the things category are negligibly small. That is, little

AI exposure can be expected through basic processing abilities, such as visual processing (VP) or auditory processing (AP), nor through abilities that deal with people, such as mind modelling and social interaction (MS) or communication (CO). However, our findings based on the tasks and occupation data indicate a relatively high need for people abilities in most occupations and a relatively low need for abilities dealing with things. Equivalently, the findings on AI research intensity suggest high activity in AI areas that contribute to abilities dealing with things and ideas and low activity for abilities dealing with people.

Lastly, we compute a single AI exposure and plot the score against average wage percentiles for all occupations in our dataset, illustrated in Figure 30.We clearly observe a positive relationship between wages and AI exposure. That is, high-income occupations seem to be more likely to be affected by AI progress than low-income occupations.

FIGURE 29. Ability-specific AI exposure scores for selected occupations
Note: patterns reflect ability categories, where stripes represent people abilities, checked patterns represent ideas abilities and no pattern represents things abilities.
Source: JRC CAS – HUMAINT.

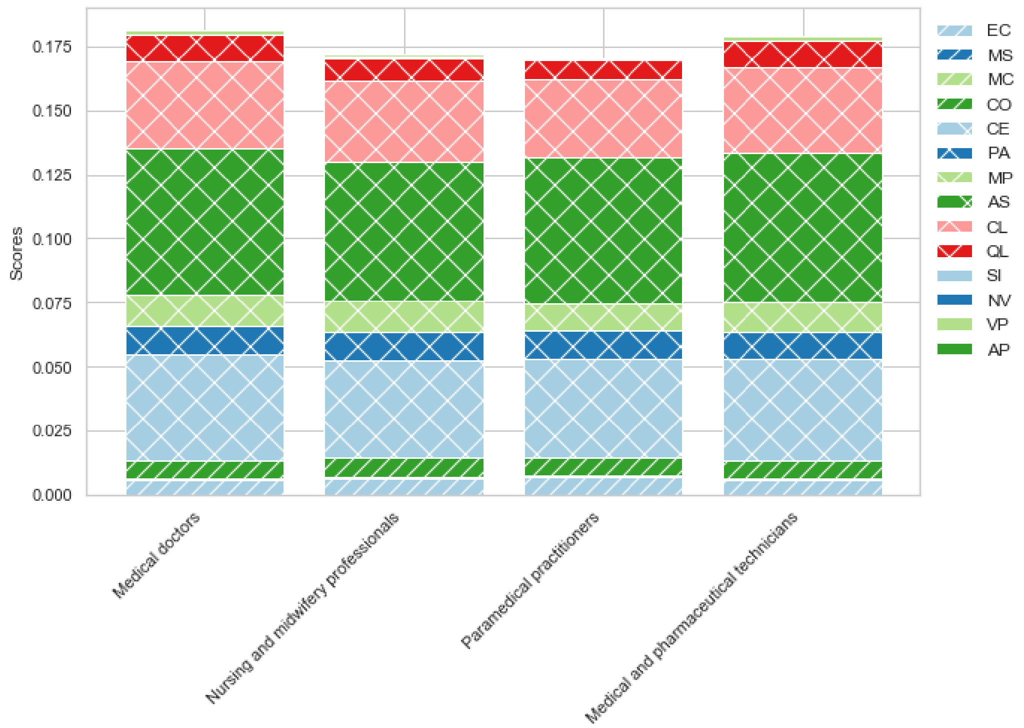
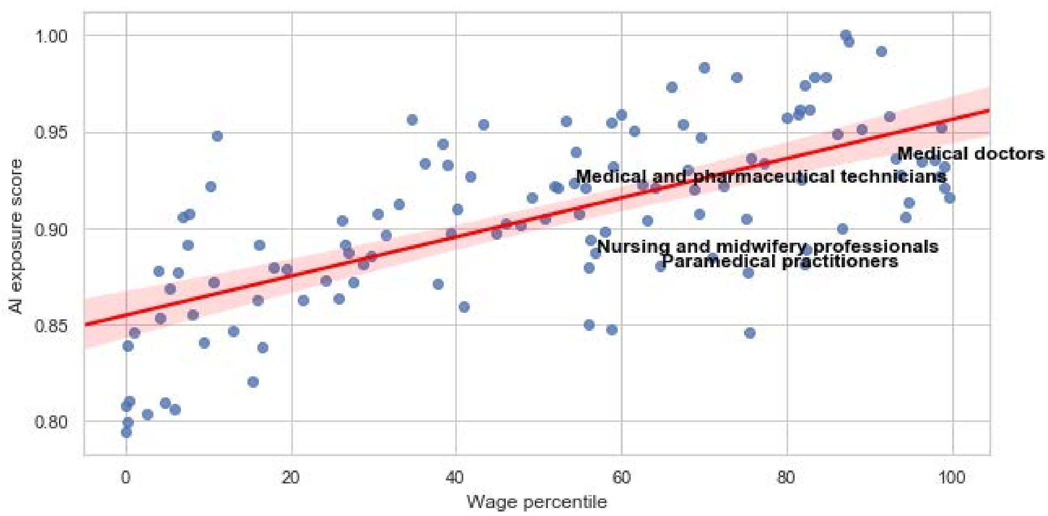


FIGURE 30. Scatterplot and best fit line, AI exposure score against wage percentiles
Source: JRC CAS – HUMAINT elaborations of Structure of Earnings Survey, 2014.



CONCLUSIONS: THE IMPACT OF AI ON LABOUR MARKETS

It is clear that there are many effects to consider when analysing the impact of AI on work (Brynjolfsson & Mitchell, 2017). This analysis is limited to the technical potential of AI (i.e. the things that AI could potentially do at work). We can use this approach to highlight occupations and abilities involved where AI could play a role. However, this framework remains silent about the complementary conditions necessary to enable the integration of AI in the workplace and the processes that occur after the integration of AI. Consequently, our results have to be interpreted in light of this limitation. Nevertheless, this study sheds light on some aspects of the relationship between AI progress and labour markets.

Firstly, these findings show that AI – as an emerging technology – could potentially play a novel role in the context of technology-driven labour market polarisation. According to some studies (Autor et al., 2003; Goos et al., 2014), previous waves of technological progress led to polarisation on the labour market where the automation of medium-skilled occupations pushed medium-skilled workers to either low- or high-skilled occupations. In contrast, our findings (according to Figure 30) suggest relatively high AI exposure for high-skilled medical doctors but lower AI exposure for medium-skilled occupations such as nursing and paramedicals. However, AI exposure can also be relatively high for medium-skilled occupations such as medical technicians. In the end, it depends on the cognitive abilities required. Overall, this can have different implications for labour market polarisation (and consequently inequality) depending on whether AI exposure is labour-replacing or labour-enhancing. If this effect is in fact a labour-replacing one, it could potentially lead to unpolarising effects and a reduction in income inequality (Webb, 2019). If this effect is a labour-enhancing, it could imply a significant expansion in productivity for high-skilled occupations, potentially leading to occupational upgrading effects and an expansion of income inequality (very much like the traditional hypothesis of skills-biased technological change; see Acemoglu (2002)).

Furthermore, our findings show that AI progress could affect how specific skills are rewarded (e.g. in terms of wages and working conditions) on the labour market. The finding of low exposure through people abilities versus high exposure through ideas abilities is parallel to Deming (2017) who explores the relationship in the labour market returns to social skills and, what he calls, cognitive skills which we refer to here as analytical skills. More specifically, we use social skills to interact with people and we use abilities that deal with ideas in areas that require analytic skills. Deming (2017) finds that social and analytical skills are complements rather than substitutes. That is, an increased labour demand for analytical skills, which increases wages for people with analytical skills, leads to an increased labour demand for people that, in addition to analytical skills, also have strong social skills. In addition, we find that many labour market tasks require high levels of people as well as ideas abilities, but AI exposure occurs mostly through ideas abilities only. Consequently, we can expect an increase in the wages for workers that combine their strong ideas abilities with strong people abilities.

4.3 AGE AND TERRITORIAL DIGITAL DIVIDE FOR TELEMEDICINE

The adoption of digital technology in the healthcare industry is generating major changes in the way healthcare services are delivered and in patients' interactions with medical workers. Many EU Member States are removing some of the regulatory and financial barriers to remote healthcare in order to strengthen their capacities and reduce the increasing cost pressures arising from healthcare expenditure related to the ageing population (EU, 2019a, 2018b; Alotaibi & Federico, 2017; Stroetmann et al., 2015; Nouhi et al., 2012).

Additionally, the acceptance of digital products for healthcare is increasingly widespread among consumers (Safi et al., 2019), and people are generally supportive of using their data to create new knowledge and improve care (OECD, 2020d). The ongoing COVID-19 pandemic is further changing users' perspectives in favour of remote healthcare even in the new normality, thus acting as an additional driver for the implementation and use of remote consultation.[74]

The main technological solutions in healthcare include mhealth, ehealth, telehealth and telemedicine, and primarily target issues related to mobility, communication, interactivity, remote monitoring and the timely provision of patient-specific information. In short, the terms '*eHealth*' and '*mHealth*' are used to describe the provision of health services using the internet and wearable devices respectively.

The term 'telehealth' is used to describe various electronic procedures related to health, while '*telemedicine*' specifically refers to the remote treatment of patients (see Box 6 for definitions). Telemedicine is categorised into three types of services using different ICT solutions, which are real-time communication, store-and-forward approach, and patient tele monitoring. Real-time communication makes use of standard communication technologies for patient contact and data exchange, including video visits, live chat, and email. Video/audio quality is therefore essential for physician and patient appointments. Official communication methods and platforms are typically used to ensure data privacy and security. Telemedicine also uses the store-and-forward approach through which clinical data - typically demographic data or lab reports - are filled in and transmitted. The healthcare provider can either use a mobile device or desktop computer to collect and send the information via email or upload it to a secure platform. Finally, with the remote patient monitoring, it is possible to track patients' vital statistics remotely through the use of electronic devices that transmit patient statistics to a healthcare provider's analytic interface. In particular, wearable devices (e.g. cardiac and activity sensors) are becoming increasingly common in people's daily lives, especially in areas with better internet coverage. Overall, these technologies and applications demand users to have adequate training on how to use them. While systems for healthcare providers may consist of a variety of analytical interfaces, ICT applications for older users are getting more user-friendly, although they require them to acquire the knowledge and skills to use electronic devices.

The adoption of telemedicine has so far been rather fragmented and limited in the EU. Challenges related to the diffusion of telemedicine are manifold and include regulatory, cultural and commercial barriers; substantial investment in infrastructure or human resources; territorial differences in broadband internet services;[75] and a significant digital and e-skills divide among the elderly patients that prevents their full involvement via mhealth. The age-based digital divide in Europe in particular is very deep, both between and within countries, and internet access is still a luxury for the inhabitants of some remote and rural areas. All these factors challenge the potential of the new digital health systems that can be used by a large part of the population.

BOX 6 Definition of key concepts: eHealth, mHealth, Telemedicine and Telehealth

The WHO defines eHealth as the 'cost-effective and secure use of information and communications technologies in support of health and health-related fields, including health-care services, health surveillance, health literature, and health education, knowledge and research'[76]. eHealth therefore includes a wide range of solutions including electronic health record systems, patient and laboratory administration systems, telemedicine and mhealth.

mHealth (or mobile health) is defined by the WHO Global Observatory for eHealth as 'medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices'. Patients can store and monitor their health data, consult electronic medical records on their mobile devices, communicate directly with doctors and therapists through text messages or video visits, and use reminders and medical applications to follow appointments or pursue a healthy lifestyle.

Telemedicine refers exclusively to the provision of remote clinical services to patients. It is defined as 'The delivery of health care services, where distance is a critical factor, by all health care professionals using information and communication technologies for the exchange of valid information for diagnosis, treatment and prevention of disease and injuries, research and evaluation, and for the continuing education of health care providers, all in the interests of advancing the health of individuals and their communities' (WHO, 2010b).

Telehealth refers to both remote clinical and non-clinical services. It is associated with telemedicine but includes a wider application of technologies, such as distance medical training, consumer awareness, nursing call centres and other digital applications designed to support health services. The terms telehealth and telemedicine are often used interchangeably as there are no universal definitions of these concepts.

ACCESS TO THE INTERNET

The presence of a significant age-based digital divide in the access to the internet[77] and the lack of ICT skills for productive purposes by a large part of the population most in need of healthcare are key obstacles to the effective implementation of telemedicine. A high percentage of the older European population, particularly those with a low level of formal education and residing in rural and remote areas, indeed do not use the internet and are not familiar with ICT.

According to the EU-SILC 2018 microdata, elderly citizens have less access to the internet in their homes than the total European population. On average, 54% of the adult population aged 65 and over had an internet connection for personal use in 2018, compared to an average of 81% of the total population. The EU-SILC survey identifies the internet access that can take place via smartphones and other devices such as tablets, laptops, desktop computers, TVs, etc. Internet activities for personal use include creating social networks, sending/receiving emails, creating web pages, internet banking, reading or downloading videos or news, searching for information, making phone/video calls, participating in online consultations or voting on civic or political issues.

There are considerable disparities between EU Member States in the proportion of adult individuals who habitually use the internet and an uneven distribution of such an access among different age groups in the population. In 2018, the percentage of individuals in the EU-27 aged 65 and over with internet access for private use was 54%. The percentages of regular users are much higher among younger individuals, with these percentages above 94% for individuals aged 16-29, between 90% and 93% for users aged 30-54 and around 55% for those aged 55-59.

At national level, the percentage of the adult population aged 65 years and over with internet access varies considerably from a minimum of 20% in Romania to a maximum of 89% in Denmark. In general, northern and western Member States demonstrate the highest levels of internet use compared to Eastern and Southern European countries. The Member States with the highest percentages of adults with internet access are indeed Denmark (89%), the Netherlands (88%) and Sweden (87%), while those with the lowest percentages – beyond Romania – are Bulgaria (22%), Croatia (24%) and Greece (23%) (Figure 31).
In order to understand the size and heterogeneity of the population that could be more involved in digital applications for telemedicine, it is necessary to determine the extent to which these people are connected to the internet and some of their specific needs.

We look at a series of questions from the 2018 EU-SILC survey on household material deprivation related to internet access – i.e. the possession of a PC, telephone, the internet – for more than 270,000 people over the age of 50 years. In particular, we highlight both the age and the geographical aspects of the internet access divide, presenting figures for four age groups (50-59, 60-69, 70-79, 80+) in the population and for the degree of urbanisation of the place of residence.[78]

Table 7 shows the presence of a divide in overall internet access across the different age groups of the adult population and by the degree of urbanisation. Overall, internet access is greater among the adult population living in large cities (87%), while the lowest percentages are observed among those living in less densely populated areas (80%). Among the adult population, the youngest group (50-59 years old) uses the internet the most, with percentages above 90% in the three geographical areas by the degree of urbanisation. In contrast, the older group (80+) has the lowest percentage of internet users, with the lowest scores observed in remote areas (41%) and the highest scores reported among the residents of densely populated areas (57%).

These data also show differences by age groups in the availability of a computer at home; the 50-59 age group has higher rates of availability of a computer at home than older groups, reporting a percentage of over 90% in the three areas of residence. Among the over-80s, only 34% of those living in remote areas have a PC, compared to 41% of older people living in intermediate areas and 46% of the group living in large cities. Most EU households have a telephone, regardless of age or place of residence.

We now turn our attention to demography and some aspects of material deprivation of the adult off-line population. The EU-SILC microdata contain information on the

FIGURE 31. Proportion of population using the internet, 2018
Note: Malta excluded due to missing values on the age of internet users
Source: KCMD elaboration based on EU-SILC microdata, 2018.

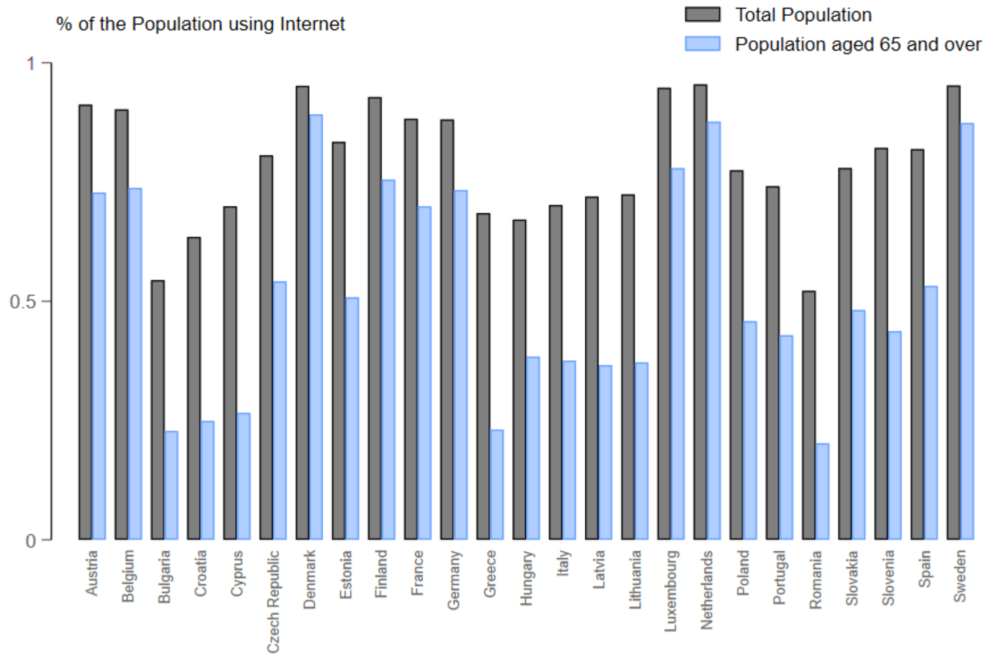


TABLE 7. Internet access and material deprivation items by age groups and degree of urbanisation
Source: KCMD elaboration based on EU-SILC microdata, 2018.

Age groups	Degree of urbanisation	Internet access	Computer	Telephone (including mobile phone)
50-59	Thinly populated area	93%	90%	100%
60-69		86%	85%	99%
70-79		68%	65%	99%
80+		41%	34%	100%
Total (50+)		80%	78%	100%
50-59	Intermediate area	94%	92%	100%
60-69		92%	90%	100%
70-79		80%	75%	100%
80+		51%	41%	100%
Total (50+)		85%	82%	100%
50-59	Densely populated area	93%	90%	100%
60-69		92%	87%	99%
70-79		83%	74%	100%
80+		57%	46%	100%
Total (50+)		87%	82%	100%

population, sufficiently detailed in their economic and socio-demographic breakdown to identify where the main challenges of internet access may operate.

In Table 8, we use a range of information on health conditions, socio-economic status, social and family networks and the area of residence, as follows. The general health status assessment is expressed with a categorical variable ranging from 1 to 5, with the lowest values indicating the lowest health condition; the presence of chronic illness or condition is a dummy variable equal to 1 (and equal to 0 in the absence of disease); activity restriction indicates the percentage of individuals who are limited in their usual activities due to a health problem; female indicates the sex of the respondent; the variable single person household indicates whether the household is composed of one person, while the household members variable indicates the total number of household components; higher education corresponds to post-secondary non-tertiary education and tertiary education (ISCED levels 4 and above). The material deprivation is measured by the indicator of poverty and social exclusion risk, expressed on a scale from 0 to 7, with 7 indicating the highest material deprivation; the variable financial ability indicates the ability to cope with unexpected expenses; financial satisfaction indicates a positive perception of one's finances measured on a scale from 0 to 10, with 10 corresponding to the highest levels of satisfaction; lastly, being together is a binary indicator indicating whether meetings with friends and relatives take place regularly.

Access to the internet is a social and economic issue and it remains particularly limited for the population that would need it the most (Table

TABLE 8. Demographics and socio-economic breakdown of the adult offline population
Source: KCMD elaboration based on EU-SILC microdata, 2018.

	Thinly populated area					Intermediate area					Densely populated area				
Age groups	50-59	60-69	70-79	80+	Total (50+)	50-59	60-69	70-79	80+	Total (50+)	50-59	60-69	70-79	80+	Total (50+)
Health status (1 Very bad –5 Very good)	3.311	3.403	3.306	3.055	3.254	3.136	3.166	3.12	3.099	3.123	2.796	3.09	3.204	3.038	3.044
Chronic illness	54%	54%	58%	71%	60%	59%	61%	59%	62%	60%	71%	59%	55%	71%	64%
Activity restriction	51%	52%	54%	73%	59%	55%	54%	64%	70%	63%	65%	53%	57%	64%	60%
Female	52%	53%	54%	66%	57%	55%	54%	60%	71%	62%	56%	66%	60%	65%	62%
Single person household	27%	16%	34%	53%	35%	46%	47%	42%	65%	52%	42%	46%	44%	73%	53%
Household members	2.123	2.416	1.779	1.673	1.935	1.732	1.725	1.686	1.403	1.596	1.86	1.83	1.63	1.272	1.603
High education	9%	5%	8%	9%	8%	11%	8%	10%	9%	9%	21%	13%	14%	16%	16%
Risk of poverty and social exclusion	1.135	0.808	1.023	1.293	1.069	2.059	1.088	0.905	0.904	1.106	3.455	1.808	0.69	0.584	1.447
Financial ability	81%	79%	85%	81%	82%	51%	66%	80%	87%	76%	27%	48%	71%	78%	60%
Financial satisfaction (0 Low – 10 High)	6.631	6.867	7.299	7.595	7.206	5.79	6.437	7.013	7.2	6.8	4.258	5.922	7.078	7.482	6.398
Get-together	75%	81%	78%	74%	77%	59%	63%	70%	68%	66%	59%	62%	70%	76%	68%

8). Around half of the respondents without an internet connection stated that they are in a medium state of health, presenting a 'health' index of approximately three points in each age group and level of urbanisation. However, more than half of the adult offline population report having a chronic illness. The older group of people over 80 certainly require more attention and healthcare, presenting the highest rate of chronic diseases, equal to 71% in remote areas, 62% in intermediate areas and 71% in densely populated areas. 71% of the population in the age group 50-59 years old, and resident in large cities, also report suffering from chronic diseases. These health conditions represent a limit in the performance of daily activities for around 60% of the total adult population (50 years and over) and for the different levels of urbanisation.

Among those lacking access to the internet, women have the highest percentage across all age groups and levels of urbanisation (Table 8). We therefore highlight an internet gender divide with differences in the access and effective use of ICT within and between countries. The highest percentages of women without access to the internet are observed among residents of intermediate areas and among the older groups of the adult population.

Approximately 52% of the adult offline population lives alone in intermediate and densely populated areas, while this percentage is around 35% of the sample interviewed in remote areas. It is in large cities where older people aged over 80 have the highest percentage of single person households (73%), followed by 65% in intermediate areas and 53% in remote areas. Families are indeed more numerous among the residents of small cities or remote areas where, on average, the family unit is made up of two components. It is therefore essential to improve the accessibility to digital services, as digital activity increasingly contributes to social and cultural inclusion and may help in preventing social isolation.

Overall, individuals with a high level of education (post-secondary and tertiary) are almost all regular internet users (Table 8). The percentage of the adult population without internet access but with a high level of education is indeed below 10% in rural and intermediate areas and for the different population age groups. Among those with a high level of secondary education, the highest percentage of offline users is in the population between 50 and 59 years old living in large cities (21%). On average, adults aged 50 years and over are exposed to a similar risk of poverty and social exclusion through the different levels of urbanisation (Table 8). However, respondents aged between 50 and 59 have slightly higher rates of material deprivation than older groups in large cities and intermediate areas, and economic affordability remains an important barrier for ICT use within the offline population. Similarly, the younger group living in large cities and intermediate areas report lower financial satisfaction, less financial capacity to sustain unexpected expenses and reduced social encounters than older groups living in the same areas.

DIGITAL SKILLS OF ELDERLY PEOPLE

In addition to having a device that can be connected to the internet (phone, computer, etc.) and an access to the internet, the implementation of telemedicine also requires a sufficient level of digital skills in the patient.
Basic digital skills or above basic digital skills represent the two highest levels of the general e-skills indicator, which is a composite Eurostat indicator based on the activities undertaken by individuals aged between 16 and 74 on the internet predominantly in the areas of information, communication, problem solving and content creation.

Table 9 summarises Eurostat's information for the year 2019 on the proportion of the total population, adult population aged 65 to 74, adult population aged 55 to 74 (by educational level and gender) and the population living in rural, medium and large cities with basic or higher digital skills. The highest percentages of individuals self-reporting to have basic or higher digital skills are in Denmark and Germany (70%), the Netherlands (79%) and Sweden (72%), while the lowest are in Bulgaria (29%) and Romania (31%). With regard to e-skills within the population aged 65-74, Finland, Sweden, Denmark and the Netherlands have the highest percentages for the adult population with basic or higher digital skills (over 40%); on the other hand, in Bulgaria, Romania, Latvia, Poland, Greece, less than 10% of the population aged 65-74 reports to have good e-skills. Lastly, in Bulgaria, Cyprus, Latvia, Lithuania, Slovakia and Poland we find the lowest percentages of women between 55 and 74 years old and the population in the same age group with a low level of formal education claiming to have good digital skills.

TABLE 9. Proportion of individuals who have basic or above basic overall digital skills, 2019
Source: KCMD elaborations of Eurostat dataset [isoc_sk_dskl_i].

EU MS	All individuals	65 to 74 years old	55 to 74 with low formal education	Females 55 to 74 years old	Individuals living in cities	Individuals living in towns and suburbs	Individuals living in rural areas
EU-27	56%	24%	12%	28%	62%	55%	48%
Belgium	61%	34%	20%	32%	57%	63%	61%
Bulgaria	29%	4%	0%	11%	40%	23%	17%
Czechia	62%	21%	3%	31%	72%	61%	56%
Denmark	70%	44%	35%	47%	77%	70%	62%
Germany	70%	36%	22%	41%	74%	69%	66%
Estonia	62%	18%	7%	29%	68%	56%	57%
Ireland	53%	19%	11%	28%	63%	50%	43%
Greece	51%	9%	2%	15%	58%	54%	35%
Spain	57%	19%	11%	26%	63%	52%	48%
France	57%	31%	15%	34%	63%	51%	54%
Croatia	53%	12%	3%	19%	67%	54%	44%
Italy	42%	14%	7%	17%	47%	40%	36%
Cyprus	45%	10%	1%	16%	50%	43%	36%
Latvia	43%	9%	1%	21%	50%	42%	35%
Lithuania	56%	12%	1%	25%	67%	55%	46%
Luxembourg	65%	37%	24%	38%	75%	57%	65%
Hungary	49%	14%	2%	19%	60%	46%	38%
Malta	56%	17%	11%	14%	53%	59%	52%
Netherlands	79%	58%	38%	56%	81%	77%	77%
Austria	66%	27%	13%	32%	71%	66%	61%
Poland	44%	9%	1%	13%	55%	43%	36%
Portugal	52%	13%	7%	17%	60%	50%	37%
Romania	31%	7%	2%	13%	39%	32%	23%
Slovenia	55%	16%	5%	23%	63%	57%	51%
Slovakia	54%	11%	1%	22%	61%	55%	48%
Finland	76%	40%	31%	57%	85%	73%	68%
Sweden	72%	42%	26%	48%	78%	73%	65%

An overview of the degree of urbanisation shows that the level of digital skills in the EU-27 was the lowest among individuals living in rural areas. In 2019, 48% of the rural dwellers had basic or higher skills compared to 55% of city and suburban residents and 62% of people living in cities. According to Eurostat data, the only exception to this general trend is seen in Belgium, where the highest percentage of e-skills is recorded among city and suburban inhabitants (63%). The digital skills gap between urban and rural residents – the difference in proportions of adults possessing basic or above basic digital skills – was, on average, 14 percentage points in 2019, with the highest skill gaps recorded in Bulgaria, Greece, Croatia and Portugal (23 percentage points), and the lowest observed in Belgium (-4), Malta (1), the Netherlands (4) and Germany (8).

CONCLUSIONS

Through an analysis of the EU-SILC 2018 microdata, this section showed that the digital divide between some demographic groups remains considerable in Europe. Reducing the existing gaps relating to access and the use of this resource is increasingly important for the implementation of telemedicine in the future.

This analysis shows in particular that older groups have less access to the internet and have fewer skills to use it productively than younger groups. The analysed group of over-50s is an extremely heterogeneous population group in terms of health situation, medical care needs or socio-economic living conditions. The demand for health services based on ICT therefore varies substantially throughout the older adult and elderly population. However, the results show that special attention needs to be paid to older people living alone in their homes, those with a low level of education and people living in rural and remote areas. Moreover, women demonstrate lower percentages of using or possessing digital skills than men.

Internet access is still a social and economic issue and affordability is an obstacle to the adoption of ICT by users. The urban/rural divide is also a central issue to be addressed for the effective implementation of telemedicine. The urban/rural divide reflects inequalities in access and barriers to productive use, with many areas that remain largely disconnected.

Training the elderly could play a key role in improving digital skills and the use of the internet for telemedicine. Educational activities and computer training courses for older people, such as free computer and internet use courses, information and educational meetings and universities of the third age could be particularly significant.

5. CONCLUSIONS

The EU is facing an unprecedented challenge. As the EU society is ageing, its elderly population is generating an ever-increasing demand for health and care services, also pressuring the fiscal sustainability of the EU's health and LTC sectors. The magnitude of this additional demand is dependent not only on the increase in life expectancy, but also on the quality of life at older ages. In other words, **ensuring ageing in good health** of the population can potentially reduce the demand and the pressure on the EU's health and LTC sectors.

It is important to stress that the challenges of population ageing on health and LTC sectors are not equally distributed between the Member States, or within the same Member State. This diversity of implications reflects not only different demographic, health socio-economic characteristics of populations, but also diversity of health and long-term care policies in place at local and national levels.

The majority of the demand for health and LTC workforce is being satisfied by domestic education systems which have the role of ensuring an adequate inflow of workers into the labour market. However, in a context of tight funding constraints, countries have been facing under-investments in education and training programmes for health workers as well as mismatches between education strategies and actual population needs. At the same time, the increasing labour demand in the EU's health and LTC sectors is being satisfied with the migration and intra-EU mobility of health and LTC professionals. Nonetheless, **the potential of migration** to alleviate the pressure of workforce shortages in the EU's health and LTC sectors has still not been fully harnessed. The reasons for this untapped potential are manifold, ranging from the absence of specific EU sectoral labour migration instruments or tools for attracting healthcare and LTC workers, complex qualification recognition procedures, to obstacles in the labour market integration of migrants.

An additional way of addressing the rising demand for health and LTC services is by harnessing **the potential of digital technologies**. Considering AI, in particular, its role in shaping and addressing the demand for workers and skills is not only limited to AI's technological availability, but is accompanied by crucial social, ethical and occupational implications, many of which are still an open debate. Ultimately, there is also a question of whether the elderly – as the growing category of recipients of health and care services – are in a condition to actually benefit from the adoption of digital technologies. Using the specific example of telemedicine, it is clear that elderly people in the EU are still facing important barriers determined by the lack of access to the internet, to computers and fewer digital skills.

In a context of the progressive ageing of the EU's society and increasing challenges that the EU's health and LTC sectors have been facing, the Commission has taken a series of policy initiatives in support of its Member States. Some of the most relevant recent initiatives include the Commission's first steps towards building the European Health Union, which, together with the 'Pact for Skills' set out in the EU's Skills Agenda and the Green Paper on Ageing, are all directed towards supporting the Member States' efforts to build resilient health and LTC systems that rely on the availability of a qualified workforce, among others. Finally, for health and LTC sectors an important forthcoming initiative is the adoption of the Action Plan to implement the European Pillar of Social Rights in 2021, as set out in the Commission Communication on the Strong Social Europe for Just Transitions (COM(2020) 14 final).