JRC TECHNICAL REPORT

AI Watch
AI Uptake in Health and Healthcare, 2020

EUR 30478 EN

Joint Research Centre

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EU Science Hub
https://ec.europa.eu/jrc
https://publications.jrc.ec.europa.eu/repository/handle/JRC122675

JRC122675

EUR 30478 EN

ISBN 978-92-76-26936-6 ISSN 1831-9424 doi:10.2760/948860

Luxembourg: Publications Office of the European Union, 2020

How to cite this report: De Nigris S., Craglia M., Nepelski D., Hradec J., Gómez-González E, Gomez E , M.Vazquez-Prada Baillet, R.Righi, G.De Prato, M.López Cobo, S.Samoili, M.Cardona *AI Watch: AI Uptake in Health and Healthcare 2020*, EUR 30478 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-26936-6, doi:10.2760/948860, JRC122675.

Contents

Abstract

This document presents a sectoral analysis of AI in health and healthcare for AI Watch, the knowledge service of the European Commission monitoring the development, uptake and impact of Artificial Intelligence for Europe. Its main aim is to act as a benchmark for future editions of the report to be able to assess the changes in uptake and impact of AI in healthcare over time, in line with the mission of AI Watch. The report recognises that we are still at an early stage in the adoption of AI and that AI offers many opportunities in the short term for improved efficiency in administrative and operational processes and in the medium-long term for clinical applications, patients' care, and increased citizen empowerment. At the same time, AI applications in this sensitive sector raise many ethical and societal issues and shaping the direction of development so that we can maximise the benefits whilst reducing the risks is a key issue. In the global context, Europe is well positioned with a strong research base and excellent health data, which is the pre-requisite for the development of beneficial AI applications. Where Europe is less well placed is in translating research and innovation into industrial applications and in venture capital funding able to support innovative companies to set themselves up and scale up once successful. There are however noticeable exception as the case of the BioNTech that is leading the development of one of the COVID-19 vaccines. It should also be noted that in AI-enabled health start-ups, many of them are in the area of drug discovery, i.e. the domain of BioNTech. Investment in education and training of the healthcare workforce as well as creating environments for multidisciplinary exchange of knowledge between software developers and health practitioners are other key areas. The report recognizes that there are many important policy developments already in the making that will shape future directions, including the European Strategy for Data which is setting up a common dataspace for health, a risk-based regulatory framework for AI to be put in place by the end of 2020, and the forthcoming launch of the Horizon Europe programme as well the Digital Europe Programme with large investments in AI, computing infrastructure, cybersecurity and training. The COVID-19 crisis has also acted as a booster to the adoption of AI in health and the digital transition of business, research, education and public administration. Furthermore, the unprecedented investments of the Recovery Plan agreed in July 2020 may fuel development in digital technologies and health beyond expectation. We are therefore at the junction of a potentially extraordinary period of change which we will be able to measure in future years against the baseline set by this report.

Executive Summary

This document presents a sectoral analysis of AI in health and healthcare for AI Watch, the knowledge service of the European Commission monitoring the development, uptake and impact of Artificial Intelligence for Europe. Its main aim is to act as a benchmark for future editions of the report to be able to assess the changes in uptake and impact of AI in healthcare over time, in line with the mission of AI Watch.

Europe's global positioning

Within the global landscape, the EU is generally well-placed in the application of AI in the health and healthcare domains, somewhat behind China but at par with the USA. The research dimension is particularly strong in the EU, with research institutions accounting for about two thirds of all EU players in this field, compared to one third of players in China, and a relatively small proportion in the US, where developments in this field are dominated by commercial companies. In terms of areas of specialisation, in the EU and the USA, most of the activity concentrates on diagnostics and health technology assessment. China has a strong focus on diagnostics, which includes image recognition technologies for which China is a worldwide leader.

Social and ethical impact of AI in health care

AI systems offer opportunities in medical applications in fields such as oncology, genetics and neurosciences, but also present possible risks and ethical questions raised by their implementation. AI is a dual-use technology: it can be used for positive applications as well as very controversial or unethical ones. Beneficial applications include software for decision support to improve diagnostic efficiency, but harmful areas may include new tools for bioterrorism. In between these two extremes, there are many applications analysed in the report that display varying degree of benefits and risk, and a social-controversy index is used to flag the potential levels of concern.

Main findings from the data analysis

Scientific medical literature: We observed a marked increase of publications in AI and healthcare in the period 2012-2014 and since 2018. The COVID-19 pandemic in 2020 is giving further impulse to the research in this domain. Similarly, the analysis of the EU R&D projects shows a growth in health and healthcare projects since 2015 and, in combination with AI, since 2017.

Industrial sector: The number of patent applications increased after 2012 and its pace accelerated after 2014, particularly in China and the USA. European companies like Siemens and Philips are among the top players, following the South Korean Samsung electronics, which however patens many sensing devices that can also be used in health-related applications, rather than patents specifically conceived for health purposes.

The percentage of venture capital (VC) investment directed towards AI and health startups has also undergone a fast expansion: from 2-3% in 2012 to 15% in 2017. The vast majority of this VC investment goes to the USA (74%) compared to Europe (14%). This confirms that whilst Europe is well positioned in terms a strong research base and excellent health data, it is less well placed in translating research and innovation into industrial applications and in VC funding supporting innovative companies to set themselves up and scale up. There are however exceptions, as in the case of the BioNTech company, leading the development of one of the COVID-19 vaccines.

Key Conclusions

We highlight, in conclusion, three axes likely to acquire relevance in the coming years: In the short term, the lower-hanging fruit of AI applications in health care is represented by operational applications, streamlining tasks and processes, which are at a mature stage and are already deployed in several industrial sectors. In the medium term, the priority is to increase access to health data and ensure its interoperability. This is critical to concretely allow healthcare actors to develop and use AI technologies. Europe is well positioned in terms of the wealth of health data gathered by the Member States but to unleash this potential needs to implement the common data spaces envisaged by the European Strategy for data. Finally, in the long term, AI applications cannot thrive in the healthcare domain without the upskilling of healthcare practitioners at all levels. Therefore, data science should become part of their education and training, so that they are empowered to become active players in the development of AI solutions and not just passive users.

Foreword

This report is published in the context of AI Watch, the European Commission knowledge service to monitor the development, uptake and impact of Artificial Intelligence (AI) for Europe, launched in December 2018.

AI has become an area of strategic importance with potential to be a key driver of economic development. AI also has a wide range of potential social implications. As part of its Digital Single Market Strategy, the European Commission put forward in April 2018 a European strategy on AI in its Communication "Artificial Intelligence for Europe" COM(2018) 237. The aims of the European AI strategy announced in the communication are:

- To boost the EU's technological and industrial capacity and AI uptake across the economy, both by the private and public sectors
- To prepare for socio-economic changes brought about by AI
- To ensure an appropriate ethical and legal framework.

Subsequently, in December 2018, the European Commission and the Member States published a "Coordinated Plan on Artificial Intelligence", COM(2018) 795, on the development of AI in the EU. The Coordinated Plan mentions the role of AI Watch to monitor its implementation.

AI Watch monitors European Union's industrial, technological and research capacity in AI; AI-related policy initiatives in the Member States; uptake and technical developments of AI; and AI impact. AI Watch has a European focus within the global landscape. In the context of AI Watch, the Commission works in coordination with Member States. AI Watch results and analyses are published on the AI Watch Portal ().

From AI Watch in-depth analyses we will be able to understand better European Union's areas of strength and areas where investment is needed. AI Watch will provide an independent assessment of the impacts and benefits of AI on growth, jobs, education, and society.

AI Watch is developed by the Joint Research Centre (JRC) of the European Commission in collaboration with the Directorate-General for Communications Networks, Content and Technology (DG CONNECT).

This report presents a sectoral analysis of AI Watch focused on the uptake of AI in the health and healthcare sectors. Its key aim is to act as a benchmark for future editions to be able to assess the changes in uptake over time in line with the mission of AI Watch. The report is based on the methodology described in Craglia et al. (2020) which centred on four components:

1. Scanning and analytics
2. Partnerships
3. Reviews
4. Longitudinal panel studies.

The restrictions to travel and meetings imposed by COVID-19 limited the ability to establish the longitudinal panel necessary for further studies of impacts. These will be available in future editions of this report. This first edition therefore focuses mainly on the outcome of the first three strands of the methodology, and in particular scanning and analytics and reviews.

Another report on AI and Health (Barbas et al. 2020) is being published by the JRC focusing on the strategic autonomy of Europe in this key value chain. The synergy between the two reports has been assured through cross authorship and reference.

1. Introduction

The potential of AI applications in health care is the object of considerable interest. Governments in Europe, but also other countries such as Japan and India, are giving AI applications in health a high priority due to factors such as aging population and shortage of health care professionals (McKinsey, 2020). As an example, the national strategies of Belgium, Cyprus, Denmark, Finland, France, Germany, Hungary, Italy, Latvia, Lithuania, Malta, Poland, Spain, Sweden, and the UK all refer to healthcare as one of their priority sectors [van Roy, 2020]. A JRC AI Watch survey of 200 European AI projects in the public sector (Misuraca 2020), found that health-related ones are the third most numerous (35) and, in this cohort, 22 initiatives are geared towards increasing performance and effectiveness of such services. Furthermore, in a survey of 18 European countries, the health sector ranked first as the policy domain to prioritize in the future (Misuraca, 2020).

The European Commission has also identified health as one of the key applications for AI in a number of policy documents reviewed in Section 5, and the High-Level Expert Group established by the European Commission in 2018 as part of its AI Strategy (EC, 2018a) has also included health as one of the three sectors for which it has provided specific recommendations on investment (the others being advanced manufacturing, and public administration).

Whilst the level of interest and the number of pilot projects and experimentations are growing, the level of diffusion is still relatively low and most projects are just at an initial stage to "test the water". As an example, a survey[1] by the Observatory on Digital Innovations in Health of the Politecnico di Milano in 2018 of practitioners and managers of health institutions in Italy revealed that only 20% of the respondents identified AI as a priority and that the overall level of investment in AI was rising but was still very low (€ 7m) against an overall expenditure for digital innovation in health of some € 1.4 bn. in 2018.

Public sector organisations are understandably more cautious in adopting AI, while there is greater interest in the commercial sector as well as research as we show in this report. Notwithstanding this increasing interest, the application of AI in health is not without its critics: for example, in a recent article in Nature Medicine (Panch, 2019), the authors express vigorous skepticism about using, at this point in time, AI algorithms and models in the front lines of clinical practice, identifying the challenges of both a cultural change and infrastructural upgrade.

While clinical applications of AI are perhaps the most visible, we adopt in this report a wider taxonomy, borrowed from the American Hospital Association report (AHA, 2019b), featuring four big areas of applications: Administrative, Financial, Operational and Clinical. These areas convey a more complete picture of the AI potential in health services, such as hospitals.

Following this introduction, Section 2 assesses the position of Europe on AI and health with respect to the global landscape, building on the AI Watch report on the AI global landscape by Samoili et al. (2020). Section 3 focuses on technology availability levels, Sections 4 and 5 review the increasing interest in AI and health/healthcare in the scientific and research domains, Section 6 focuses on industrial innovation through the analysis of patents and venture capital, Sections 7 and 8 give examples of local and European initiatives, and Section 9 draws the conclusions.

2. Global positioning

The AI landscape based on the Techno-economic segment (TES) methodology described in Samoili et al. (2020) identified just over 31,000 key players active in the AI global scene from 2009 to 2018, of which 28,000 are firms and 3,000 research institutions. A key player can be a company, research institution or governmental authority involved in one or more of the following economic activities: R&D processes -research and innovative developments-, general economic processes -industrial production, marketing and other services-, firms funding –venture capital funds or other types of investment (De Prato et al. 2019).

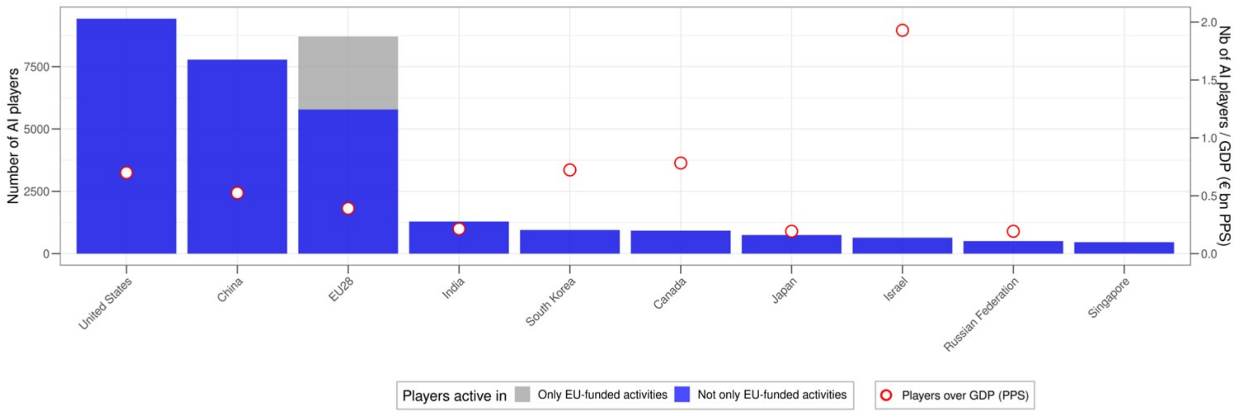
Players with same names, but different geographic location, as e.g. multinational enterprises with several branches, are considered as distinct players as they may engage in different sets of activities with different partners. Therefore, when considering the number of activities, they are treated separately, but when considering the number of players they are merged to avoid double-counting.

Figure 1 shows the overall geographical distribution of identified AI players. As shown, the US has the largest number of players, followed by the EU and China. The EU is notable for the large number of players active in

1 https://www.osservatori.net/it_it/osservatori/comunicati-stampa/spesa-sanita-digitale-italia

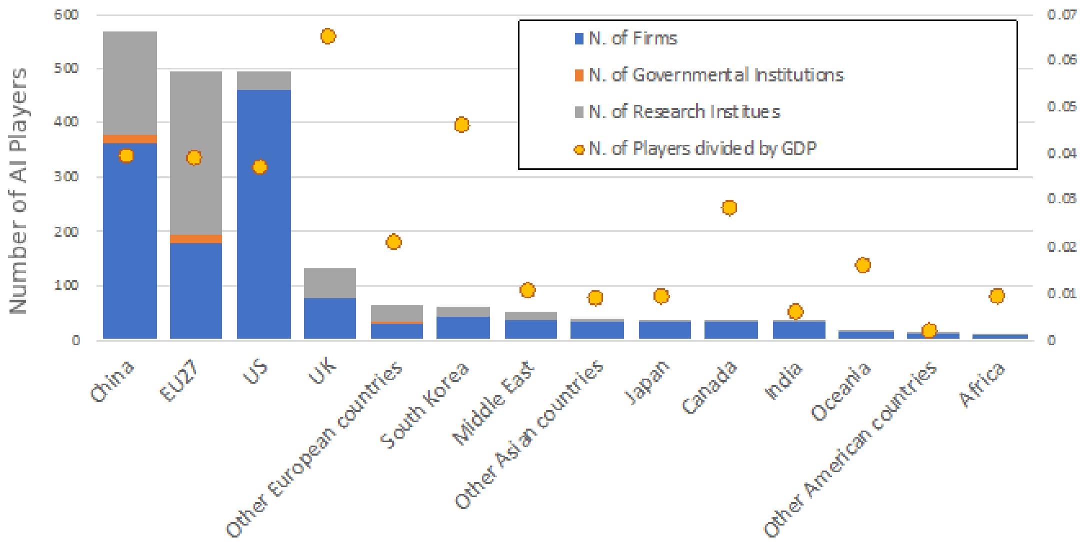
the European Union research programmes. When compared to their national GDP, Israel, Canada and South Korea stand out for their number of players. When filtering these players to search for those active in both AI and health, we found some 2000 players, i.e. about 6% of the total distributed as shown in Figure 2.

Figure 1: Top 10 world geographic areas by number of AI players: Absolute number and Relative to GDP(€bn in PPS), 2009-18



Source: Samoili et al. 2020a

Figure 2: Number of AI and Health players by geographical macro-area and type of players.



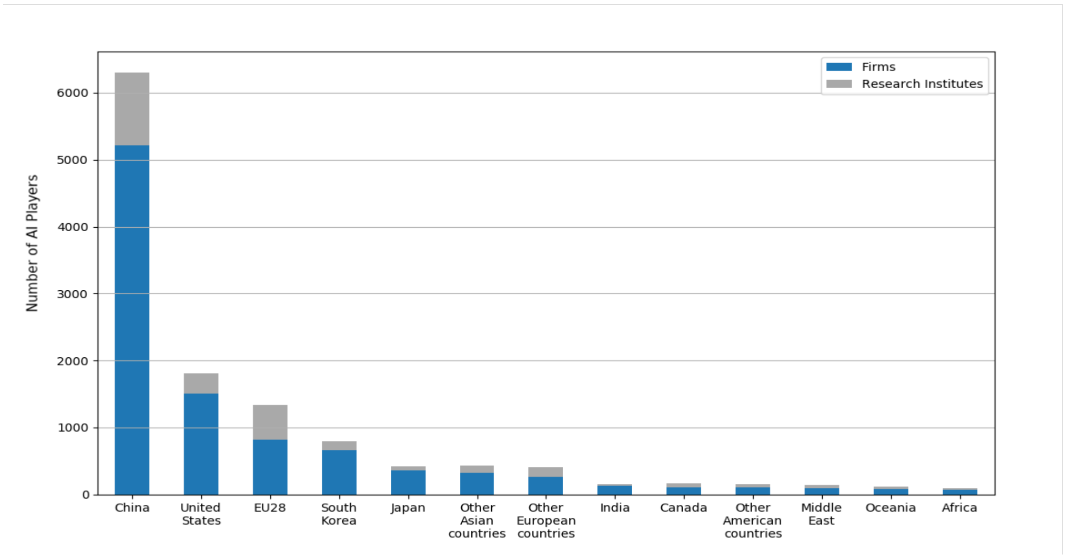
Source: Barbas et al. 2020.

Note: a governmental institution is a governmental research organisation or institution that, as in the definitions of players, has participated in one or more of the following economic activities: R&D processes, industrial production and marketing, specific AI-related services.

The figure shows that China is the most active country in AI and health, followed by the EU27 (to note that in Figure 1 the EU included 28 Member States, as UK was still a Member State at the time) and the US. What is very noticeable is that, in the EU, almost two thirds of players are involved in research, against the approximately one third in China, while in the US the number of research institutions involved in AI and health is negligible compared to the industrial players. Looking at the numbers of players weighted by GDP, the UK stands out as having the greatest number followed by South Korea.

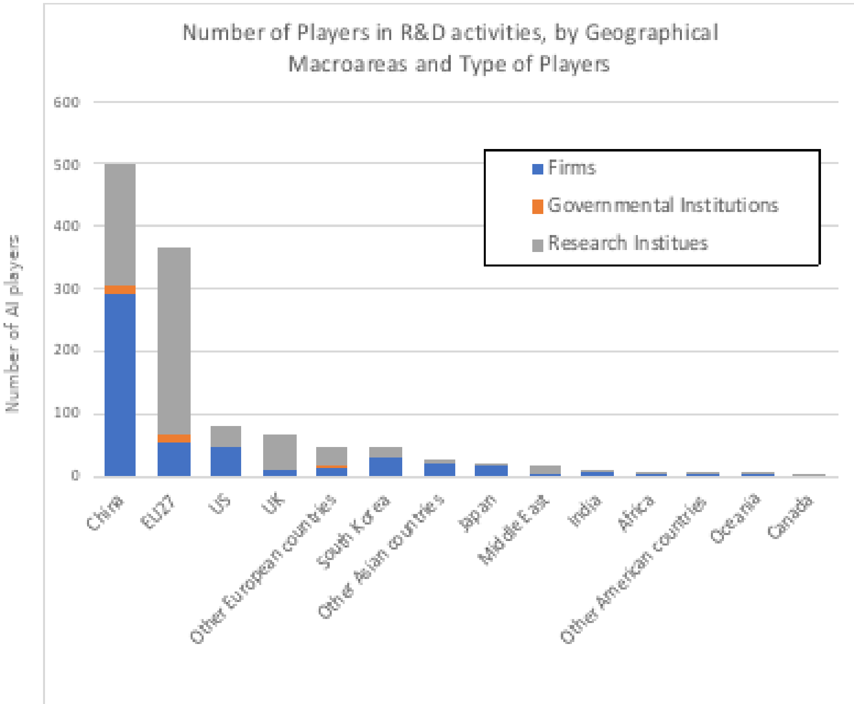
When focusing on the number of players active in research (i.e. submitting abstracts in top level AI conferences, participating in research projects or patenting) Figure 3 shows the situation across all AI players, while Figure 4 focuses on the ones active both in AI and health.

Figure 3: Global AI players in R&D



Source: Samoili et al. 2020a

Figure 4: AI & Health players in R&D



Source: Barbas et al. 2020

Comparing the two figures, it is worth noting that China is way ahead in the global landscape for all AI players (Fig. 3) largely because of the large number of patents it files (Almost 60% of the world total, see Sec. 6.2) while in the AI and Health domain, its position is still in front but not so dominant. Furthermore, the EU27 shows a very strong research component that puts it ahead of the US insofar the number of research institutes is concerned (Fig. 4). At the same time if we compare Figure 4 with Figure 2, it is also clear that in the US the sector of AI and Health is strongly dominated by commercial firms that may be doing internal R&D

without being very visible in the research community. Therefore, it is not so surprising that when focusing on the R&D sector, the US does not seem to feature so strongly.

2.1 Analysis by health topic

The profiles of the key players in China, EU, and the USA, using or developing AI for health were analysed with respect to the health subtopics summarized in Table 1. The methodology and full list of topics included in each group are described in Barbas et al. (2020).

Table 1: Application categories in AI and Health

Health sub-topic	Topics included (examples)
COVID-19	studies and activities related to pandemics and contact tracing apps
Sovereignty	cybersecurity, data governance, stakeholder involvement
HTA	health technology assessment
Prevention	wearables, hospital info systems, cardiac devices
Diagnostics	screening, diagnostics, image analysis, health data analysis
Public health	big data analysis, social medicine
Devices	modelling of physical properties, device design and development
Pharmaceuticals	drug and vaccine development.

Figure 5 compares the profile of the three key macro-areas based on the health sub-topics of Table 1 by looking at the activities in which the players have been involved.

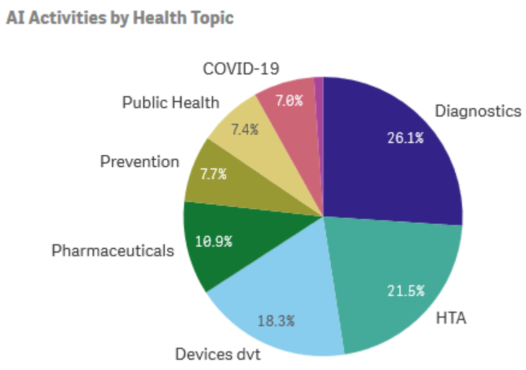
An activity can be research and innovation processes, industrial production, trade and marketing, specific AI-related services, firms funding (venture capital funds or other types of investment). These activities may be either stated explicitly, e.g. inside the description of company activities in business registers, or derived from analysis of their R&D activities, e.g. inside text of conference proceedings, research projects or patents. Furthermore, the number of activities includes:

- Industrial Capacity: number of activities related to firms (production, trade, investments),
- Innovative (disjoined) potential: number of patents filed by single applicants – carrying "potential" for development,
- Inner innovative network capacity: number of internal (same geographical area) collaborations in filing patents – shows effectiveness of internal innovation network,
- R&D (disjoined) potential: number of single-authored research publications in top AI conferences,
- R&D network capacity: number of internal (same geographical area) collaborations for publications in top AI conferences – effectiveness of internal research network,
- Strategic Worldwide Network Influence: number of external collaborations across geographical areas – measures the degree of centrality of individual macro-areas and their capacity to influence the overall AI & Health ecosystem network,
- Knowledge accumulation (with/without Horizon 2020 projects): access to information and knowledge for individual macro-areas through their own activities and all types of collaborations (Barbas et al., 2020).

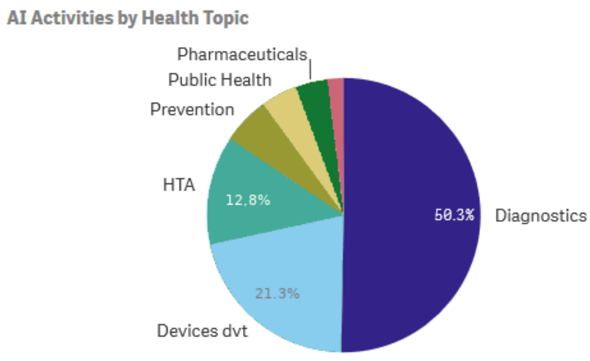
As shown, China is particularly active in technologies and methods related to diagnostics which includes image processing/recognition while the EU and the US have similar profiles with Europe having a slightly stronger focus on diagnostics and the US a stronger focus on prevention methods and technologies.

Figure 5: AI Activity by health topic

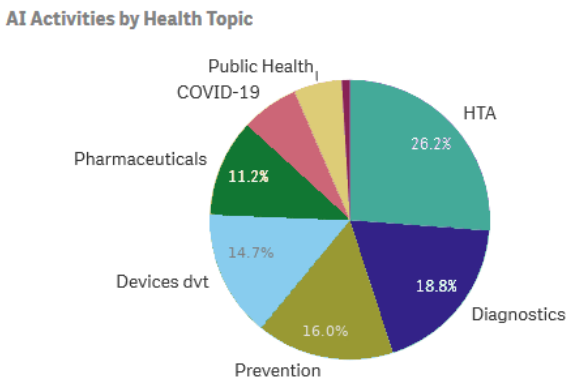
EU



China



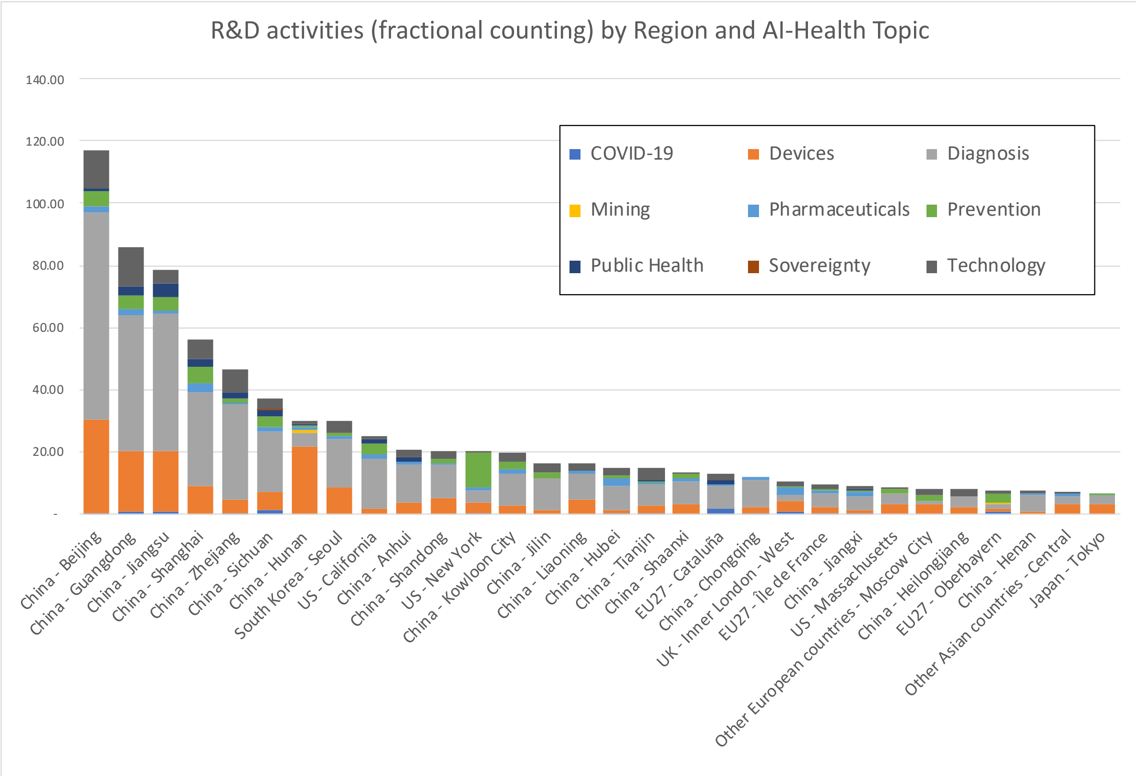
USA



2.2 Regional specialisation

Figure 6 uses the same categories of Figure 5 to show the geographical specialisation by regions. As shown, all the top regions are in China with a large focus on diagnostic equipment and methods, followed by Seoul in South Korea, California and New York in the USA. European regions that emerge are Cataluña, London and Paris in the lower end of the graph. The data here is however strongly influenced by the number of patents filed in China (see also Section 6).

Figure 6: R&D activities by region and AI & Health topic



3. Technology availability of AI in medicine and healthcare

Gómez-González and 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 over 600 references representing the state-of-the-art research and technology, including software, personal monitoring devices, genetic tests and editing tools, personalized digital models, online platforms, augmented reality devices, and surgical and companion robotics.

Figure 7 presents a 'visual overview' of this 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 the figure, the different applications are assigned a Technology Availability Level (TAL) scale, presented in Table 2. 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 the Figure that applications such as algorithms for computer-aided diagnosis or imagining 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 types of scales are useful to convey practical information about the closeness to the market of a given technology.

AI systems offer opportunities in medical applications in fields 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 7. This level ranges from ‘positive’ or beneficial applications of AI such as software for decision support to improve diagnostic efficiency, to ‘negative’ or harmful areas such as new tools for bioterrorism or the possibility to engineer biological weapons targeted against certain populations.

There are many controversial issues as the same technology can be used for positive applications as well as very controversial or unethical ones (dual-use technology). For example, genetic editing can eliminate inherited defects but could be used to create “designer” babies, while neural interfaces and neurostimulation can help control prostheses but cold also become a vehicle manipulating neural signals and limiting free will (Gómez-González and Gómez 2020).

Table 2: The Technology Availability Level (TAL) scale

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 7: A visual overview of the classification of AI and AI-mediated technologies in Medicine and Healthcare according to their ethical and social impact.

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 inferfaces.	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

Source: Gómez-González and Gomez, 2020.

Note: SW: software, AR: augmented reality, VR: virtual reality, IoT: internet of things. TAL: Technology Availability Level.

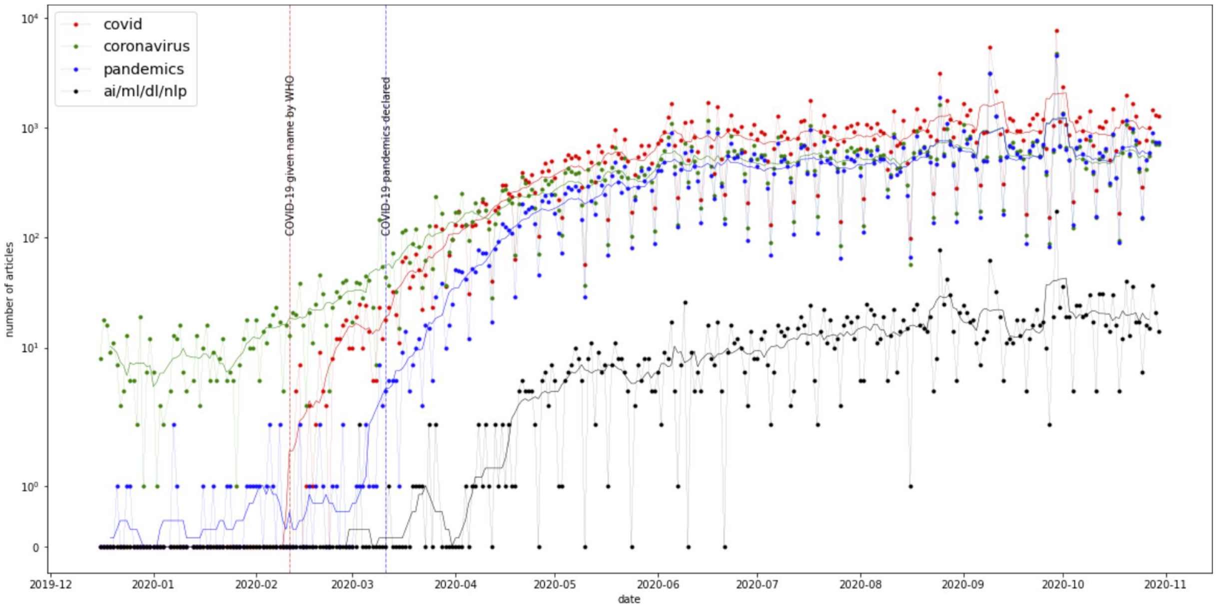
4. Scientific Research

4.1 PubMed Data Analysis

Starting from the medical literature, we have analysed all the citations and abstracts of the papers published in PubMed, around 30 million since 2010, the world's largest and most up-to-date source of medical scientific articles. Pubmed represents a formidable source of scientific literature in medicine, covering the United States and most other countries for articles published in English.

In Fig. 8, we depict the number of daily published articles which contain the words covid/coronavirus/pandemics since December 2019 While the number of articles on coronavirus averaged at about 10 a day up to the beginning of February, it started increasing in mid-February to almost 1000 articles per day, and has plateaued since June 2020. The reason can be attributed to several reasons - from lengthy data collection for the articles to shifting focus of scientists involved in other strands of research down to saturation of research capacity from June 2020 onwards. On the other hand, the sheer quantity of available data allowed data-driven analytics and we see the first articles (black dots in Fig. 8) utilizing artificial intelligence, machine and deep learning and natural language processing being published since April 2020 and increasing ever since. Even with flattening curve of the COVID-19 related articles, the number of articles referring to AI methods still increases.

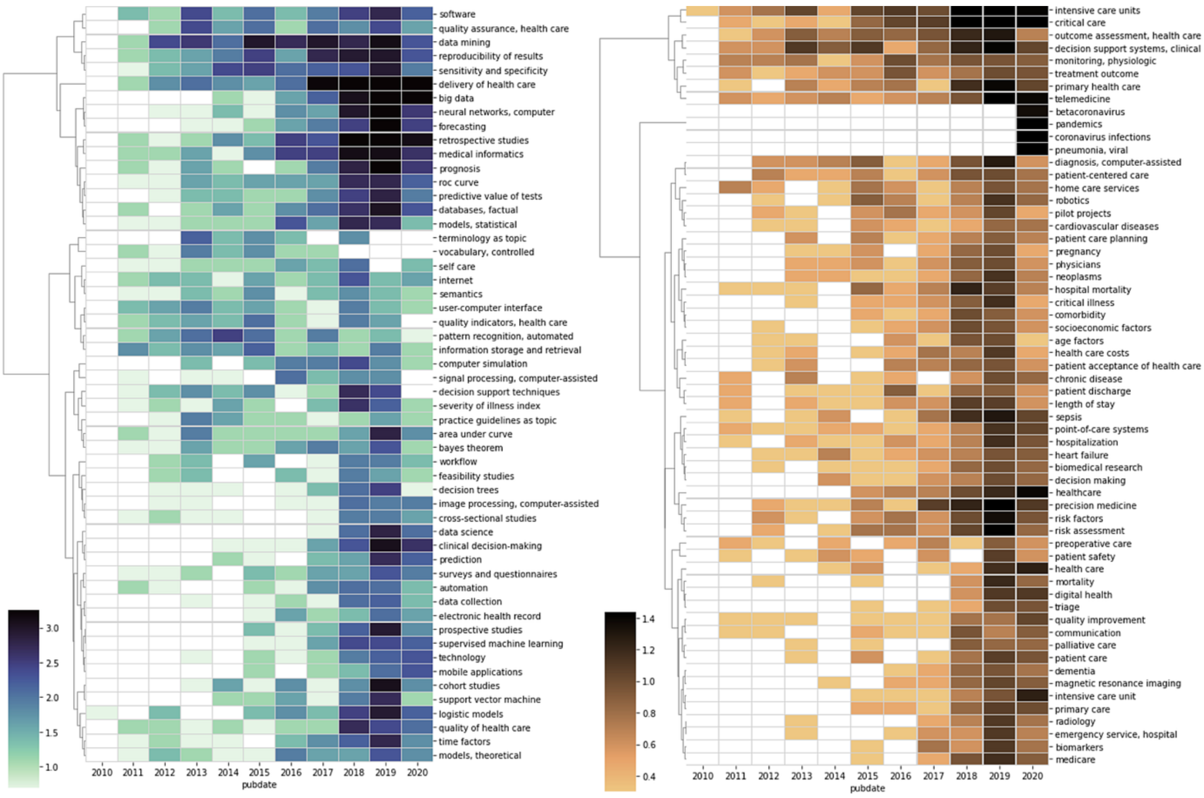
Figure 8: Number of publications on AI and COVID Jan-November 2020



Source : JRC based on PubMed data

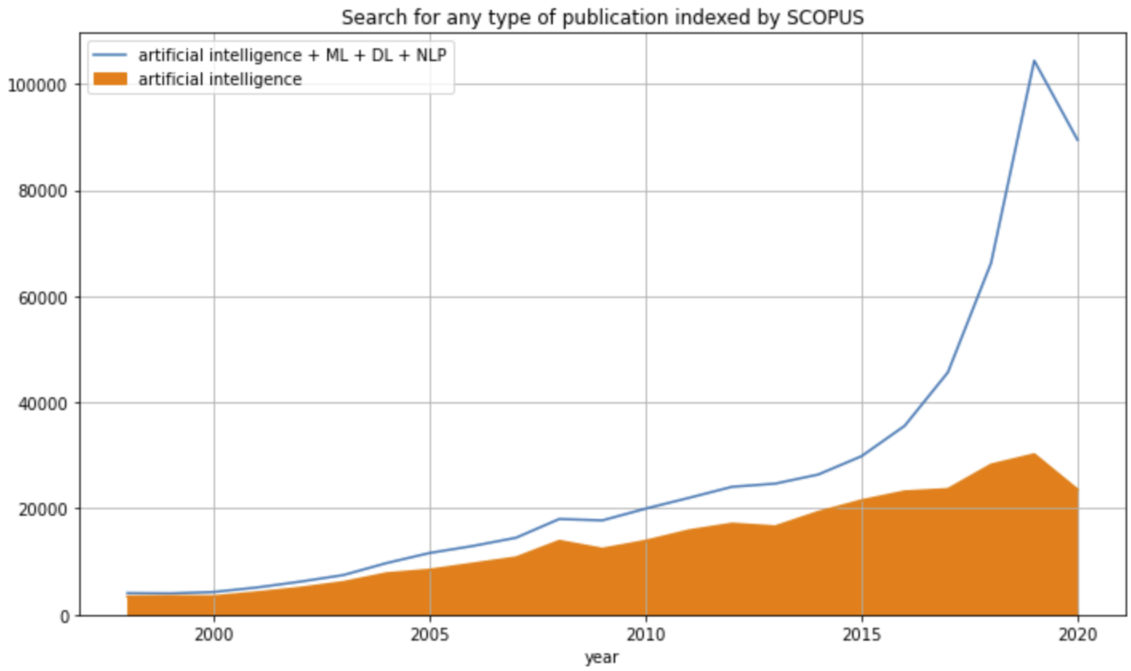
Looking at the 10-year period since 2010 in Figure 9, the first cluster of papers discussing AI-related technologies in PubMed appears in 2012-2014. The strongest concepts emerging are 'data mining', 'algorithms', 'electronic health records' and 'natural language processing'. After a hiatus in the years 2015-2017, two other clusters are visible in 2018-2019: the first is characterised by keywords 'machine/deep learning', 'telemedicine' and 'delivery of health care'; while the second cluster includes 'precision medicine', 'electronic health records' and 'algorithms'. In the first four months of 2020, the range of topics co-occurring with AI is much wider, including concerns, such as ethics, and new applications (e.g. 'critical care'), alongside pandemic-related keywords. The pattern above is also confirmed when looking at the overall growth of AI-related publications in Scopus (Fig. 10), where in 2015, the curve becomes steeper as a consequence of the increasing traction of deep learning.

Figure 9: Publications mentioning AI in the 2010-2020 in ln scale



Source: JRC based on PubMed data

Figure 10: Papers published per year featuring words related to artificial intelligence in Scopus-indexed publications.



Source: JRC based on PubMed data

Digging further into the AI and health articles' topics, we used the Medical Subject Heading (MeSH) thesaurus, by which PubMed articles are tagged. The huge advantage of this thesaurus is its hierarchical structure that allows for finding categories by aggregating the term trees to which the terms pertain.

The 1972 terms found in the 1640 PubMed articles referring to artificial intelligence, machine and deep learning and natural language processing can be used to understand better the dynamics of AI uptake for medical research.

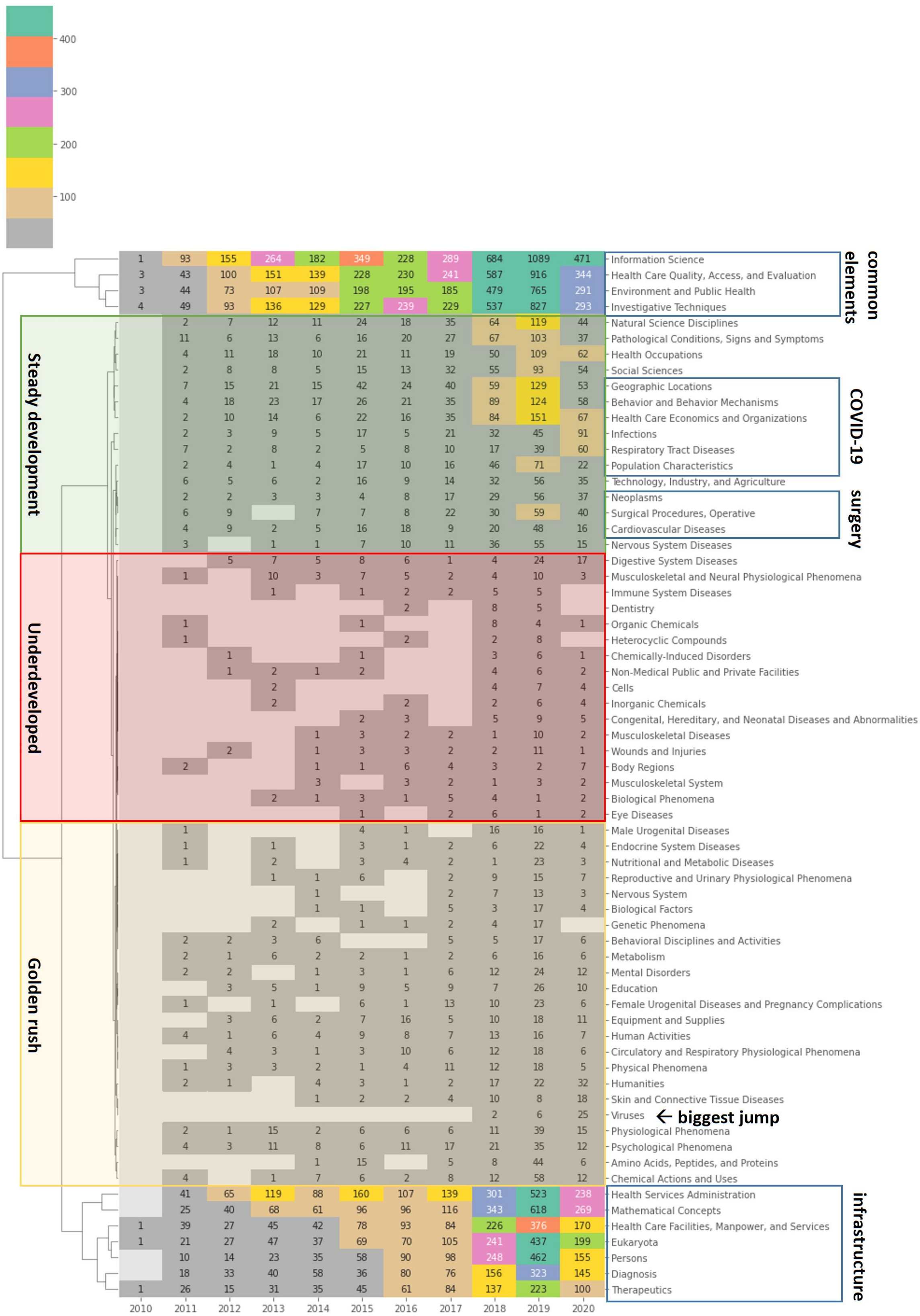
Figure 9 shows two distinct types of the keywords, on the left - the concepts on "how" - the methods, and on the right, those on "what" - the application domains. The terms describing applications are 10-15 times less frequent simply because there is substantially less AI and supportive methods than the areas of application and thus the "what" keywords get diluted when cardinality of terms is the main criteria.

The "application domain" plot (Fig.9 right) has an eye-catching cluster on coronavirus/pneumonia which is new in 2020. The 2020 pandemic-related abundance of data created opportunity to massive application of the AI methods. Critical care gets boost in 2020 as well but there has already been AI applied traditionally. Most striking difference is the 2020 vs 2019 research focus. Since we have used PubMed 2020 data until end of October 2020, we can see how research in several domains (e.g. computer diagnosis, pilot projects radiology, biomarkers, ...) has been superseded by the COVID-19 related research, which is also demonstrated in the Figure 8.

The “methods” plot (Fig. 9 left) shows two large groups of methods. First is the "traditional" one based on databases, data mining and massive big data on the top, which has a long tradition in medical research. The second domain on the bottom shows the increase of novel approaches based on data science and smaller data sets, e.g. coming from cohorts.

To see the whole picture, we have further taken advantage of the hierarchical structure of the MeSH thesaurus, which, as aforementioned, allows for finding categories by aggregating the term trees to which the terms pertain. We have aggregated all 1972 terms found into super-categories (Fig. 11), where the numbers indicate the articles featuring a specific term every year. There are five main clusters of terms as found by hierarchical agglomeration: the two obvious outlier clusters of common elements and infrastructure and three clusters grouped together by the speed of development. In this latter group, the green top category is the steady development group that refers to articles on symptoms, infections, neoplasms, and nervous and cardiovascular diseases, technologies including IoT.

Fig 11: Clusters created by aggregation of MeSH categories.

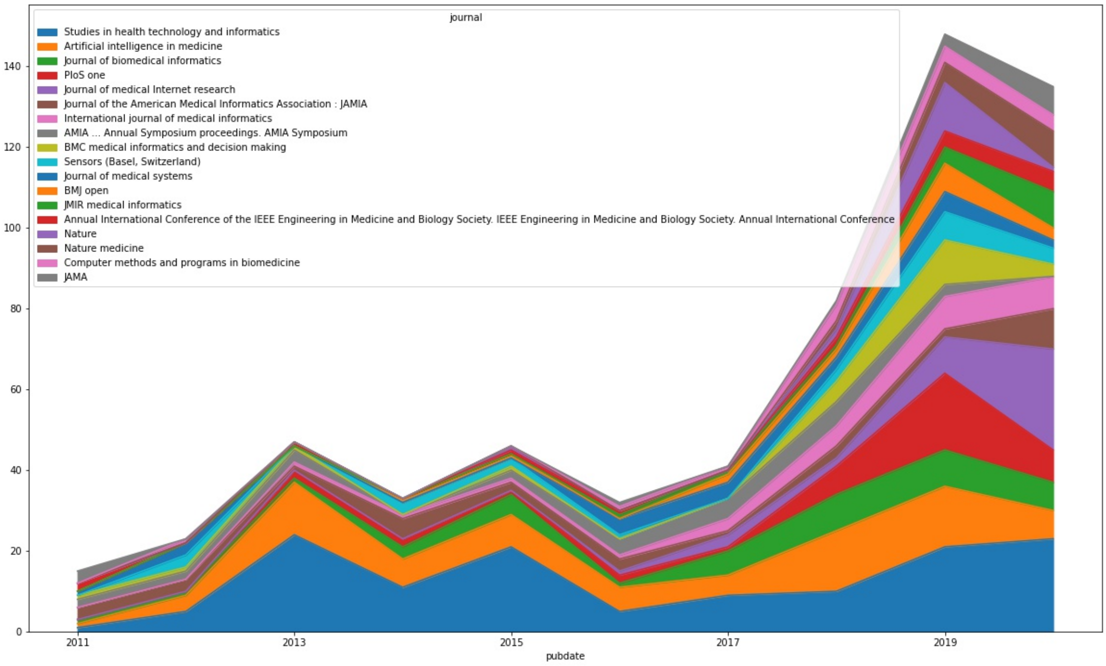


Source :JRC based on PubMed data

Coming to the most active journals and venues in the field of AI and health, we also used the publication date and journal name data to highlight the top ones. As selection criterion, we picked the journals and scientific conferences that have published at least 15 articles on AI and health in the 2010-2020 period.

In Fig. 12, we can see the 18 journals and conferences matching the criteria sorted by the overall number of relevant articles. Most articles have been published in the Studies in health technology and informatics and presented in the American Medical Informatics Association (AMIA) Symposium.

Figure 12: Top journals and conferences in AI and health in the 2010-2020 period



Source :JRC based on PubMed data

In summary, the analysis of PubMed, which is the most comprehensive source of medical publications in the open domain shows a steady increase of articles featuring AI since 2012, with a significant acceleration since 2017, which is in line with the increase in the number of AI and publications in all domains as we see in Scopus. (Fig 10). The Covid-19 pandemic has given further impetus with published articles and citation increasing by 3 orders of magnitude in 2020 form around 10 to about 100 per day.

4. 2 Highlights from the literature

AI applications hold a significant potential for enhancing and streamlining existing tasks in medical practice and creating new opportunities, for instance giving patients more control over their health. In this section we briefly summarize some of those opportunities along with some challenges, highlighted in the literature, both for patients and health care practitioners, stemming from the introduction of AI in the healthcare.

4.2.1 Opportunities

Support to Health care professionals AI applications can support healthcare professionals in fields from radiology to mental health (Topol, 2019a). Image processing with deep learning algorithms over large datasets can provide more accurate and faster assessment of X-rays, CT scans and images. Furthermore, natural language processing and knowledge management can be used to build sophisticated clinical decision support systems which can match symptoms to the related illnesses and suggest treatment, drawing on large corpora of medical documents and texts. Furthermore, the ability of AI to learn patterns in time-series of data is used in an array of smart wearables that, for instance, monitor blood sugar levels and administer insulin accordingly.

Beyond the purely clinical standpoint, there is an increasing awareness of the impact AI can have on the whole health system particularly for administrative and operational tasks. For example, Rajkomar, (2019) analyses applications such as patient triage and streamlining billing. The technologies involved in these cases are speech recognition and chatbots, which are also very powerful in mental health applications, recommender systems and process optimization. AI technologies to make workflows more efficient, such as optimising appointments scheduling or stocks managing, are often very mature. They can leverage algorithms that have been operational since the nineties and therefore, as noted by AHA (2019b), could be the low-hanging fruit for AI deployment in healthcare in the short term.

Support to Patients On the patients' side, AI applications can extend their control over their health and wellbeing (Gómez-González, and Gomez 2020; McKinsey, 2020) through telemedicine. In chronic care management, for instance, medication compliance can be enhanced by mobile apps suggesting the treatment in a timely manner and alert systems powered by computer vision can support patient oversight. Systems as these can help reduce the need for assistance or hospitalization, allowing the patient to stay for longer periods in a familiar environment, and can also provide physicians with a comprehensive bulk of data on the patient's condition. Furthermore, smart wearables such as insulin pumps or portable electrocardiogram devices can help manage ailments such as diabetes and cardiac diseases, preventing critical episodes.

Empowerment for patients from AI can also come in the form of information (Gómez-González and Gomez, 2020). Symptom checkers can give an immediate assessment to the patient, possibly avoiding long waiting times in emergency rooms. Such tools, together with affordable genome-sequencing tests, can lead to a much more informed patient, also reducing the 'information asymmetry' between patient and the doctor. Internet platforms dedicated to health contribute to such awareness of the patient, with the danger, however, of being exposed to sometimes erroneous and unreliable information.

Synergy between doctors and developers Most AI solutions and applications are developed in research centers and companies to be then deployed in the clinical workflow (McKinsey, 2020). However, as detailed further in the following sections, building models drawing from the domain knowledge of clinicians could dramatically improve their quality and, to this end, an interdisciplinary setting between computer science and medicine should be envisioned for their development (McKinsey, 2020, Topol, 2019a, AHA, 2019a, Bortolin, 2020). Practical examples of knowledge transfer from the computer science community exist in the medical literature: for instance, Rajkomar (2019) articulates the conceptual flowchart of a supervised learning model and a list of questions to assess the type of model required to tackle a given problem through the lens of AI.

On this synergy between the practitioners and the 'machine', Topol (2019a) draws inspiration from the five levels of automation defined by the Society of Automotive Engineers (SAE) for vehicles: with Level 0 corresponding to no automation at all, an unassisted human driver, up to Level 5 being full control by an automatic system, without possibility of human intervention or backup. In their assessment, medicine will likely plateau at Level 3, i.e. a conditional automation with human oversight over algorithms' outputs, given the high social and ethical stakes.

4.2.2 Challenges

The nexus between AI and health care is characterised by conflicting priorities, such as the paramount importance of data privacy against the necessity of aggregating masses of data to train models accurately.

Technical From a technical standpoint, many scientific papers featuring AI applications for healthcare are often in their early stage, carrying a number of methodological flaws noted in the literature (Topol, 2019a, Panch et al., 2019, Ghassemi, 2019).

Firstly, there is concern over AI models that are based on small and statistically biased datasets, which can critically hinder their accuracy and reliability. Algorithmic bias can be introduced, for example, by under-represented cohorts of patients or, for supervised learning, by inconsistency in labelling the training data (Ghassemi, 2019). This last step, relying on human experts discerning signals of the disease in the data, is pivotal for the quality of the AI model's output. However, as clinicians' assessment may vary, techniques from unsupervised learning can be deployed to mitigate labelling uncertainty. To counter data paucity, dataset sharing should be a desirable practice and, in this regard, the COVID-19 emergency already catalysed the emergence of dedicated platforms. "Data against COVID"[2], for instance, is an exemplary initiative matching data brought by practitioners and expertise brought by data scientists. The development of a European common data space for health envisaged by the European Strategy for Data (EC, 2018b, EC, 2020a) is also a very important step in this respect.

Secondly, the quality of the studies themselves is of paramount importance: Nagendran, (2020) and Liu et al., (2019) performing a review of deep-learning applications in medicine, identified in their sample a majority of studies of poor statistical design. Some of the flaws included not using randomized trials, not adhering to existing guidelines and hindering reproducibility by not sharing code and datasets. This lack of quality is particularly pernicious when paired, as the authors remark, with overpromising language opening the door to misinterpretation and fuelling the hype around AI in medicine.

Incorporating domain knowledge is another fundamental ingredient to have an efficient deployment of AI solutions. As mentioned earlier, the design of an AI model needs to incorporate the expertise of both computer scientists and medical practitioners to make sense of the data correctly . A promising example of this virtuous synergy emerged among COVID-19 AI applications. Shan et al. (2020) used a human-in-the-loop approach, alternating rounds of training and manual labelling of CT scans. Both the AI model and the expert labelling process were improved by this protocol, demonstrating the effectiveness of such hybrid approach.

Last but not least, further development of the health IT infrastructure is needed, with a particular focus on interoperability (Topol, 2019b). Most existing medical data is not “AI-ready” for algorithm development, or of high enough quality, for example often not exchangeable, difficult to process or interpret and error-prone. The electronic health record would constitute a formidable source of patient-level data for AI development, but it is available in only a few OECD countries, where national data are organised following a “one patient, one record” criterion and are standardised and interoperable (OECD, 2020). Nevertheless, as pointed out by Topol (2019b), the implementation of the health care record and of a sustainable infrastructure are the necessary foundations for delivering on AI in health care.

Social and ethical issues The caveats raised by AI technologies in healthcare extend their ramifications far beyond the technical ones. Gómez-González and Gomez (2020) provide a high-level overview of the ethical and social implications, building on the analysis of more than 600 scientific references. They identify three overlapping groups of implications: common aspects to the use of AI at large (e.g. security and anonymity), aspects of particular relevance for healthcare (e.g. empathy) and ethical issues related to applications such as gene editing and bio-terrorism.

The first group includes most of the challenges mentioned in the technical paragraph above which become more important in healthcare given the sensitivity of the data involved and the possibly catastrophic implications of errors and failures.

The second group considers the human aspects of medical practice such as the relationship between doctor and patient which is based not just on professional knowledge but also on empathy and trust, both of which are possibly affected by the introduction of AI in clinical practice. The impacts can be either positive or negative depending on how the process is handled: for instance, empathy can be enhanced by streamlining cumbersome and repetitive administrative tasks and freeing up time for face-to-face interaction with the patient. On the other hand, empathy may be reduced in the context of telemedicine, where long-distance monitoring and assistance reduces human contact. Furthermore, in the context of online tools for symptom checking, it is often difficult for a patient to discern the pertinent information and interpret it correctly without the skills of a trained doctor. These tools could also exacerbate inequality: digital literacy is a prerequisite for their use, and seeking health information online varies strongly with education, with those less educated also being less able to engage in such searches (EC, 2019) and in Europe 30% of citizens declared feeling uncomfortable with their ICT skills (Eurobarometer, 2020). Therefore, the opportunities for patient empowerment tend to empower those who already are in a better position and leave further behind the disadvantaged groups. This was also observed in the lock-down response to the COVID-19 pandemic of 2020 which exacerbated inequalities for the elderly, the young, and disadvantaged groups (Craglia et a. 2020).

The third group of issues focuses on the ethical dilemmas of applications that have potentially dual effects. They include for example, the possibility of reading and decoding human brain signals which may challenge the very definition of free will if tampered with, but also offers impaired patients the possibility to directly control their prosthetic limbs through interfaces with their neural system.

Regulation As Gómez-González and Gomez (2020) observe, no AI technology is good or bad in an absolute sense; however, as some of these do have the potential to be harmful, it is necessary to regulate the introduction of AI in healthcare, as in other sensitive areas, with a risk-based approach able to reduce negative effects whilst allowing innovative and beneficial applications to thrive. This is the approach proposed by the European Commission in its White Paper on AI (EC, 2020b) that launched a wide consultation on its risk-based approach to AI regulation with a view to propose legislation in the second half of 2020.

Beyond health data, regulatory barriers may slow down the AI diffusion in health: for example, apps and software for health application are treated as medical devices and vetted through the same strict process for general medical devices. The length of this process is, however, often incompatible with the fast development in the field of smart health; therefore, according to (EASME, 2019), a streamlined approval process for AI applications should be envisioned, also considering the different interaction with a patient that AI solutions may have with respect to more traditional medical devices (EASME, 2019).

5. Horizon 2020 Research projects

Research is one of the main areas of European strength, as was shown in Figure 4. For this reason, we have analysed the over 30,000 research projects funded by the Horizon 2020 R&D programme of the European Union in 2014-21. The project descriptions available in CORDIS, the EU public database of research projects ( ) were analysed for projects related to AI, health and healthcare. The problem is, of course, that the human language is a highly sophisticated and complex instrument, and the same thing can be described in multiple ways. Semantic similarity is a very important tool for being able to identify which projects fall in our scope. Therefore, we have used AI methods in the form of the neural network (Word2Vec) to extract semantically-related concepts. The results for AI, Health and Healthcare are shown in Box 1,2 and3. Box 1 shows the terms semantically related to artificial intelligence.

Box 1: Word similarity for artificial intelligence in H2020 projects

ai, machine_learning, big_data_analytics, computer_vision, deep_learning, big_data_analysis, analytics, deep_machine_learning, big_data, intelligence, data_science, nlp, advanced_machine_learning_engine, advanced_artificial_intelligence, ai)-based, machine-learning, data_analytics, natural_language_processing, machine_learning_algorithms, data_mining, semantic_technologies, artificial_intelligence_algorithms, model-driven_engineering, affective_computing, speech_recognition, computer, ai_algorithms, algorithms, image_recognition, ml, iot, visual_analytics, machine_intelligence, question_answering, cognitive_computing, data-mining, augmented_reality, ai-based, predictive_analytics, information_retrieval, ict_technologies, cloud_computing, image_processing, language_understanding, ai_models, ai_techniques, ai_technologies, natural_language_understanding, vr/ar

As we can see, the neural network was able to extract not only AI-related words in purely mathematical sense, but the applications as well. If a researcher used an AI related word in the description of his/her project, we were able to use it even when the term 'artificial intelligence' was not used.

Box 2: Word similarity for health in H2020 projects:

well-being, wellbeing, overall_wellbeing, overall_health, heath, nutrition, workplace_conditions, wellness, lifestyle, health_outcomes, mental_health, good_health, health_status, social_care, social-economic, psychosocial, public_health, vital_component, poor_health, occupational, life_style, dieting, welfare, overall_mobility, lasting_consequences, consumer_health, health_care, workplace, sensory_impairment, later_life, consumer_behaviours, major_economic_burden, women´s, ageing_european_population, active_monitoring_policy, healthy_ageing, increasing_burden, ageing, reproductive_health, older_age, animal_welfare, european_citizens, pets', lifelong_health, animal_health

Again, the network returns not only the obvious. Wellbeing is mostly associated to good health but social care comes high in the list after health as well as welfare, healthcare and nutrition. Interesting to find economic burden as related to health, cognitive and sensory impairments, and burdens, all concepts that indicate health-related topics. Animal health and economic consequences are just a reminder that the health topic is very broad.

The most interesting results came for the domain of Healthcare, obviously partially overlapping with Health domain but fundamentally different as shown in Box 3.

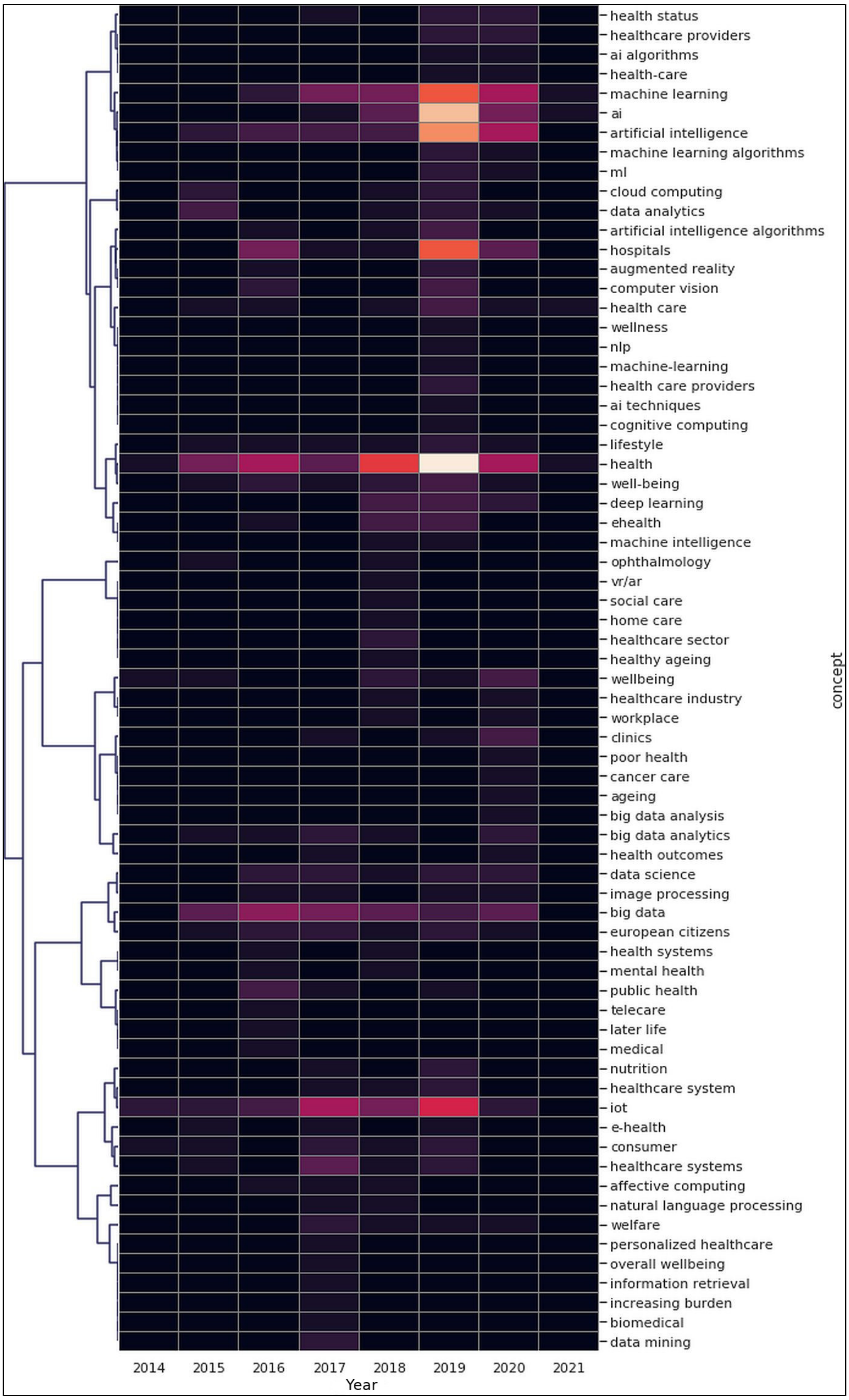
Box 3: Word similarity for healthcare in H2020 projects:

health_care, medical, vital_component, healthcare_sector, healthcare_systems, radiologic, care, social_care, healthcare_products, health-care, clinics, assistive_technology, hospitals, home_care, consumer, healthcare_providers, eldercare, increasing_cost, healthcare_industry, ehealth, health, e-health, critical_care, mre, eu_society, ophthalmology, bioelectronics_implants, better_life, re-treading, medical_technology, personalized_healthcare, digitizing, relieves, health_care_systems, increasing_burden, health_care_providers, food_and_pharmaceutical_industries, telecare, healthcare_system, emergency_care, orthopedic, health_systems, patient-centered, global_healthcare_systems, safer_products, cancer_care, biomedical, care_homes, hydrocephalus

An interesting observation is that the neural network correctly assigns eHealth to the Healthcare and not the Health domain. In the second step, every project has been parsed for presence of the words from the domains above and a score calculated as AI*HEALTH+AI*HEALTHCARE so if AI-related words were not present at all, a score of zero was assigned.

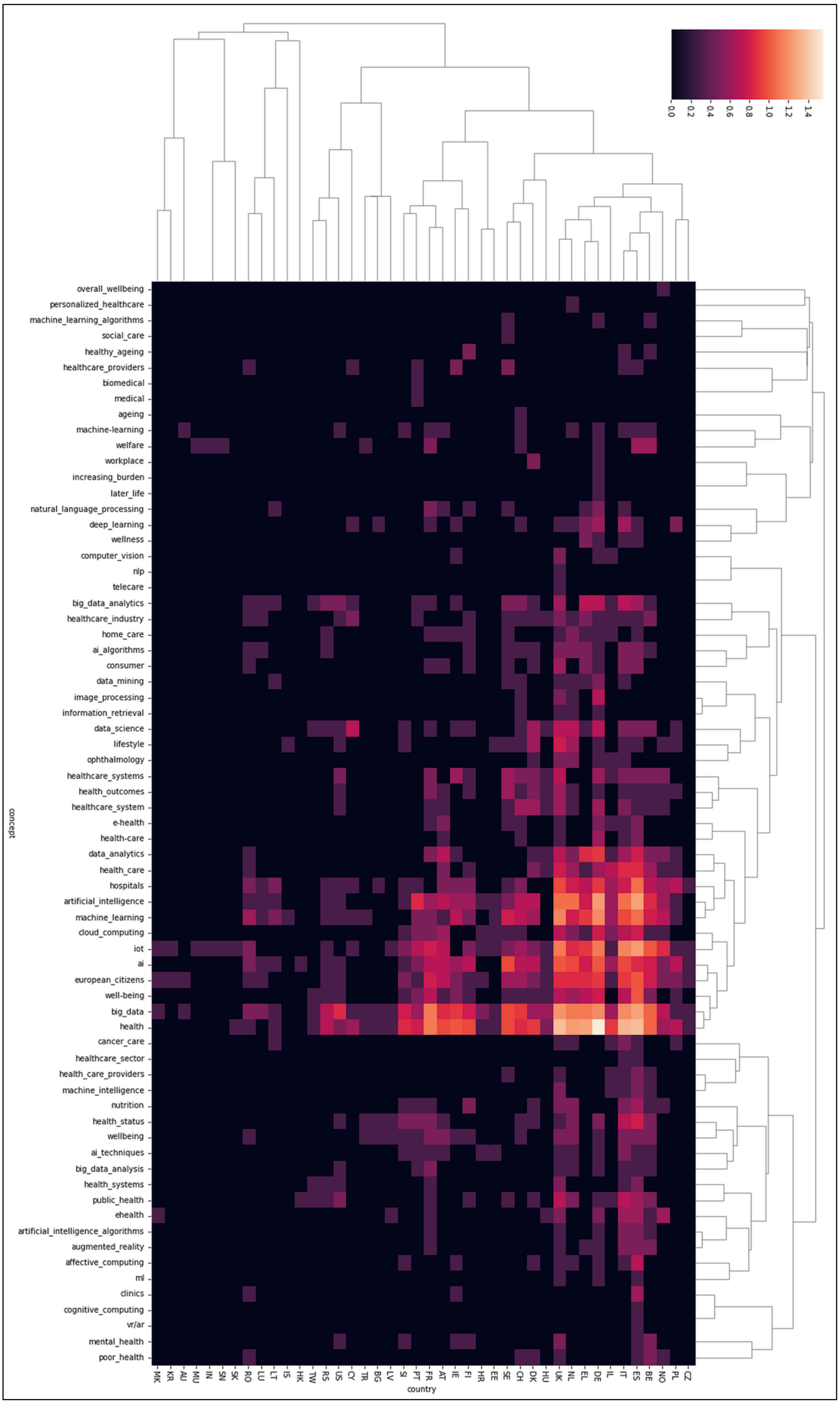
As a result, we identified 146 projects on AI and Health that were also manually checked to identify any wrong assignment: for example, a project on cloud-computing from the AI domain and health referred not to human health but to health in computer uptime monitoring. Figure 13 shows the frequency of topics in the identified project in the period 2014-21, while Figure 14 analyses them by the country of the partners in the projects.

Figure 13: Relevant topics in AI-Health-Healthcare H2020 projects per year.



Source : Cordis data

Figure 14: Relevant topics in AI-Health-Healthcare H2020 projects by country.



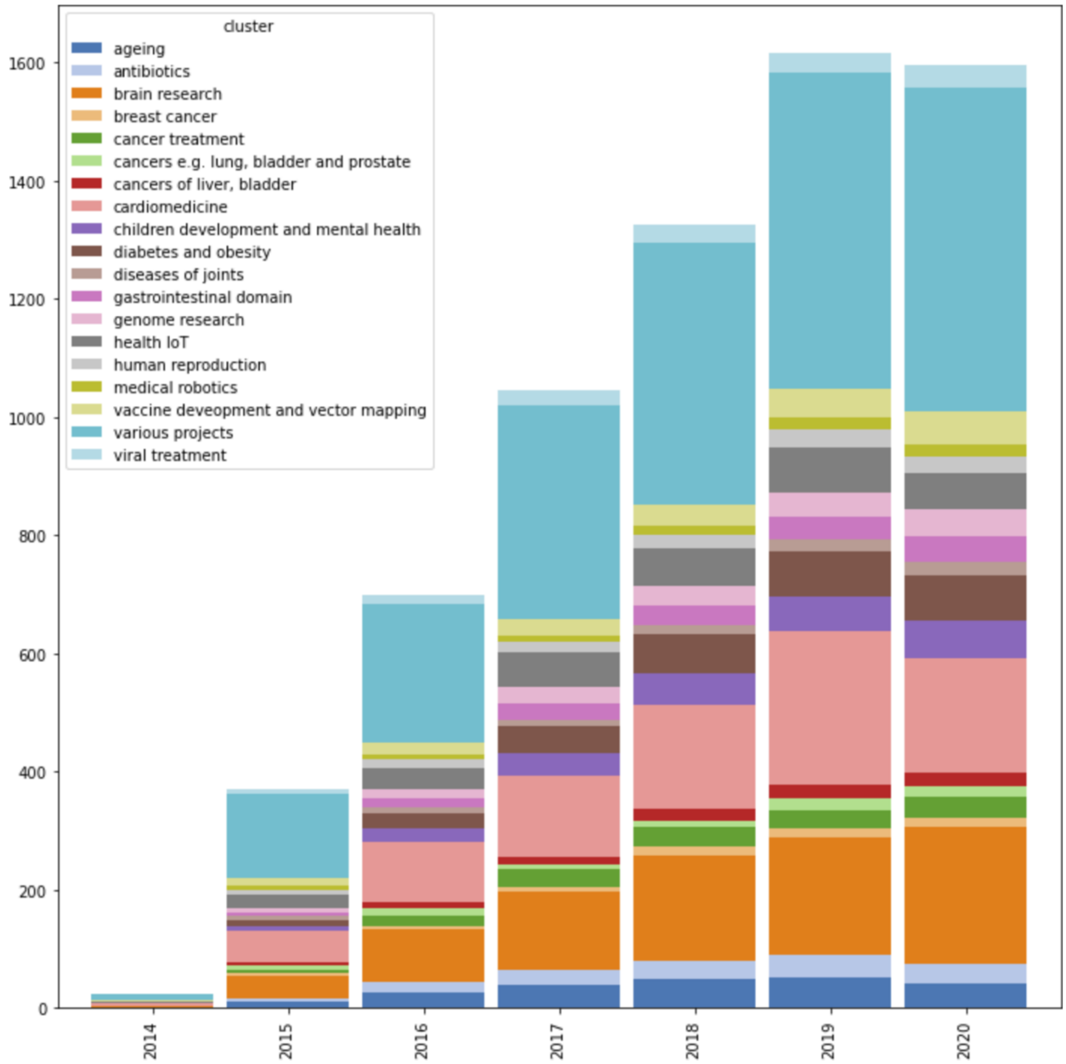
Source : Cordis data

The stronger presence of AI topics, such as machine learning, and health appears after 2017 (Fig. 13). Furthermore, it is visible how 'IoT' gained attention since 2017 (in orange in the figure). Concerning the geographical distribution (Fig. 14), the strongest cluster of concepts (in orange in the figure), is related to projects with partners in Germany, Belgium, Italy, Greece, France, Spain, the Netherlands and the UK.

The emergence of topics such as 'IoT' and 'robotics' appears also when analysing H2020 projects related to health in general. To this end, we have selected 4916 projects containing the word "health" from all the 30902 projects funded under H2020 programme. To understand how the projects group together by semantic similarity, we have calculated sentence embedding for all projects' titles and objectives using SciBERT transformer fine-tuned on natural language inference tasks. The resulting latent space was projected using UMAP algorithm and clustered in HDBSCAN. We obtained groups that, besides human health, span ecosystem health, economic health, animal health and system health.

Focusing on human health, we have identified 30 major groups of H2020 projects in the domain of human health and health care. In Fig. 15, each project is counted for every year it runs and it is possible to observe 'health IOT' and "medical robotics" gaining traction after 2017.

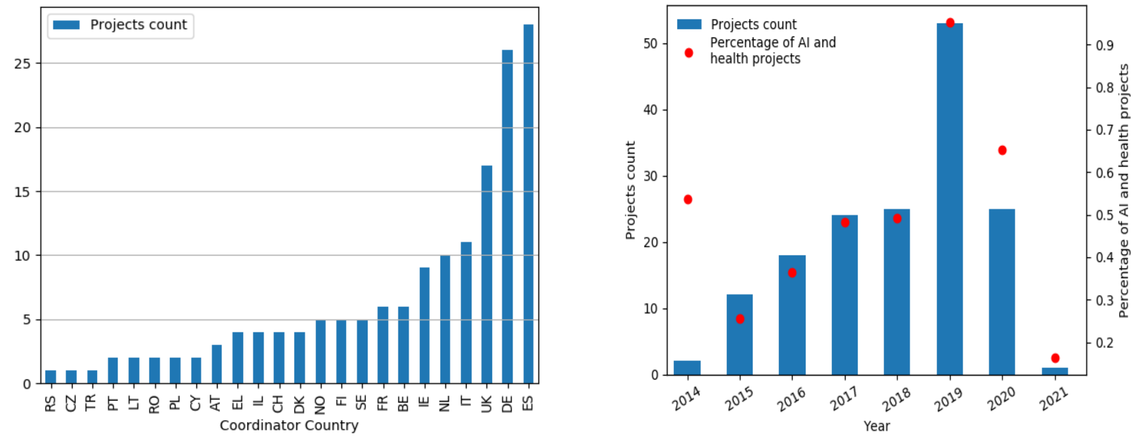
Figure 15: Topic clusters in H2020 on health.



Source : Cordis data

Going deeper in the analysis of the original cohort of 146 projects in AI and health, Spain and Germany lead in coordinating projects, with 28 and 26 projects respectively, followed by the UK and Italy, with 17 and 11 projects respectively (Fig. 16 left). In terms of timeline, 2017 marked the start of the take up in number of projects, peaking in 2019 with 53 starting projects, more than double that of 2018 (Fig. 16 right). As indicated the number for projects due to start in 2020 and 2021 is provisional.

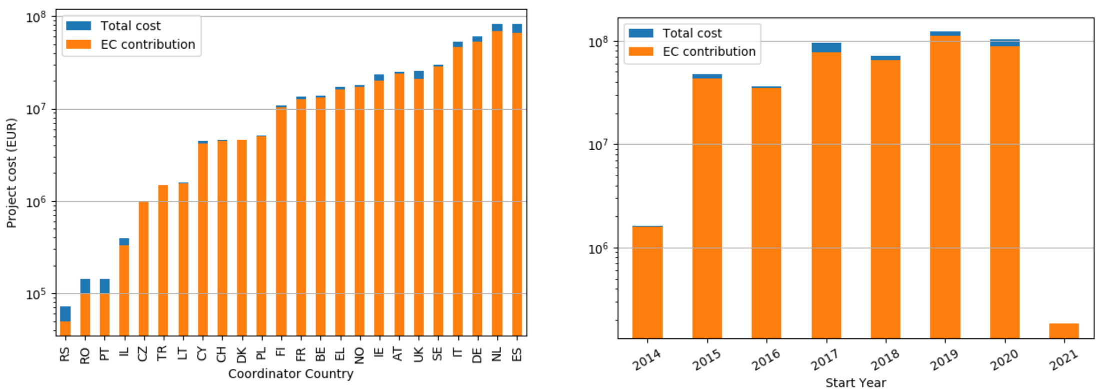
Figure 16: Distribution of AI and Health projects per (left) coordinator country and (right) per year.



Source : Cordis data
Note: number of projects in 2020 and 2021 are provisional

On the financial side, the project funding follows a different pattern, both for geographical distribution and timeline: for this latter aspect, the aggregated funding per year remained relatively steady in the 2017-2020 period, its lowest point being in 2018 with approximatively 71 million EUR and its peak in 2019, with around 122 million EUR. Interestingly, in 2020 the funding already amounts to around 108 million EUR, which is already very close to the 2019 figure (Fig. 17 right) even though the figures on the projects are not yet complete. The geographical distribution of funding (Fig. 17 left) shows that Spain and the Netherlands lead, with around 82 million EUR (for 28 projects) and 81 million EUR (for 10 projects) respectively, followed by Germany and Italy, to which 60 million EUR (for 28 projects) and 52 million EUR (for 11 projects) have been allocated. The value added of European R&D funding is illustrated well by the case of BioNTech spotlighted in Box 4.

Figure 17: Distribution of AI and Health project spending per (left) coordinator country and (right) per year.



Source: Cordis data. Note: number of projects in 2020 and 2021 are provisional

Box 4. Vaccine against COVID-19 enabled by EU-funded research and AI made in Europe

At the beginning of November 2020, Pfizer and Biopharmaceutical New Technologies (BioNTech) announced that their mRNA-based vaccine demonstrated evidence of efficacy against COVID-19. Whereas Pfizer is a well-known multinational biopharmaceutical company, BioNTech has not been at the centre of public attention until recently. Founded in 2008, BioNTech is a spin-off of the Johannes Gutenberg-University Mainz, Germany. Today, with over €20 bn. of market capitalisation and over 1300 employees[3], it belongs to the club of European deep-tech unicorns and develops novel RNA-based technologies that are used to fight COVID-19. BioNTech is an example of a company that integrates Artificial Intelligence (AI) technologies in traditional industries. Discovering and developing new drugs and setting up a production and supply system providing hundreds of thousands of patients with personalized medications requires the development and convergence of innovations in a range of different advanced technologies, such as big data, artificial intelligence, and fully automated analytics and production lines. To this aim, BioNTech uses both proprietary Artificial Intelligence (AI) technology platforms and AI solutions provided by small and large European ICT firms. The research of BioNTech has benefited from the European support for research and innovation since its early days. Until today, BioNTech and its subsidiaries have participated to ten EU Framework Programme projects and received nearly 10 M. Euro of funding. As early as in 2009, the German start-up participated to the PERSIST FP7 project where it explored the use of highly innovative gene-modifying in developing new therapies.[4] In 2013, it set-up and coordinated the MERIT FP7 project aiming at clinically translating and industrially validating the pioneering RNA-based immunotherapies. According to the MERIT project proposal, BioNTech and its partners were committed to generate scientific knowledge and technologies that would stimulate the development of new mRNA-based products, tools, patents, and innovative marketable applications. Today, we can say that the EU-supported project lived up to its promise. Its results have contributed to the creation of a remedy to a disease that has paralysed the entire world.

6. Industry

6.1 Overview of uptake

There is strong interest in AI and related technologies in the commercial sector in Europe as detected by a recent survey of almost 10,000 companies in Europe, mostly SMEs, carried out on behalf of the European Commission in 2020 (IPSOS, 2020). The key findings are that across all sectors, including health, 42% of companies are already using one or more AI solutions, with an additional 18% planning to adopt within two years, while the remaining 40% indicated that they have not implemented or have no intention of implementing AI-based solutions in the near future. We see therefore a high level of interest but with a significant minority yet to be convinced. This is important to ground the discussion which is often characterised by hype and inflated expectations (Topol, 2019a).

6.2 Patents

In order to get insights into the technological innovation flow, we analysed a comprehensive patents database, mined using Orbit Intelligence software by Questel. This database covers the World Intellectual Property Organization (WIPO), the European Patent Office (EPO) and the national authorities in UK, Canada, France, Germany, China, Japan, South Korea and India, totalling over 100 patents authorities.

The database records come in the form of 'FamPat family numbers': such families of patents are invention-based collating together all the publication stages of an invention as well as documents from different patenting authorities.

In the database, we filtered for patents featuring both AI-related and healthcare-related keywords, obtaining 46036 results[5] which represent the 1.75% of the records mined with just healthcare related keywords (N= 2 619 216).

In our analysis, we also considered the distinction between patents and utility models[6] : the latter type of invention protection differs from the patents in duration (they are usually shorter, between 6-10 years), faster

3https://www.wallstreet-online.de/aktien/biontech-1-aktie

4https://cordis.europa.eu/project/id/222878

5 As per 6/7/2020.

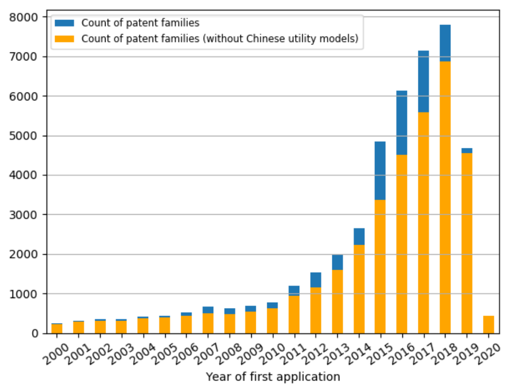
and cheaper to obtain. Furthermore, the degree of innovation carried by the invention is generally lower for a utility model and, according to the specific country regulation, it may be absent altogether. Another important difference with patents is that they can be granted without a search for previous similar patented invention.

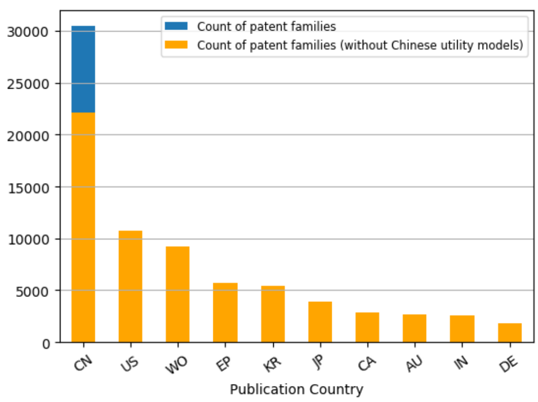
Utility models are a protection tool present in many countries, such as Germany, France, Japan and China, but only China makes a widespread use of them. According to the WIPO[7], the total number of utility model applications worldwide reached 1.76 million in 2017. The IP office of China received 95.8% of the world total – the remaining 74 offices accounted for just 4.2%.

Similarly, our dataset of AI and health applications dropped by 18% to 37673 results when removing Chinese utility models. Conversely, all the other countries' utility models contributed to only 177 results[8], approximatively the 0.4% of the dataset. Hence, in the following analysis we differentiate between numbers with or without Chinese utility models.

The number of applications for inventions (Fig. 18 left) in the healthcare and AI nexus has seen a substantial increase since 2013. China dominates in the number of patents (Fig. 18 right) with 22129, which reach 30492 when including the utility models. US is second with 10735 and WIPO is third with 9173 patents (in Fig 14, under 'WO').

Figure 18: Year of first application and country of patents in AI and health/healthcare





Note: The data for 2019 and 2020 are to be considered provisional because of the 18-months gap between the filing of an application and its publication. As a patent family may cover several publication documents for the same invention, it may therefore be counted in several columns.

Source: based on data from Questel

Having a closer look at the top players (Fig. 19), both with and without utility models from China, the South Korean Samsung Electronics appears to dominate by far the field with over 1400 patents, followed by Siemens Healthcare with around 300. However, as we show in Fig. 22, Samsung patents mostly concern applications and protocols for smart IOT devices, that can be used in healthcare context but they are not specific to it.

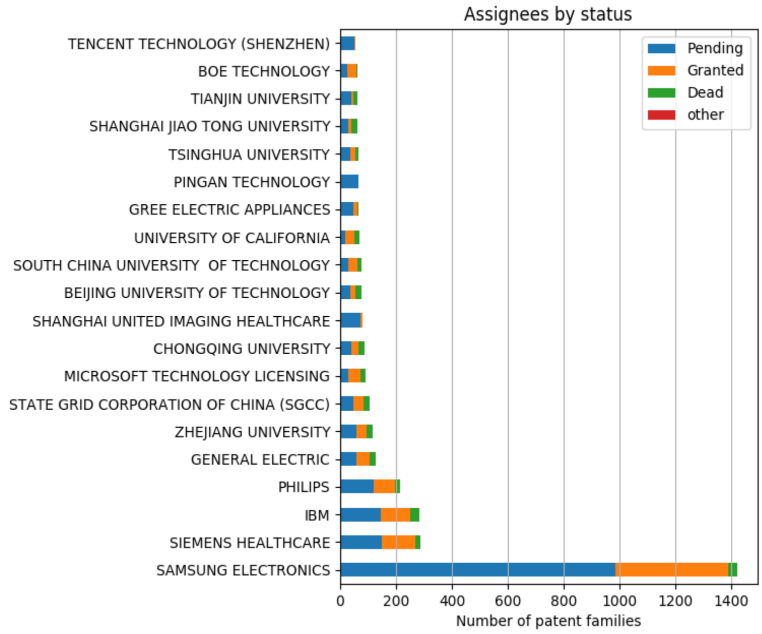
The difference, when removing utility models, is visible in the bottom half of the ranking, with some Chinese universities and companies losing position, as for example the South China University of Technology, while others rank higher such as Tencent Technology.

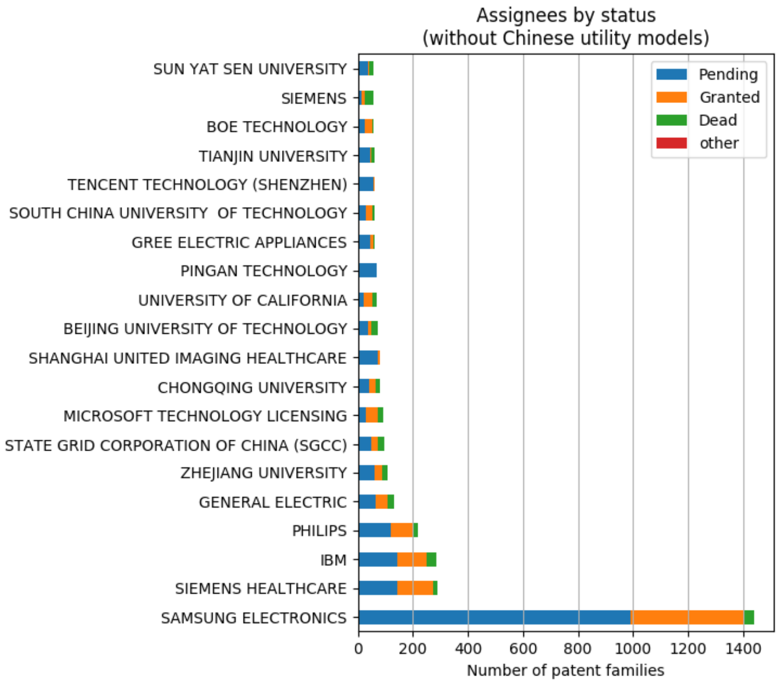
6 A comprehensive description can be found on the WIPO website https://www.wipo.int/patents/en/topics/utility_models.html

7 https://www.wipo.int/edocs/pubdocs/en/wipo_pub_941_2018-chapter2.pdf , pag. 33 and pag. 63 fig. A55.

8 Worldwide breakdown of utility models as per 13/7/2020: DE: 80, KR: 74, JP: 17, FR: 3, BR: 2, PT: 1, DK,MD,AU,CR: 0.

Figure 19: Top-20 patents assignees with (top) and without (bottom) Chinese utility models in the period 1980 - 2020.

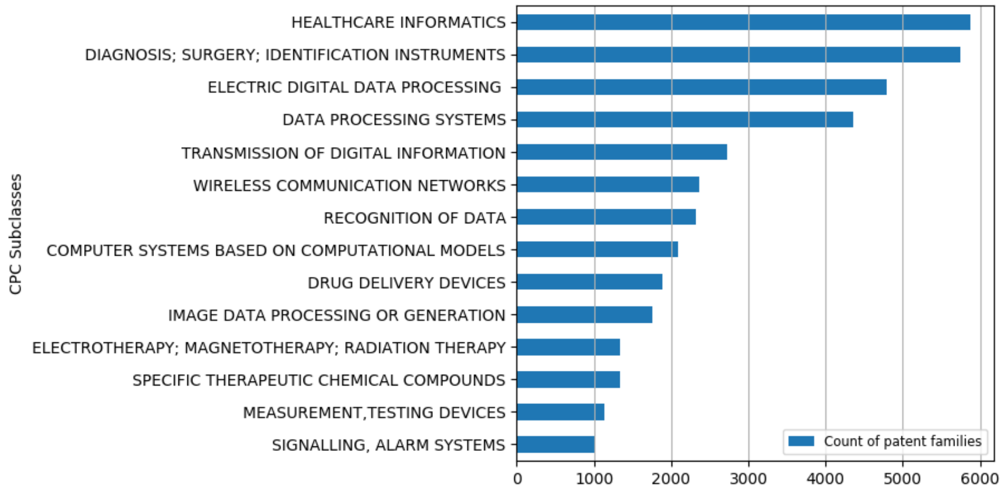




Source: based on data from Questel

Cooperative Patent Classification (CPC) and International Patent Classification (IPC) codes allow better understanding of the patented inventions themselves (Figs. 20-21). Instruments for medical procedures and health care informatics are the dominant classes for CPCs, with about 6000 patent families each, followed by data processing systems (Fig. 20).

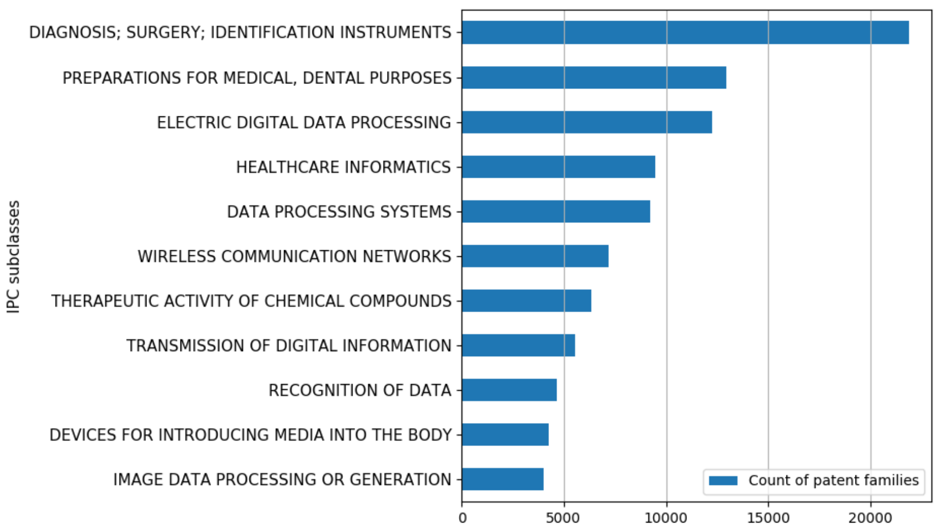
Figure 20: Patents distribution according to the CPC subclasses.



Source: based on data from Questel

However, as CPC codes are a harmonization of classification codes by the European Patent Office and the United States Patent and Trademark Office and they have only recently been introduced in China and Korea[9], we also contrasted the distribution in CPC codes with the one of the International Patent Classification (IPC) (Fig. 21). In this case, the dominant class, by far, is instruments for medical procedures, featured in over 20,000 patent families, followed by preparations for medical purposes and electrical and digital data processing, both featured by around 12,000 patent families. Interestingly, the healthcare informatics moves into fourth position with around 9,485 citations, while it was first in the distribution based on CPC codes.

Figure 21: Patents distribution according to the IPC subclasses.

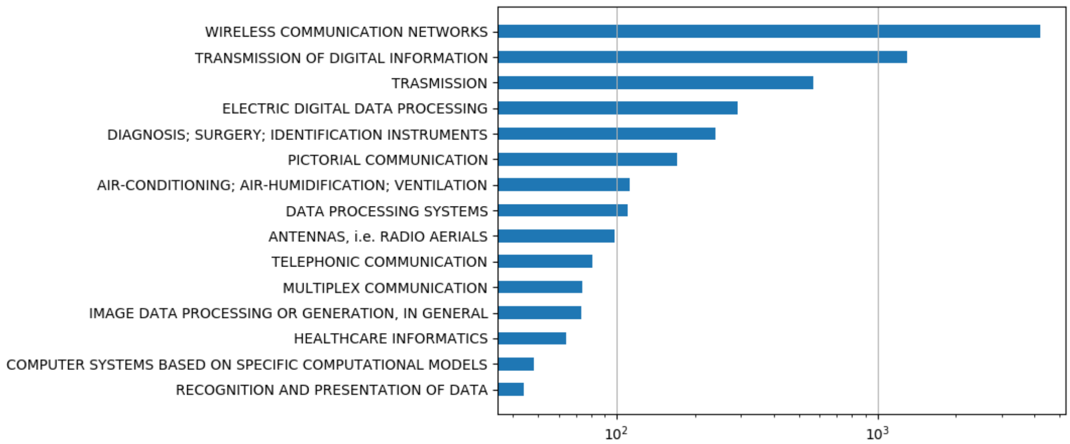


Source: based on data from Questel

9China and Korea agreed to start introducing the CPC system from 2013.

IPC codes allow for a clearer breakdown of Samsung Electronics patents which, as previously noted, concern mostly protocols and application for IOT devices and they are not specifically geared towards health (Fig. 22).

Figure 22: Patents distribution according to the IPC subclasses for Samsung Electronics (log10 scale).

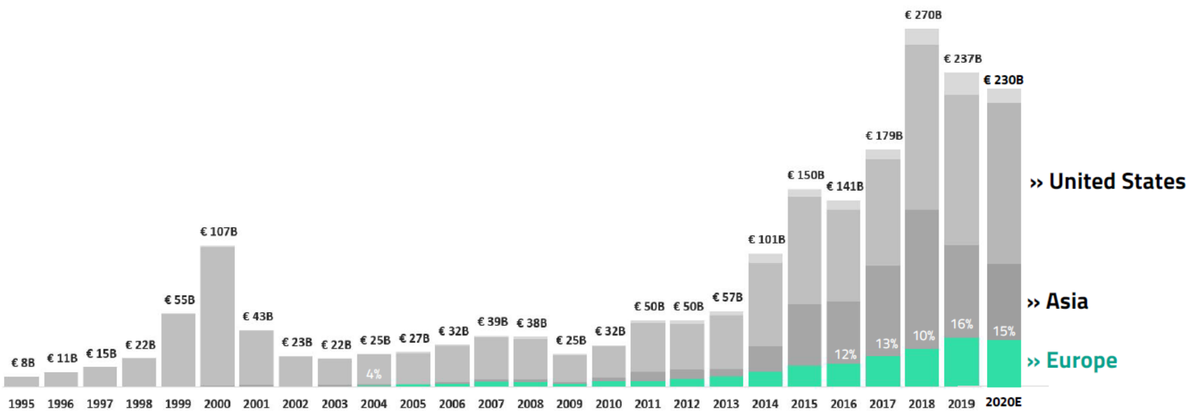


Source: based on data from Questel

6.3 Venture Capital Investments

Another facet of industrial take-up, venture capital investments, was analysed leveraging a dataset provided by Dealroom[10] of 37504 companies active in the health/healthcare domains. Founded in 2013, Dealroom is an Amsterdam-based data and software platform, which provides worldwide intelligence on startups, innovation and venture capital investment. Dealroom data is used to search and compare the performance characteristics of innovative companies, generate reports and track industry trends. Dealroom data has been extensively used for monitoring the developments of the European start-up landscape (Fig. 23). For example, funded in 2020 with the support of the European Commission and European Parliament, European Startups[11] is a project aimed at facilitating informed conversation and collaboration among European tech ecosystem stakeholders to help to develop Europe's startup economy. European Startups is entirely based on Dealroom data.

Figure 23: Global venture capital invested, 1995-2020



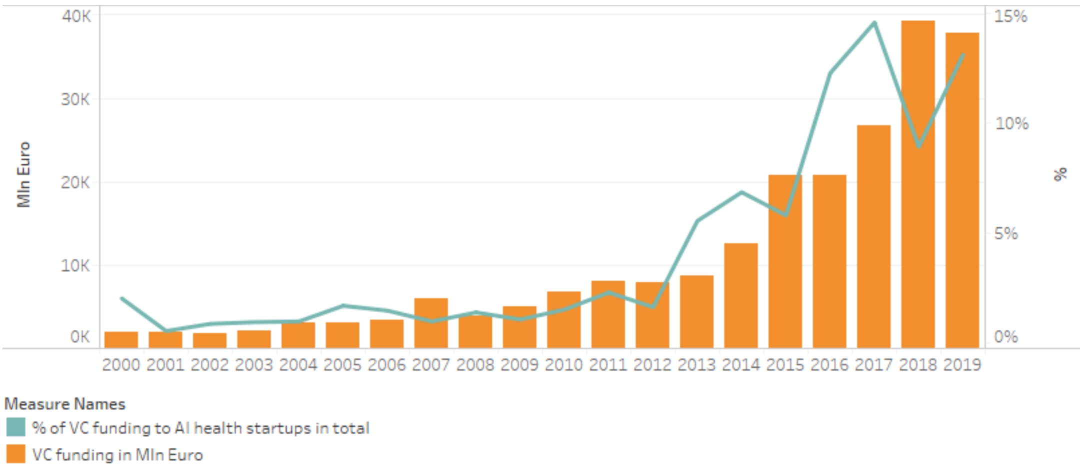
Source: Dealroom.co. Note: 2020 is annualized based on Jan – Oct.

10 https://app.dealroom.co/
11 https://europeanstartups.com

For our analysis, we filtered in the health related dataset the companies with funding compatible with being a startup[12], giving a first cohort of 13199 companies. Furthermore, we mined the companies featuring AI-related keywords in their description to isolate a subset of 1917 AI companies from the total. At the intersection between these two subsets, we found 1071 companies featured both in the startup cohort and in the AI one.

As shown in Fig. 24, venture capital (VC) investments in health-related startup companies have seen a rapid growth, especially steep after 2014. The percentage of such investments directed towards AI related startups has also increased, passing from ~7% in 2014 to around 14% in 2017. Many of the VC investments in AI-enabled health start-ups are in the area of drug discovery, i.e. the domain of BioNTech (see Box 4).

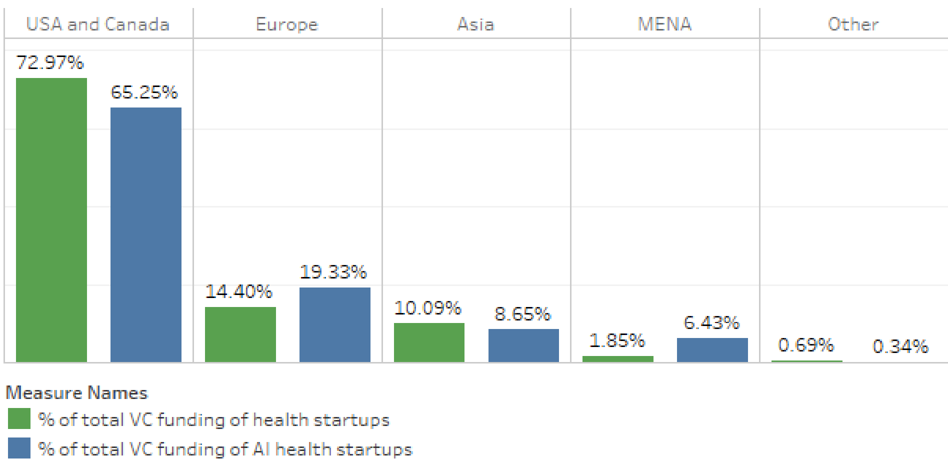
Figure 24: Global venture capital investments on startups aggregated over the years and the percentage of capital invested in AI related startups.



Source: based on data by Dealroom

The geographical distribution of investments in Fig. 25 shows that the US and Canada hold the lion's share, with ~73% of the total VC capital directed towards health startups (green bar in the figure) and AI & health receiving 62% of such investments (blue bar in figure). Europe follows with much smaller figures: 14.40% of total VC investments concerning health startups and 19.33% of these investments going to AI & health startup companies.

Figure 25: Venture capital investments on startups per region.



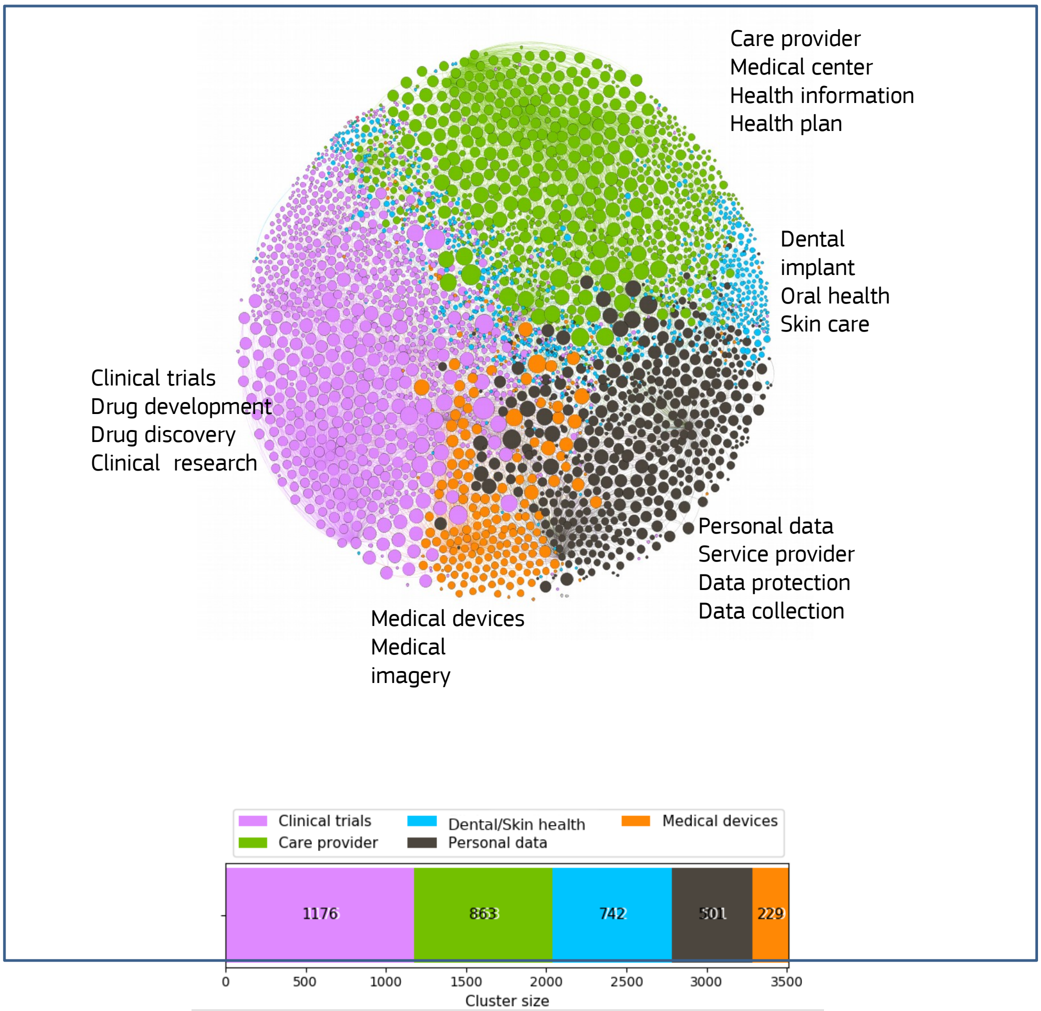
Source: based on data by Dealroom

Deepening our analysis of the dataset, we mined the websites of a subset of companies, randomly chosen, corresponding to about 10% of the original set (3511 companies). We clustered the companies' website

12 More in detail, companies whose funding rounds were of the type : 'angel', 'seed', 'early vc', 'series a-i', 'late vc', 'growth equity'.

descriptions in an unsupervised manner according to their similarity, so that similar companies were clustered together, highlighting the presence of five main groups as shown in Fig. 26..

Figure 26: Communities of similar companies in health and healthcare.



Source: JRC based on data from Dealroom..

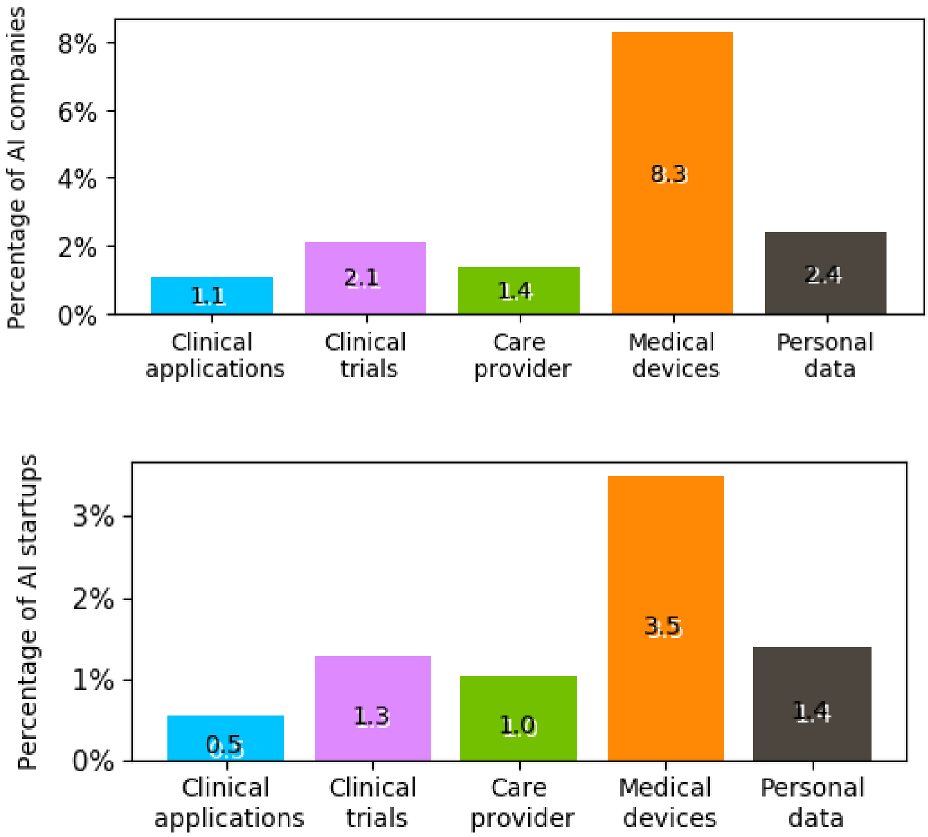
Note: Sample of size N=3511. The dots' sizes are proportional to their degree (i.e. the number of connections), the tags are the most frequent bigrams (i.e. couple of adjacent words) shared by the companies.

In Fig. 26, we can observe three tightly knit clusters, composed of companies similar to each other with many linkages. These clusters are thus relatively uniform and concern clinical trials and research (in purple), medical centres and healthcare providers (in green) and healthcare data and service providers (in grey).

The blue cluster concerns very specific clinical applications, such as dental and skin care. Since the companies in this cluster are more heterogeneous, they have very few connections (thus the small size of the blue dots in the figure) and the cluster is spread at the rim of the aforementioned three main clusters. Last but not least, the small but densely connected orange cluster concerns medical devices.

Within each cluster, we isolated the companies working with AI-related technologies which are, proportionally, more present in the 'Medical devices' cluster, totalling 8.3% of the companies in the cluster. On the other hand, the remaining four clusters have a much smaller percentage of AI presence, ranging from 1.1% to 2.4% (Fig. 27 left). As a last step, we filtered with the above criterion, which of the AI related companies were also startups (Fig. 27 right) and the 'Medical devices' class still leads proportionally to its size, with 3.5% of AI startups. The high proportion of AI technologies in the medical devices' class is unsurprising as AI software for healthcare applications is legally considered as a medical device and it is vetted as such.

Figure 27: Percentage of (top) AI-related companies and (bottom) AI-related startups within each cluster, normalized to each cluster's size.



Source: JRC based on data from Dealroom

7. Local and hospital scale initiatives

The deployment of AI applications requires going beyond the proof-of-concept stage to the validation in real-world setting (Topol, 2019b, Topol, 2019a). Field testing AI applications at the hospital or regional level, especially in terms of data access and domain knowledge transfer is therefore crucial. A real-world setting is also likely to shed light on unforeseen issues: a well-known case was IBM Watson for Oncology that often made the wrong recommendations for cancer treatment, for instance recommending a drug conflicting with a patient's pre-existing morbidity (Ross, 2018). In this case, the flaw stemmed from the paucity of real input data, giving a practical example of why repeated trials in the medical practice are so fundamental for a proper vetting. This approach, rounds of debugging through actual use leading to a stable version, is customary in software development and it should be all the more so for AI applications in health care.

In more general terms, hospital scale deployment could embody an implementation of the "innovation sandbox" concept presented by the authors of the Villani mission report on the AI strategy for France (2018). In their view, the advantages of such closed environments would be threefold: firstly, provide a fertile ground for experimentation in real-world conditions, second, they could familiarize the actors involved, e.g. clinicians but also computer scientists, with new duties and responsibilities. Lastly, a sandbox could (temporarily) benefit from less tight regulation constraints to foster innovation further.

Facing the COVID-19 burden, several hospitals started adopting AI solutions to deliver care at scale. As an example, the Providence St. Joseph Health system used an online screening to facilitate pre-hospital triage distinguishing potential COVID-19 patients from the ones with less severe pathologies. As a clinical application, radiologists at the Zhongnan Hospital in Wuhan, China, were assisted by an AI classifier which, detecting the disease from CT scans, could help isolating Covid-19 patients. Similarly, in Europe, the French teleradiology firm Vizyon uses an algorithm to unveil the onset of COVID-19 in chest X-rays, made by the

Korean firm Lunit, and teamed up with the Centre Médical Europe for its deployment[13]; while a classifier for chest X-rays, developed by Mumbai-based Qure.ai, is used at the San Raffaele Hospital in Milan.[14.]

As we mentioned previously, AI products pertaining to the clinical side are less mature than the ones tackling operational, financial and administrative tasks. The American Hospital Association (AHA, 2019b) analyses in depth this point, highlighting how through the streamlining of such tasks it could be possible to deliver a higher quality care by an improved time management. An example of this already possible automation could be obtaining prior authorizations from insurances for specific medical procedures.

The benefits of a limited and controlled deployment of an AI product at hospital level do not come without challenges. A recurring theme is the "fear of replacement" (Polton, 2018, NHS, 2018) expressed by the health care workforce with respect to AI. For its mitigation, training and exposure to data science practices is a necessary future step along with, in the long run, the creation of new professional roles, as we shall discuss in the next section.

8. Examples of national and European governmental scale initiatives

The scaling up of Ai application requires nationwide initiatives tackling the consolidation of health data. Europe, can leverage large nationwide health systems and several countries have already started to design strategies to use the richness of the data available (McKinsey, 2020).

France, for example, has created the Health Data Hub (HDH, 2018) and, in 2016, the SNDS (Système National des Données de Santé) for the exploitation of medical data. The SNDS tries to overcome the traditional fragmentation of existing datasets[15]: It collates data from medical prescriptions, financial data from the hospitals and causes of death from different systems. Furthermore, it plans to incorporate the regional databases concerning handicapped citizens and, finally, a sample of private insurance reimbursement data (HDH, 2018). This wealth of data, following some 60 million French citizens, is not, however 'AI ready' (Polton, 2018): such datasets were conceived for administrative purposes, and thus require additional work to extract clinical information. Nevertheless, the SNDS is very rich data source spanning over 20 years.

The use of these datasets is regulated by the Health Data Hub which grants access to the anonymised data, processing the requests and assessing their eligibility together, if needed, with the CNIL (Commission Nationale de l'Informatique et des Libertés). This lightweight approach produced, during the first year of operation (2017-2018), an average of 70 days waiting time for approval when vetting from the CNIL was required (HDH, 2018), which represents a considerable improvement from the 3-6 months waiting time in the previous system.

Similarly, in UK, the Health Data Research UK (HDR UK) Institute, established in April 2018, provides access to health datasets through the HDR Innovation Gateway, gathering more than 500 datasets, along with tools for data analysis and a community forum. Furthermore, HDR features eight Hubs, which are collaborations with patients, UK Universities, third sector, government organisations and industry, either geared towards a specific group of ailments, such as cancer and respiratory diseases, or towards improving processes, such as care delivery. Beyond research building on health data, the HDR UK outlined plans also focused on education, aiming to train 10000 health data scientists over the next five years (HDR, 2019).

At the European level, the European Commission already identified health in its Communication on AI (EC, 2018a) as a sector where Europe has world-leading industry and a wealth of industrial, research, and public sector data. The richness of this data is the focus of the European Strategy for Data that envisages the establishment of several thematic data spaces, of which one on health to support "advances in preventing, detecting and curing diseases as well as for informed, evidence-based decisions to improve the accessibility, effectiveness and sustainability of the healthcare systems" (EC, 2020a). The strategy builds on the 2018 Communication on eHealth (EC, 2018b) and envisages both sector-specific legislation including greater access to and portability of personal health data by citizens, dedicated infrastructures and analytical tools, and the development and interoperability of national electronic health records. Other important forthcoming developments are the launch in 2021 of the Horizon Europe R&D programme as well the Digital Europe Programme with large investments in AI, computing infrastructure, cybersecurity and training. The COVID-19 crisis has also acted as a booster to the adoption of AI in health and the digital transition of business, research, education and public administration (Craglia et al. 2020). Furthermore, the unprecedented

13https://www.technologyreview.com/2020/04/23/1000410/ai-triage-covid-19-patients-health-care/

14https://www.business-standard.com/article/technology/how-a-mumbai-start-up-is-helping-italian-doctors-test-covid-19-patients-120040700994_1.html

15 https://www.indsante.fr/fr/les-composantes-du-snds

investments of the Recovery Plan agreed in July 2020 may fuel development in digital technologies and health beyond expectation.

Last but not least, a key issue for the adoption and use of AI methods in health and healthcare is the training of the healthcare workforce to master the use of AI products and help their development. In this respect, several reports (AHA19a; Topol 2019b; Health Data Hub, 2018) discuss at length the need for such education, both in the form of upskilling the existing workforce and through the creation of new professional figures. For example, in France, the Health Data Hub (2018) foresees the introduction of a data science course in the medicine curriculum and, in the UK, Health Education England is developing a portal for the NHS to foster digital education[16]. Similarly, the Technion Israel Institute for Technology has launched a double degree, leading to a BSc in Medicine and Computer Science (McKinsey, 2020), which would then be followed by clinical school to form practitioners who also possess a deep understanding of computer science. These early examples show the increasingly recognised importance of introducing AI in the education and training of healthcare professionals. A similar conclusion was reached by the High-Level Expert Group on Artificial Intelligence (HLEG, 2020). The group recommended on the one hand the establishment of mechanisms to make AI developers knowledgeable of health-related issues and, on the other to pay particular attention to the reskilling and upskilling of health practitioners so that they are better equipped to understand and challenge AI-generated advice.

9. Conclusions

In this report, we have explored the different facets of the adoption of AI in the health and healthcare domains, drawing observations from several datasets and bibliographical sources. In this last section, we summarize the key results to be revisited in future editions of this report to see how the domain has changed, in line with the mission of AI Watch.

In Section 2 we noted that while the analysis of the global AI landscape shows Europe behind the USA but ahead of China, when it comes to the health and healthcare domains, China is the leading player followed by Europe and the USA. The characteristics of the three regions are however distinctively different. While the USA is dominated by commercial firms with relatively few pure research players, in China about one third of the players are research institutes, rising to almost two thirds in the EU27. This confirms the very strong research vocation of the EU, and the key role also played by the European R&D programme. In terms of areas of specialisation, the EU and the USA are comparable, while China has a strong dominance in the technologies and methods for diagnostics which include image recognition where China has a strong worldwide lead. As detailed in Craglia et al. (2018) the AI ecosystem in China is characterised not only by a young population eager to adopt innovations, and a wide spectrum of innovative companies, but also by the strong governmental support for companies through favourable economic and regulatory conditions, and a multiple role as strategic investor, consumer of digital technologies, and provider of access to key data. The state control on user data has been key in developing the lead in facial recognition technology which then supports the lead in diagnostic medical technology we detect in this report. As Europe has a very varied and rich set of health-related data it is potentially in a very strong position and the development of a European common space for health data is a very promising initiative.

Section 3 reviewed the technology availability level of AI in medicine and healthcare and their potential social impacts. These ranged from the very positive for computer-aided diagnosis and workflow efficiency to the controversial for merging medical and social data and social engineering, to the distinctively negative for bioterrorism, biohacking with evil intent and the weaponization of AI. The Section which builds on an extensive review of over 600 sources by Gómez-González and Gomez (2020) helps to highlight both opportunities and challenges of AI applications in this domain. How to guide the development and grasp the opportunities while reducing the risks to the minimum is a key issue, and one that is being addressed in Europe through the proposal for a risk-based regulatory framework for AI (EC, 2020b).

Section 4 analysed the scientific medical literature observing a definite increase (although from a low base) of interest in AI and healthcare in the period 2012-2014 and since 2018, accelerating further as a result of the COVID-19 pandemic in 2020. This interest towards the AI and health nexus is mirrored by the analysis of H2020 projects in Section 5 where we observe a stronger growth in health and healthcare projects since 2015 and, in combination with AI, since 2017.

16 https://www.hee.nhs.uk/

The industrial sector, investigated by the means of patents (Section. 6.2) and venture capital investments (Section 6.3) follows closely the timeline set by scientific publications. For patents, the number of applications filed started to rise steeply after 2012 and its pace increased after 2014. In terms of countries, China and USA are the major contributors, although, as discussed, China makes an extensive use of a "lighter" form of patents, called utility models. Utility models correspond to less mature and potentially less innovative products because of less stringent requirements, and, in China's case, correspond in our data to roughly a third of the applications filed.

The distribution of companies holding the majority of patents is led by the Korean giant Samsung Electronics, whose patents however are mostly directed towards smart IOT at large that can also be used for health-related devices rather than patents targeting health specifically. Siemens Healthcare, IBM, and Philips follow Samsung, marking a strong European presence in the top four patents holders.

Finally, the percentage of venture capital (VC) investment directed towards AI and health startups rose from 2-3% in 2012 to 15% in 2017. In this case, North America and Europe are the major players, with however very different patterns, as the former represents around 74% of VC investment on health startups against 14% in Europe. There is a strong difference also in the proportion of such investments devoted to AI and health startups: of the total VC investment in health startups, around 65% in the USA and Canada is directed towards startups on both AI and health against 19% for Europe.

Overall, the data shows that AI in health and healthcare is a field undergoing a fast expansion but is still relatively small. For example, relevant H2020 projects account for only 0.5% of the total number of R&D projects while AI-related patents are less than 2% of the total of health patents. Notwithstanding this low starting point, the report highlights three trends likely to strengthen in the coming years:

1. Short term: Adoption of AI applications for operational improvements.

AI technologies can be at very different stages of maturity. At the present time, applications streamlining workflow processes are the most promising as they are based on mature technologies and applications already available in other industrial sectors as indicated by American Hospital Association (2019b; NHS, 2018, and McKinsey, 2020)

2. Medium term: Availability and interoperability of health data.

The quality of AI models critically depends on large volumes of good quality, semantically-structured data, labelled to provide also information-rich context. Therefore, a necessary step in the medium term to boost the adoption of AI in health and healthcare is the creation of shared repositories of health data at the national and European level, as envisaged by the European strategy for data (EC, 2020a). The challenges are many as data is currently fragmented in many repositories, with different formats and definitions, and bringing the data together faces regulatory challenges as recognized also by the report of the High-Level Expert Group (HLEG, 2020). European health systems are nevertheless among the best in the world with respect to the richness and diversity of data available, so the opportunity for Europe to become world leader but above all to bring tangible benefits to European society is here to be grasped. Because European health data is so rich, we need also to be conscious that it attracts considerable interest from non-European players, so data sovereignty and security of the European data spaces is crucial. The strong political commitment to the development of a common European data space for health as a key pillar of a forthcoming European Health Union was reiterated by European Commissioner Kyriakides and Germany's Federal Minister of Health Spahn at the Digital Health conference[17] held on the 11th November 2020. An initial step in this direction was presented by Estonian President Kaljulaid who indicated that at least in the area of e-prescriptions an interoperable data space has already been established between Estonia, Finland, and Portugal.

3. Long term: Empowering the healthcare workforce.

The development and effective use of AI technologies in health and healthcare needs a strong partnership across disciplines: for computer scientists to work with health practitioners and understand their needs, and for health practitioners to acquire digital skills and, in the long run, even become familiar with data science as part of their education and training, so that they can be empowered to shape the direction of the development of application as well as challenge products coming onto the market. To this end, as recommended by the High-Level Expert Group on AI (HLEG, 2020), upskilling the existing workforce by providing an environment for education and training, and creating environments for multi-disciplinary dialogue are fundamental enablers for AI uptake in health and healthcare systems.

17 https://hlc2020.de/programme and

The purpose of this report as outlined in the introduction was to set a benchmark against which we can measure change in the adoption, use, and impact of AI in health and healthcare. From this point of view, finding that we are at a relatively early stage of AI adoption means we are in a better position to shape future directions exploiting the many opportunities for European society and reducing the potential risks.

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doi:10.2760/948860
ISBN 978-92-76-26936-6