ARTIFICIAL INTELLIGENCE IN THE CLINIC

SIX TRENDS FOR THE HEALTH SERVICE OF THE FUTURE

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FOREWORD

High expectations are placed on the importance artificial intelligence may have for society. According to the most optimistic estimates, this technology can, among other things, contribute to solving the climate problem, speeding up slow global productivity growth, and improving the world's health services.

Like any new technology, artificial intelligence brings with it both opportunities and risks. It is therefore important to investigate how these new tools can change the health service, and what consequences this will, in turn, have for patients, citizens and society. This report therefore identifies six trends for artificial intelligence in healthcare, and discusses the opportunities and challenges associated with each trend.

The report is not a catalogue of everything that is happening within artificial intelligence in healthcare. The objective is rather to identify certain specific developments. We hope this can contribute to a better discussion about how the health service can develop in the coming decades, and about what should be done to steer developments in the desired direction.

The expert group for the project consisted of the following members:

- Damoun Nassehi, General Practitioner, Researcher at the University of Stavanger and Member of the Norwegian Board of Technology.
- Helga M. Brøgger, Medical Doctor, Head of the Norwegian Radiological Association.
- Michael Riegler, Chief Research Scientist at SimulaMet and Associate Professor at The University of Tromsø – The Arctic University of Norway (UIT).
- Erik Fosse, Chief Attending Physician at the Intervention Centre, Oslo University Hospital.
- Steinar Madsen, Medical Director at the Norwegian Medicines Agency.

Anne Siri Koksrud Bekkelund was the Norwegian Board of Technology's project manager and wrote the report. She received good assistance from Hilde Lovett during the initial phase.

The Norwegian Board of Technology is an independent body that advises the Norwegian Parliament (Stortinget) and the government on new technology and promotes an open, public debate. We hope this report will contribute to a future-oriented discussion regarding artificial intelligence in the Norwegian healthcare system.

Tore Tennøe

Director, The Norwegian Board of Technology

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SUMMARY

There are high expectations for how artificial intelligence can assist in providing better and more efficient health services. Even restrained academics use words like "revolutionary" to describe the potential changes for administration, medical research, public health work, diagnosis and treatment.

This report primarily addresses artificial intelligence in clinical healthcare. The computers can both relieve the burden on doctors and other health personnel and provide better treatment for each individual patient. For example, faster diagnosis and shorter waiting times will improve the quality of treatment. Finally, there is a realistic path towards the goal of personalised treatment, based on the characteristics and medical history of each patient.

There are a number of drivers which indicate that we will see major growth in the use of artificial intelligence in healthcare in the coming decade:

- *Demand*: As a result of demographic changes, demand for health care will increase, while the supply of labour will not keep pace.
- *Algorithms:* The major advances in machine learning algorithms are designed to find patterns in health data.
- *Data*: Vast amounts of health data from public and private sources are being made available, aided by the growth in sensor technology.
- *Research and innovation:* There is strong growth in academic articles and patent applications for machine learning and deep neural networks in healthcare.
- *Investment:* Commercial players with AI expertise are increasing their investments: Google, Amazon, Apple, Microsoft and Facebook are focussing on healthcare.

- *Political will:* Governments around the world, including in the EU, USA and China, are exhibiting strong political will to invest in AI in the health services.

Society faces some significant legal, ethical and technical challenges for AI to be a success in healthcare, including:

- *Privacy:* How do researchers and developers obtain access to large amounts of high-quality health data without compromising patient privacy and their right to self-determination?
- *Discrimination:* Historical health data contain biases, such as an overrepresentation of Western men. How can it be prevented that solutions based on such data result in discrimination?
- *Monopolisation*: Large, global technology companies can combine increasingly more information about each of us, including health information. This allows them to grow larger, while it becomes difficult for new operators to enter the market. How can it be ensured that services which are developed based on citizens' health data will benefit as many people as possible?
- *Organisation*: While many of the new solutions that are launched can cite good tests in the lab, there is no certainty that they will work equally as well in an actual, day-to-day hospital situation. What organisational and cultural changes need to be made in the health service to derive benefits from the new opportunities?

This report identifies six trends that have important implications for the health service, society and policy. They do not describe the present situation in the health service, but rather describe what *may* become the reality in the coming decade. *Whether* or *when* these trends eventuate will depend on technological, political and organisational choices. The aim of this report is to shift the focal point of the discussion from what we *think* will happen to what we *want* the future health service to look like.

The trends are based on patient contact with the health service: The dialogue with the first line, meeting with health personnel, followed by diagnosis and treatment, and possible monitoring of the health condition. We then look at how equipment with artificial intelligence can improve itself across these situations and, finally, how AI can contribute to preventive healthcare.

What the healthcare service of the future should look like is not just a technical question, or something that should be left to doctors and health bureaucrats to consider. It is very much a political question. The aim of this report is to contribute to more political debate concerning the healthcare service of the future.

1: THE FIRST LINE GOES DIGITAL

Computer systems with artificial intelligence can speak the patient's language and respond to them quickly and accurately. These types of digital first lines can provide better healthcare across the entire country.

WHAT COULD THAT MEAN?

- *Relief for the health service/greater capacity*: Artificial intelligence can enable health personnel to spend less time on the phone and more time on treatment. There are several places, including in the United Kingdom, where digital first lines are being tested for both GPs and emergency wards. For example, the Norwegian Directorate of Health's chatbot for coronavirus services had more than half a million conversations during its first year.
- *Direct referral and treatment*: One can envisage artificially intelligent systems that make diagnoses based on a conversation, chat, or data uploaded by the patient. This could be an image of a skin change or a heart rate reading. The systems can make a direct referral to a specialist or treatment. In some cases, for example in mental health care, a chatbot can also perform the actual treatment.
- *Faster and more equitable access:* A digital first line will be just as accessible no matter what part of the country someone lives. For example, the major disparity in access to mental health services in Norway could be reduced by digital solutions.

CHALLENGES

- *The role of the doctor:* When more of the communication between doctor and patient is taken over by digital systems, this may weaken the ties between GP and patient. The doctor's role as gatekeeper may be taken over by a robot with limited discretion.
- *Centralization of power:* When a computer system makes a recommendation, or even makes a decision, about the patient's health, power

is shifted away from the patient and the doctor. This particularly applies if it is difficult to understand how the algorithm arrives at its conclusions.

- *Discrimination:* Machine learning is generally based on historical health data. When these types of solutions are introduced, it must be ensured that they do not contribute to discrimination, for example, based on gender or ethnicity.

2: HEALTH PERSONNEL ARE GIVEN DIGITAL ASSISTANTS

Virtual health assistants can help health personnel make diagnoses, find the best treatment, or monitor a patient and alert him/her of possible complications.

WHAT COULD THAT MEAN?

- *Personalised treatment*: New technologies and research have resulted in the amount of information doctors are able to access about individual patients having multiplied in the past 20 years. The amount of information is simply too vast for a doctor to review manually. By using machine learning, virtual assistants can analyse medical literature, interpret images or other patient data, or plough through thousands of patient records to retrieve relevant information. Machine learning may become the key to personalised treatment.
- *Safer and less dependent on the doctor's experience:* With the help of virtual assistants, doctors can obtain easier access to experiences from both research literature and former patients. This could also enable the healthcare that is provided to be less dependent on the individual doctor's specific experience, and less specialized health personnel may be able to perform more tasks. This may mean that we need to take a new look at the distribution of tasks in the health service.

CHALLENGES

- *Health data must be made available*: Digital assistants represent major opportunities, not least for the Norwegian health sector. In order to succeed, health data must be made more easily accessible in a manner that is compatible with good data protection. New techniques for stronger data protection can assist with this.

- *Transparency and verifiability*: Many research findings within the field of AI are criticised for being difficult to replicate. Norwegian researchers can contribute with transparency and strict requirements for their own results being able to be verified.
- *Overriding the system*: The better the digital assistants, the more difficult it will be to know when the system should be overridden by humans. Good routines need to be developed to maintain the competence of health personnel.
- *Overtreatment*: When introducing new systems to flag risks, there is a risk that they send too many patients for further examinations, just to be on the safe side. Overtreatment is an unnecessary burden for both the patient and the health service. The balance between too many and too few flags must be carefully weighted for each new system.

3: DIAGNOSIS AND TREATMENT MERGE TOGETHER

Artificial intelligence assists with the patient being assessed, receiving a diagnosis and being treated at one and the same doctor's visit.

WHAT COULD THAT MEAN?

- *Diagnosis and treatment in one:* With the assistance of artificial intelligence, doctors can quickly obtain relevant information from many different sources, and make faster and more accurate diagnoses. For example, when tissue samples from the brain can be analysed in a few minutes instead of 30 minutes, it becomes possible to operate and remove a malignant tumour immediately. Artificial intelligence can thus make the idea of a seamless patient pathway a reality, where examination, diagnosis and treatment are intertwined.
- *Organisational distinctions are erased:* When diagnosis and treatment take place closer together, perhaps during the same session, the different professions need to work more closely together than many have previously been used to.
- *Fewer and less unpleasant visits to the doctor*: For the patient, this may mean fewer unnecessary treatments, shorter waiting times and

fewer visits to the clinic. In the long-term, this could also mean that examinations may become less invasive, for example, by ultrasound replacing more extensive MRI or CT scans, or by pill camera replacing colonoscopies.

CHALLENGES

- *Division of responsibilities:* The more the diagnosis and treatment process are interrelated, the more important it is to assign clear responsibility. The patient needs to be able to know who is responsible if something goes wrong.
- *Transition from lab to clinic:* The introduction of new computer systems is as much about how they can be incorporated into everyday clinical practice as it is about the technical aspects. Even if a system exhibits good results during the testing phase, it can be difficult to precisely recreate the same conditions in everyday clinical practice. Minor differences in how data is measured and recorded can reduce efficiency.
- *Competence:* Knowledge about systems with artificial intelligence needs to become part of healthcare education and training. If multiple departments and professions are to work more closely together, it is important that they have basic, common knowledge of the technical systems, and use these in the same manner.

4: EVERYONE CAN MONITOR THEIR OWN HEALTH

Home sensors have become commonplace, and can record everything from heart rate to tone of voice. Artificial intelligence interprets the data and provides users with continual information about their physical and mental health.

WHAT COULD THAT MEAN?

- *Follow-up at home*: The prevalence of cheap sensors makes it possible to continuously collect data. Patients can then be monitored at home, instead of having to go to a hospital or outpatient clinic. Hospital beds are expensive, and more follow-up at home can better utilise resources.
- *Better for people with chronic illnesses*: The new equipment could make life easier for people with chronic illnesses and others who need

to monitor their own health, and provide them with greater assuredness and control over their own situation.
- *Earlier risk detection:* When more and better data on the individual patient's health are available, it is possible to detect more conditions at an earlier stage, and thus get started with treatment more quickly.
- *Knowledge about one's own health:* Each individual can obtain an overview and insight into their own health in a way that has not previously been possible.

CHALLENGES

- *Trusting the technology*: Self-monitoring and telehealth place greater responsibility on the individual, who may end up placing too much reliance on the technology for detecting health problems. It is important that health personnel understand the new solutions and can provide guidance to patients.
- *Health anxiety:* For some, the quantity of information can also trigger health anxiety. Continuous self-monitoring can cause us to contact a doctor more often, which in turn can lead to overtreatment.
- *Disparities:* Digital literacy varies greatly among the population. This also includes the financial prerequisites for purchasing technology for private use.
- *Who will receive the data*: Many of the solutions involve disclosing intimate health information to private actors that have varying data management practices. Health data could become an important currency in the digital economy, where giant companies such as Google, Facebook and Amazon are growing ever larger. Health data requires good protection.

5: EQUIPMENT IS CONSTANTLY IMPROVING ITSELF

By using artificial intelligence, software in medical devices can learn from a continuous stream of data. The equipment can therefore continuously improve and update itself.

WHAT COULD THAT MEAN?

- *Faster improvement*: Medical devices have traditionally been approved once before being launched on the market. They then function in more or less the same manner for as long as they are in use. Sooner or later, the equipment becomes obsolete and is phased out. Continuous machine learning changes this logic: The software component in medical devices is becoming far more important, and can be updated as more knowledge is acquired. The development can lead to faster improvements in healthcare, because the physical equipment does not need to be replaced in order to access improvements.
- *Local adaptation*: Continuously learning systems can also provide greater precision for local conditions, or for illnesses that change over time. It is of course far cheaper to replace software than to replace physical equipment.

CHALLENGES

- *New risks along the way:* Continuous learning means that new risks may arise along the way. Excellent controls of equipment during their entire lifecycle and new routines for quality control are required. The fact that the models developed by machine learning may not be very intuitive for humans to understand can make this more complicated.
- *Updated regulations for approval*: There are several different approaches to solving this challenge. One possibility is that the actual development process is quality controlled, not the product itself. The United States Food and Drug Administration (FDA) is moving in this direction. Another possibility is to operate with a "digital twin", whereby the algorithm is allowed to develop itself, while the alternative algorithm has to be tested and approved once more before it can be used to replace the previous algorithm in actual treatment.

6: PREVENTION IS TAILORED

By using machine learning, the health service can become better at finding people who are at greater risk of illness, and implementing preventive measures that actually have an effect.

WHAT COULD THAT MEAN?

- *Better screening*: Artificial intelligence can revolutionise screening programmes in the health service. In the initial stage this will take the form of helping to select who should be examined. An example is algorithms that select which people should be prioritized for breast cancer screening, thus increasing the probability of finding those who actually have cancer. The efficiency of the examinations themselves can thereafter be improved with the support of artificial intelligence systems for image analysis.
- *Know what works*: Machine learning also increases the possibilities for determining which preventive measures actually have an effect, and can be used to adapt recommendations to the individual. This can provide much better opportunities for what is known as “nudging”, i.e. that the authorities make it easier for individual citizens to make better choices for their own health.

CHALLENGES

- *The right to an explanation*: A weakness of machine learning is that the system cannot always explain why it has arrived at a result in a way that humans can understand, such as someone being at high risk of an illness. It may then be more difficult to use this knowledge for prevention. Therefore, new methods and standards have to be developed for how the algorithms need to explain their decisions.
- *Who should know about risk*: For some illnesses, especially illnesses for which there are limited options for prevention or aversion, living with the knowledge that one is at high risk can be a major stressor. There also needs to be a particular level of awareness about who should know about this risk.
- *Research or healthcare*: The law currently makes a strict distinction between the use of personal health data for helping the individual patients and for research. Machine learning challenges this distinction, and legislative amendments may be necessary for utilising the opportunities AI represents for prevention.

MEGATREND: ARTIFICIAL INTELLIGENCE IN HEALTH

Artificial intelligence (AI) is considered one of the greatest technological advances of our time. In its broadest sense, AI is about enabling machines to solve tasks that previously required human intelligence. One of the areas in which there are high expectations for what AI can contribute is healthcare.

We can roughly divide the possibilities of artificial intelligence in healthcare into four areas:[1]

- *Administrative health systems,* where AI can automate time-consuming routine tasks and free up time and resources for patient treatment.
- *Medical research,* to look for new medicines and vaccines, or learn more about diseases, disease progression or routes of transmission. AI can reduce the time it takes to discover new medicines or treatment methods by several years.
- *Clinical use of AI systems* means that the systems are used "in the field", i.e. in hospitals, by GPs or by the practitioner. This can contribute to earlier and faster diagnoses, better and more accurate treatment, personalised health care and democratisation of access to health care.

[1] The categorisation is based on OECD (2020), albeit somewhat expanded.

- *Public health work*, where AI tools can be used to provide a better overview of the health status of the entire population, examine the physical and socioeconomic factors that impact public health[2], or determine which measures can be implemented and those that actually help.

These areas are, of course, interrelated. For example, medical research is the basis of all clinical treatment. Despite artificial intelligence having major potential within all of these areas, this report primarily concerns the clinical applications of the technology.

MACHINES THAT LEARN ON THEIR OWN

It is difficult to draw a sharp distinction between traditional IT systems and artificial intelligence. The development of artificial intelligence is about enabling computer programmes to simulate human intelligence.

For a long time, programmed, rule-based *expert systems* were the prevailing discipline for developing artificial intelligence. One example is IBM's DeepBlue, which defeated reigning world chess champion Gary Kasparov in 1997. An alternative to expert systems is *machine learning*. What differentiates systems based on machine learning from expert systems is that they can learn connections, rules and strategies by analysing data and real-world examples, without anyone telling them what these connections are. In practice, the term artificial intelligence is predominately used today to refer to machine learning, and it is this type of AI that we primarily discuss in this report.

When we search the web, navigate traffic with a GPS, use Google Translate or talk to the voice assistant on the telephone, we use artificial intelligence based on machine learning. Few people devote much thought to the technological development behind these everyday tasks. However, the reasons that these tasks function so much better now than they did just 10-15 years ago are:

- breakthroughs in machine learning algorithms,

[2] Feller et al. (2020).

- access to large quantities of data to learn from,
- powerful computers that are able to perform the calculations,
- broadband, which enables large amounts of information to be transmitted over the network within milliseconds.[3]

An algorithm is a recipe that specifies how something is done and, simply put, consists of a set of instructions that transform inputs into outputs. A machine learning algorithm is the recipe the system uses to construct a model of reality, based on the data that is fed in (the training data). This model can then be used to make new decisions about new data that comes in. Figure 1 provides a simplified outline of how this functions.

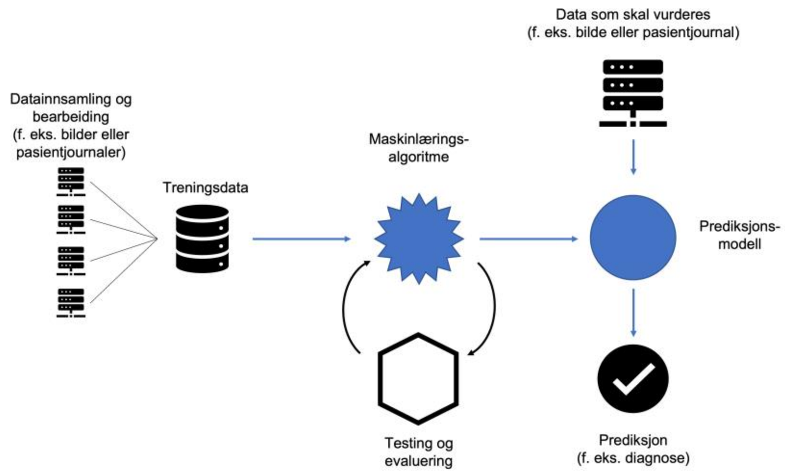

Figure 1: Machine learning illustrated

The most important machine learning algorithms are currently so-called deep neural networks. These were described mathematically as early as the 1940s. However, they were long disregarded as unrealistic and unproductive because they required excessive computing capacity for their practical application. However, some researchers did not give up, and in 2012 they achieved a breakthrough, when an image recognition algorithm based on machine learning won

[3] See also Norwegian Board of Technology (2018).

the annual ImageNet competition by a wide margin.[4] Machine learning with deep neural networks is now dominant within AI. [5,6]

DRIVERS OF ARTIFICIAL INTELLIGENCE IN HEALTHCARE

For a long time, digitalisation was about making paperwork redundant and transferring administrative tasks to computers. This is also occurring in the health sector. However, systems with artificial intelligence are now also making their way into health research and clinical use. The first AI system to make a diagnosis entirely on its own was approved by the US Food and Drug Administration (FDA) in 2018.[7] By the start of 2021, the FDA had approved 72 products that use AI algorithms.[8] There are several developments which indicate that AI will be seriously adopted in healthcare in the coming decade.

INCREASING DEMAND FOR HEALTHCARE

The demand for health services in Norway and in the rest of the world is set to increase sharply in the coming decades. Both the number and proportion of elderly residents will increase. From 2018 to 2060, the proportion of the Norwegian population over the age of 79 will increase from 4 to 11 per cent. It is highly probable that an older population will have a greater need for healthcare, despite each individual potentially having more years of good health.

As early as 2035, the proportion of people employed in health and care services may have to increase from the current 13 per cent to 20 per cent, and then further to about 25 per cent in 2060.[9] Artificial intelligence may help provide relief to a health service that is under pressure. It can also assist politicians and health authorities with public health work, such that illnesses and ailments can be prevented, and thereby reduce the burden on the health and care services.

[4] ImageNet (2012).
[5] Krizhevsky, Sutskever, and Hinton (2012).
[6] Albeit mostly in pilot projects or geographically delimited areas. See, for example, Norwegian Board of Technology (2020b).
[7] Office of the Commissioner (2018).
[8] The medical futurist (2021).
[9] Hjemås, Holmøy, and Haugstveit (2019).

MACHINE LEARNING IS CREATED FOR PATTERN RECOGNITION

One of the greatest advantages of machine learning is the ability to process and extract lessons from very large quantities of data, i.e. pattern recognition. Within healthcare, this could be used to improve the accuracy of both diagnoses and treatment, and to make the idea of personalised healthcare a reality.

Computer programmes have been developed that can interpret medical images from, among other things, radiology and endoscopy, images of tissue samples, moles, the eye and the face. Other measurements may also be suitable for pattern recognition, for example, heart rate, lung function and other vital signs.[10]

Machine learning can also use patterns in the data to make forecasts of the next stage in the progression of an illness. Models that learn from patient records have shown promising results for recognizing illnesses in a patient, predicting clinical events and how a patient will respond to treatment in the future.[11]

THE RAW MATERIAL IS AVAILABLE: ENORMOUS QUANTITIES OF HEALTH DATA

The development of AI systems requires large quantities of high-quality data. In 2020, it was estimated that the total amount of data in the world is increasing by more than 59 zettabytes each year. It is difficult to comprehend such large quantities of data. If one was to store this amount of data on a tablet with 256 GB of memory (such as a new iPad), you would need 215 billion tablets. Growth has also been extremely rapid, and the quantity of data created over the next three years will be greater than the quantity created in the previous 30 years.[12]

Health systems produce as much as 30% of the world's stored data. Collectively, this data contains an enormous amount of useful information about health, disease, treatment and efficacy.[13] In Norway, we have a number of high-quality medical registries, biobanks and other sources of health data. Examples are the Cancer Registry of Norway[14] and large population surveys such as the MoBa (Norwegian Mother, Father and Child Cohort Study by the Norwegian Institute of Public Health (FHI)),[15], HUNT (Trøndelag Health Study)[16] and the Tromsø

[10] Topol (2019).
[11] Xiao, Choi, and Sun (2018).
[12] IDC (2020), European Commission (2020a).
[13] OECD (2019).
[14] Cancer Registry of Norway (2021).
[15] Norwegian Institute of Public Health (2021).
[16] NTNU (2021).

Study[17]. The Health Data Programme[18] and the new Health Analysis Platform have[19] been established to strengthen the infrastructure for research and development.

In addition to public registries, there are also private sources of data. For example, more and more of us are walking around with wearables such as smartwatches or other activity bands. The wearables are part of the focus on new health services at many technology companies, including Apple and Amazon, where data from different sources are combined to offer users better insight into their own health.

The existence of data is a necessary, but not sufficient, prerequisite for the development of AI in healthcare. However the data must also be able to be used. There are still major challenges associated with accessibility, quality, standardization and safety which need to be solved to really accelerate the distribution.[20]

RESEARCH AND INNOVATION ARE ACCELERATING

Machine learning research within healthcare is growing rapidly. In recent years, the number of scientific articles in the field of medicine with the keyword "*deep learning*" has almost doubled annually, see Figure 2[21].

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[17] University of Tromsø (2021).
[18] Norwegian Directorate of eHealth (2021b).
[19] Norwegian Directorate of eHealth (2021a).
[20] Norwegian Board of Technology (2019).
[21] Pubmed.gov (2021).

Another sign of the activity within artificial intelligence is the growth in patent applications. As shown in Figure 3[22], ten times as many patent applications for artificial intelligence were registered in 2019 as in 2013.

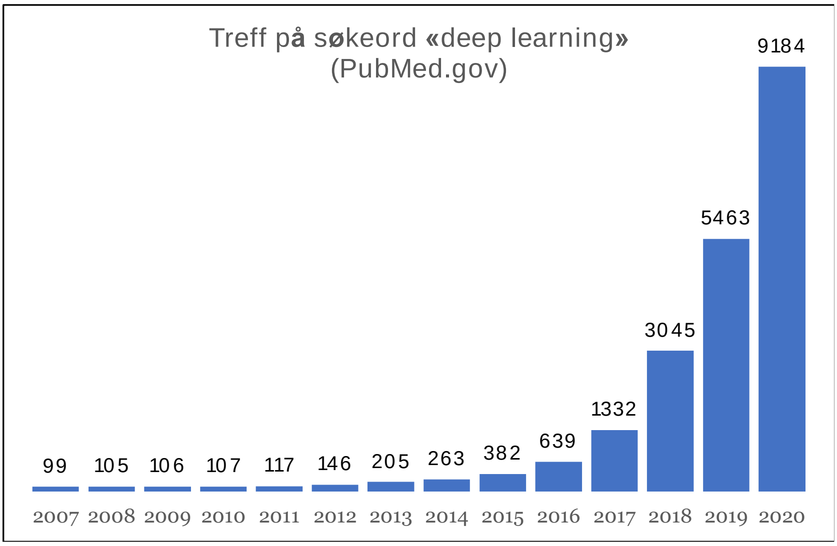

Figure 2: Rapid increase in hits for "deep learning" in medical database

[22] P. Thomas and Murdick (2020).

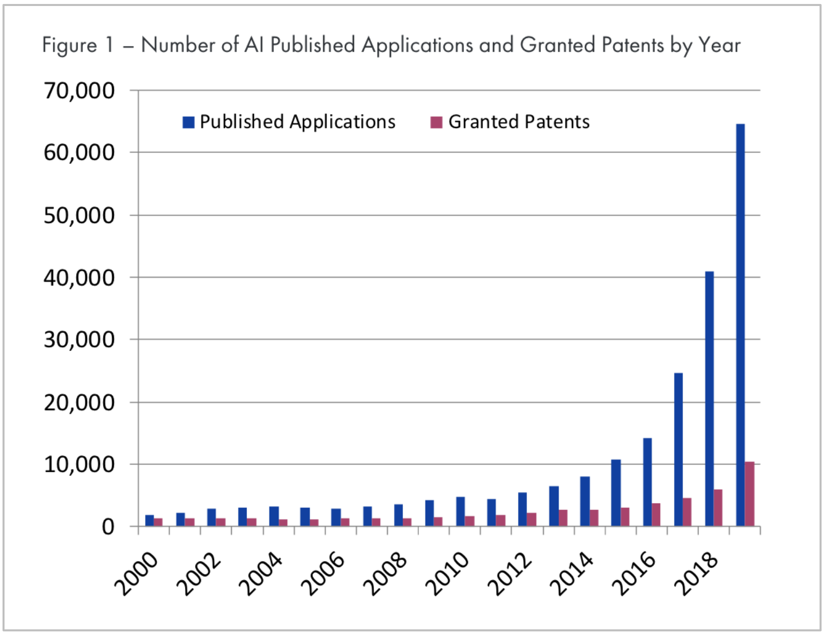

Figure 3: Patent applications for artificial intelligence

The figures for patent applications apply to all uses of AI, not just health, however clearly illustrate the growth. According to a study that looked at patent applications for AI up to 2017, 19% of the applications concerned life science and medicine, which was therefore the third largest area of use for AI patents, after telecommunications and transport (with 24% each).

There are also signs which indicate that there is a shorter path from research to product for systems based on deep learning than for other technologies. While it normally takes ten years from the time a technique is published in scientific journals until a significant growth in patents can be observed, the growth in patents appears almost immediately after the scientific breakthrough in deep learning.[23] If this trend continues, we can expect a high number of products on the market in the future.

[23] WIPO (2019).

COMMERCIAL PLAYERS ARE STEPPING UP THEIR EFFORTS.

The commercial players are investing in artificial intelligence, not least for use in healthcare. Global investments in AI more than quadrupled from 2015 to 2020, from approximately USD 13 billion in 2015 to USD 68 billion in 2020. During the same period, investments in artificial intelligence in healthcare (including medicine and medical devices) grew from less than USD 1 billion to about USD 18 billion (Figure 4). The increase is largely due to the formidable growth in the category of pharmaceuticals over the past year, which naturally must be viewed in light of the search for vaccines to combat COVID-19. However, even if this category is disregarded, investments almost doubled from 2019 to 2020.[24]

Investments in AI healthcare start-ups have also increased sharply, from approximately USD 3.2 billion in 2018 to NOK 6.6 billion in 2020.[25] A new record was set in the first quarter of 2021, with investments of USD 2.5 billion.[26]

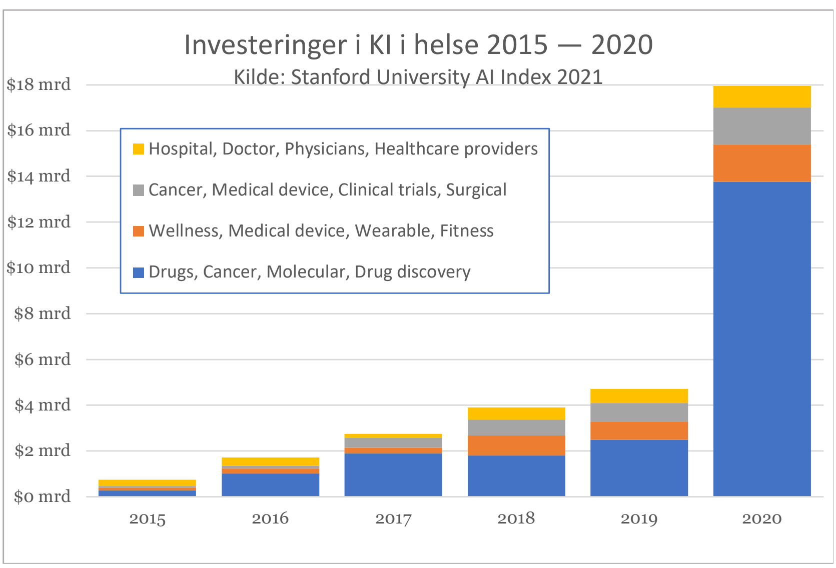

Figure 4: Investments in artificial intelligence in healthcare

[24] Zhang et al. (2021).
[25] CB Insights (2020).
[26] Masters (2021).

All of the five largest technology companies, Alphabet, Amazon, Apple, Microsoft and Facebook are strengthening their investments in the healthcare market.[27]

- *Alphabet (Google)*: The company's CEO, Sundar Pichai, has stated that healthcare is the area in which artificial intelligence can make the greatest difference.[28] In 2019, Google acquired FitBit, the company behind one oof the most popular smartwatches in the market and a source of massive quantities of health data. The company has also acquired DeepMind, one of the leading companies in the development of AI in healthcare. Google launched several new AI tools in 2020. These included both specific tools for making diagnoses, and tools intended to help researchers analyse free-text data in patient records.[29, 30]
- *Amazon* has its own health initiative known as Amazon Care, which offers a variety of medical services, including medical care. Amazon Pharmacy is the ecommerce giant's own online pharmacy. Amazon also took up the fight against Google/FitBit in 2020 with the Halo health and wellness band. The band can monitor physical activity, sleep, mood and body fat percentage.[31]
- *Apple* CEO Tim Cooke has stated that Apple's "greatest contribution to humanity" will be within healthcare.[32] The company has built its healthcare efforts around Apple Watch, and has partnered with both health research institutions and insurance companies.[33]
- *Microsoft* is investing heavily in infrastructure and professional solutions for healthcare, including the cloud storage service Microsoft Cloud for Healthcare. The company recently launched software to administer vaccines, as well as a joint venture with pharmaceutical player UCB.[34, 35]
- *Facebook* has launched its own tool known as "Preventive Health" to help users monitor their own health and, for example, remind them

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[27]See, for example, Business Insider (2021).
[28] Reuters (2020).
[29] Muoio (2020).
[30] Kleinman (2021).
[31] Bohn (2020).
[32] Gurdus (2019).
[33] LaRock (2019).
[34] Dodge and Stewart (2020).
[35] CB Insights (2021).

when it is time for a medical check-up.[36] Among other things, the company has also entered into a vaccine partnership with Boston Children's Hospital.[37]

POLITICAL WILL:

Governments and politicians around the world strongly support the development of artificial intelligence in healthcare. The European Commission considers there to be huge potential economic benefits from using artificial intelligence in the health sector.[38] Through the Horizon 2020 research programme, the EU will support the development of AI in key sectors such as health. In 2019, the European Commission presented its strategy for artificial intelligence in a major report, which places an emphasis on both developing the industry in Europe and how it can build upon trust and ethical principles.[39] In 2021, the European Commission also presented the draft of new, common legislation for artificial intelligence in the EU in the form of the so-called *AI Act*. The proposal is now under consideration. The objective is for the EU to become a leader in the responsible development of artificial intelligence.[40]

In 2020, the Commission also presented its own strategy for data and data sharing. Central to this strategy is the establishment of sector-specific, pan-European data spaces. Among these, the establishment of a European health data space has been assigned high priority.[41]

The more or less explicit goal of the EU is to be able to compete with the USA and China in artificial intelligence. Among China's advantages is that its huge population provides a similarly large data base without the same strict rules for data access.[42] The Chinese government has high ambitions for artificial intelligence, and the AI market in China's health sector is growing rapidly.[43] China is also in the process of surpassing the USA in terms of research efforts.[44] While

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[36] Shieber (2019).
[37] CB Insights (2021).
[38] European Commission (2017).
[39] European Commission (2020b).
[40] European Commission (2021).
[41] von der Leyen and Šefčovič (2020).
[42] Simonite (2019).
[43] Meinhardt (2019).
[44] Vincent (2019).

the USA has traditionally led the race and has also launched its own AI strategy, there is no certainty that this advantage will continue.[45]

Norwegian authorities and politicians also want to utilise the new opportunities that artificial intelligence represents. One goal is for AI to contribute both to greater competitiveness in the Norwegian health industry, and to more sustainable healthcare services.[46] In January 2020, the government launched a separate strategy for artificial intelligence in which health was specified as an important area. Access to good health data is highlighted as an important prerequisite, and the planned Health Analysis Platform is one of the solutions to ensure this.[47] In 2021, the Norwegian Parliament (Storting) adopted statutory amendments to make health data more accessible for the development of artificial intelligence.[48]

ARTIFICIAL INTELLIGENCE HAS PARTICULAR RISKS

All types of medical devices and treatment entail risks. So what exactly makes medical devices based on artificial intelligence stand out and require special treatment? A report from the European Commission describes some of the characteristics that entail particular risk:[49]

- *Interconnected equipment poses security risks:* Virtually all digital equipment is now connected to the internet. This opens up completely new vulnerabilities. For example, it has been demonstrated that it is possible to hack pacemakers.[50] Security breaches can occur both as an unintended consequence and as a result of deliberate malicious use.
- *Data-driven systems can discriminate:* Large, historical data sets are the raw material for machine learning. This means that historical biases and historical discrimination can be perpetuated and even reinforced.

[45] Rasser (2019).
[46] Ministry of Trade, Industry and Fisheries (2019).
[47] Ministry of Local Government and Modernization (2020).
[48] Ministry of Health and Care Services (2019a).
[49] European Commission (2020c).
[50] Vallance (2015).

- *Non-transparent systems threaten trust:* It can be difficult to explain how a machine learning algorithm arrives at diagnoses, decisions, recommendations, or ultimately, actual treatments. Both health personnel and patients may require an explanation, for example, of the characteristics that make a patient considered to be in a risk group. However, this may be difficult to provide in practice.[51]
- *Dynamic and complex systems result in unpredictability:* Machine learning enables equipment to be improved as new data to learn from becomes available. However, quality control and approval of equipment become more difficult when the equipment is constantly changing. Very many parties are also involved — including researchers, programmers, those who collect data, and those who use the equipment.

These general issues are constantly emerging as specific challenges relating to the application of AI in healthcare, which are described in more detail under each trend later in the report.

TRENDS FOR ARTIFICIAL INTELLIGENCE IN THE CLINIC

This report presents six trends for artificial intelligence in the clinic. The report is not intended to provide a comprehensive overview of mature technology, or a presentation of the current situation in the health service. The report is also not a technological roadmap, nor a precise prediction of the way forward.

However, the six trends represent what conceivably or plausibly could become a reality in the coming decade (or thereabouts). It also means that it is far from certain that all of the trends will catch on, or exactly when they will do so. It will depend on a number of external factors, in addition to technological, political and organisational choices.

The trends describe the effect the technology may have on the health service. In other words, the categorisation is not technological, but rather functional. All of the trends are driven by the same underlying technology. The trends have been selected because they offer interesting and important implications for the

[51] OECD (2020).

health service, society or policy. The goal is to move the discussion from what we *think* will happen, to what we *want* the future health service to look like.

STRATEGIC FORESIGHT: TRENDS, SIGNALS AND CONSEQUENCES

This method of looking into the future and identifying certain trends that may occur is also called horizon scanning. It is one of several techniques used in so-called future analysis or strategic foresight. The objective of future analyses is to provide a basis for better discussions, and thereby make better decisions that bring us closer to the future we would prefer to have.

For each trend, we briefly describe what the trend involves. What is the current situation, what does the shift away from this situation entail, and what are important technological drivers? We also highlight examples of how the trend manifests itself in practice (also known as signals). These may be examples of a system being used in the clinic, or that it is under development. Some of the signals are scientific articles or other relevant research, with the knowledge that these examples are further away from actual use in the clinic.

We will then identify what the trend will mean if it catches on: What consequences could this development have for the health service and for society, and what opportunities does it bring with it?

Finally, we also include significant challenges. What issues will society, and especially politicians, have to consider as a result of the trend? What negative consequences need to be dealt with, or what steps can potentially be taken for society to benefit from the trend?

Some of the implications and challenges we discuss are common to several of the trends. For example, problems with assigning responsibility can apply rather generally to the use of artificial intelligence in the health service, and the risk of discrimination is a general problem when machine learning is used for personal data. We have nevertheless chosen to discuss the challenges under one of the trends, in order to better link the challenges to the specific examples and changes we are seeing, without too much repetition.

TRENDS CAN CHANGE

Technological developments are not predetermined. When we envision the future, we also play a role in shaping it. Sometimes active "political obstetrics" are required to adopt new technology. There are other occasions on which possible negative consequences may indicate that we should avoid or even prohibit something.

The trends we describe in the following chapters are possible, plausible, and probable futures. However, they are not inevitable or unable to be influenced. A challenge associated with trend analysis and other foresight work is that knowledge relating to actual developments and their consequences increases over time, while the opportunities to influence developments and consequences fade away (Figure 5). In his 1980 book on the social consequences of technological advances, David Collingridge called the phenomenon "the dilemma of control".[52]

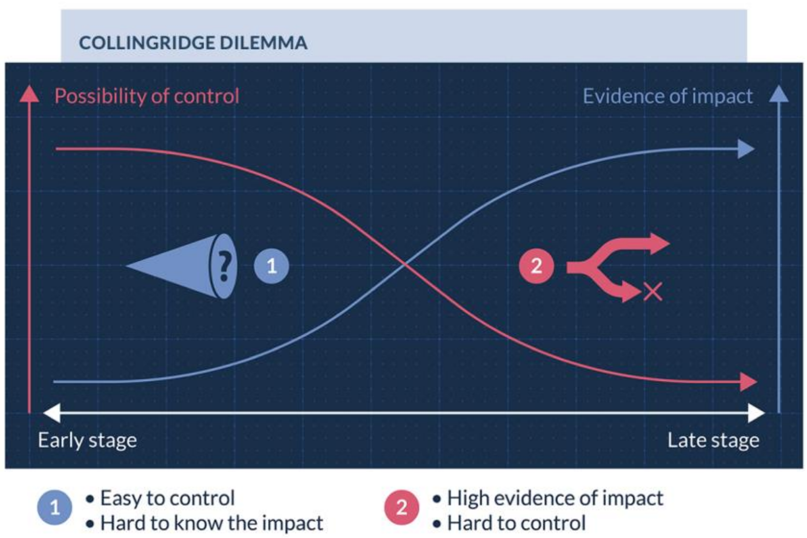

Figure 5: Collingridge's Dilemma (Source: OECD Observatory of Public Sector Innovation)

We know the phenomenon from fields that are completely different to health, such as the development of nuclear power or social media: When one found oneself at the point in time when such technologies could actually be stopped or prohibited if one had wished to do so, one knew very little about the far-

[52] Collingridge (1980).

reaching consequences they might actually have. Once the consequences become known, it is very difficult (or costly) to change course.

Therefore, the goal of presenting new trends is to find the right balance. We need to describe the trends and their possible consequences at a point in time when there is still uncertainty about whether they will catch on. However, there is then also political scope for shaping the technology, and thus the future, as one wishes this to be.

1: THE FIRST LINE GOES DIGITAL

Computer systems with artificial intelligence can speak the patient's language and respond to them quickly and accurately. These types of digital first lines can provide better healthcare across the entire country.

While digitalisation in the health service has previously occurred with small, cautious steps, the coronavirus crisis has acted as a catalyst for adopting new solutions. At the beginning of March 2020, about five per cent of GP visits were digital. Two weeks later, this figure was 57%. The number of psychologists who have adopted the use of video conferencing has doubled.[53] The pandemic has demonstrated the benefits of a digital first line, especially in a pressure situation.

Contact between a patient and the health service has traditionally started with the patient contacting his/her GP, emergency ward or the 113 emergency number. A doctor or nurse then assesses the patient's needs based on conversation and observation.

A digital first line could mean that this initial consultation takes place via video, images, email or chat, instead of in person. However, it may also mean that the

53 Norwegian Directorate of Health (2020).

patient has no communication whatsoever with a human, but with a computer system with artificial intelligence.

This type of solution is based on machine learning that finds patterns in historical inquiries and learns to recognize what the patient's reported symptoms mean. Another important driver of this development is that machines are becoming increasingly better at interpreting and communicating in natural language, both in writing and orally.

A digital first line can now typically answer patient questions regarding health and symptoms. It can provide quality-controlled and relevant information, something which is not always the case when patients, for example, search for information on the internet by themselves.

The long-term goal of the digital first line is that it will be able to do much more than just answer questions or set up appointments. The idea is that these types of systems will also assess symptoms that the user reports or submits. Based on this, the system can either transfer the patient on for relevant examinations, or even make some diagnoses directly, and refer the patient for further treatment.

SIGNALS

A DIGITAL FIRST LINE IS BEING TESTED IN THE UNITED KINGDOM

The United Kingdom is one of the countries that is testing out digital first line solutions in healthcare on a large scale. Among other things, British health authorities have entered into agreements with several virtual health assistants. For example, Babylon Health provides the "GP at hand" service, which is being tested in selected districts in London and Birmingham. This solution triages patients almost as accurately and safely as humans, with far fewer questions (an average of 13 questions compared to 23).[54]

"Ask NHS", a service developed by Sense.ly, checks symptoms and allows the user to book a video consultation or appointment with their GP through the

[54] Buchard et al. (2020).

app. [55, 56] NHS 111 Online is an "online emergency ward" that offers automated symptom checks. The system asks questions about symptoms and finally recommends what kind of help the user requires and where they can obtain this.[57]

DIGITAL ASSISTANTS INCREASE THE AVAILABILITY OF CORONAVIRUS CHECKS

The coronavirus pandemic has demonstrated the role smart chatbots can play in relieving the first line of the health system. At the start of the coronavirus pandemic, the alarm centre (alarmsentralen) (113 emergency number) experienced that the telephone exchanges were blocked by concerned callers.[58] Both commercial and voluntary organisations quickly established different types of digital health assistants to help citizens with information, contact tracing or for diagnostic purposes related to the coronavirus. Helsenorge's Koronasjekk (Coronavirus Check) is a basic variant of this.[59] These types of services have become commonplace all over the world.[60]

In June 2020, a research team evaluated 82 digital coronavirus services. Most achieved high scores for usability, functionality, design and information. Solutions that have been quality-controlled and approved by the authorities score best, and are also more widespread than non-verified solutions.[61]

EASIER ACCESS TO A PSYCHOLOGIST WITH DIRECT REFERRAL

In order to receive mental health care, citizens currently need to go through their GP to get a referral to a specialist working in private practice, i.e. a psychologist for whom the State covers large parts of the bill. However, there is typically a long wait in the public system. The alternative is to go directly to a private psychologist, but this can be expensive, because the patient then has to pay the entire bill him/herself. Many people also experience stigma related to mental health, and are reluctant to seek help.

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[55] NHS (2020a).
[56] Sensely (2021).
[57] NHS (2020b).
[58] Hunshamar and Øverdal (2020).
[59] Helsenorge.no (2020).
[60] Miner, Laranjo, and Kocaballi (2020).
[61] Chidambaram et al. (2020).

A digital first line for mental health could lower the threshold for seeking help. For some, it may be easier and less stressful to contact a practitioner digitally (and anonymously) than to seek out a practitioner directly.[62]

In Australia, the government established a national digital mental health platform already in 2013. The Australia MindSpot Clinic provides information, self-help programmes and online consultancy. An assessment from 2020 reported good experiences from this platform and concluded that these types of solutions should be a component of the modern healthcare system.

VIRTUAL THERAPISTS TREAT MENTAL HEALTH PROBLEMS

Cognitive behavioural therapy (CBT) is a form of therapy where one talks to people about what preoccupies and possibly afflicts them in their everyday life. The digital assistant Woebot uses theories from cognitive behavioural therapy and has a dialogue with the user, providing tips and advice to them based on the dialogue. One study demonstrated that symptoms of depression were reduced among Woebot users over a two-week study period. The study indicated that digital assistants appear to be an effective means of conducting cognitive behavioural therapy.[63]

WHAT COULD THAT MEAN?

A MORE EFFICIENT FIRST LINE

There are a number of industries in which a digital first line and self-service have generally already been introduced. For banking, public transport and tourism, digital self-service is the norm. The prevalence of digital contact in the health service has been given a boost by the corona pandemic. According to the citizen survey from the Norwegian Directorate of eHealth, the percentage of people who used digital health services once or more during the previous 12 months without visiting a doctor or hospital increased from 29% in 2019 to 44% in 2020.[64]

[62] Norwegian Directorate of Health (2018b).
[63] Fitzpatrick, Darcy, and Vierhile (2017).
[64] Norwegian Directorate of eHealth (2021c).

Nevertheless, in-person or telephone contact is still most common, and you generally have to go through your GP, irrespective of what kinds of symptoms you may have, unless you have an acute condition. At the same time, there is a shortage of GPs in many places, and GPs have a high workload.

Digital health assistants can help relieve the situation. For example, they can be used to sort out who requires emergency help, who can be referred directly to a normal consultation in the specialist health service, who should contact their GP and who can monitor the development and possibly receive treatment at home.

Digital health assistants can also help citizens interpret symptoms themselves by asking questions to a digital health assistant. This can be particularly useful in a situation where first line capacity is under heavy pressure, for example, as we have seen during the coronavirus epidemic.

This enables patients to receive quicker responses, while the health service can better utilise its resources.

However, a fully digital first line across the entire health sector, with automatic referrals to the specialist health service is still probably a long way from being realised. It is more likely that there will be "narrower" digital first lines for some parts of the health service, for example, within mental health.[65] These solutions will also initially be a supplement to the traditional first line, not a substitute.

FASTER AND MORE EQUITABLE ACCESS TO HEALTHCARE

The GP is currently the gatekeeper for the specialist health service. The GP assesses whether the symptoms and health condition indicate that the user should receive an assessment or treatment from a specialist, and then refers the patient further.

With a digital first line, the assessment and referral process can be done digitally and automatically, and thereby partially take over this gatekeeper role. Possible examples are diagnoses made by artificial intelligence based on data that the user uploads, such as a picture of a skin change or a heart rate reading, or that the diagnoses are made based on dialogue with a chatbot.

[65] See also Norwegian Board of Technology (2020a).

A digital first line will be just as accessible no matter where you live in the country, something which can contribute towards democratizing and equalizing access to healthcare. In countries with weak infrastructure and health services that are less developed than in Norway, these solutions can provide health services to many who would otherwise not have received them. In Rwanda, for example, the digital frontline app Babyl reaches over two million users.[66]

However, there are also major geographical differences in the health services provided in a rich country such as Norway. For example, a report from the Office of the Auditor General shows that the treatment options available for mental health problems depend significantly on the part of country in which one lives.[67] A digital first line may contribute to at least the initial contact with the healthcare system being more equal. Web-based treatment programmes with greater or lesser elements of artificial intelligence have also been developed for certain mental disorders and ailments and have shown good results.

CHALLENGES

WEAKENING OF THE GP'S TIES TO THE PATIENT

Part of the point of going to the same doctor over time, and something which the general practitioner scheme currently enables, is that the doctor gets to know you. This includes your entire life situation and your ailments and challenges. This enables your doctor to pick up on different signs which together form a pattern for your health. This is precisely what allows your doctor to provide the best possible medical care.

If automatic services increasingly replace regular personal contact, we will lose this close connection between doctor and patient. Some data relating to patients is also subtle, and is never recorded in any medical record. The doctor gains both conscious and unconscious sensory impressions in the physical meeting with the patient. This is data that the algorithms will never have access to, and cannot utilise. While the current health service relies heavily on physical tests

[66] Crouch (2018).
[67] Office of the Auditor General (2021).

and other specific data, doctors will also have developed an intuition that is difficult to transfer to the machines.

The question is whether a digital first line can read enough signs to adequately assess our health situation, and whether the system with artificial intelligence succeeds in communicating the knowledge that it has to the doctor, when this is necessary. Among other things, it may be difficult for the doctor to understand why the system arrived at a particular answer. This is often referred to as a "black box" issue.

THE GATEKEEPER BECOMES A ROBOT WITHOUT DISCRETION

Doctors, and particularly GPs, currently play a key role in deciding who should receive what treatments. They also have a major responsibility for deciding who should be entitled to, for example, sick pay and other benefits. That is why we often say that doctors have an important gatekeeper role.

When fully or partially automated digital systems are assigned responsibility for providing advice, or ultimately making the decisions themselves, they take over part of this gatekeeper role. As described above, this can provide faster and more equitable healthcare.

At the same time, these more or less automatic systems can result in discrimination. Firstly, they are based on data that may contain biases. For example, the training data may originate from too narrow a sample of the population, and thus lead to poorer search results for other groups. Furthermore, machine learning models typically provide better results for common rather than for rare illnesses.

Secondly, apparent technical choices are also not always neutral. Choice of values and priorities are baked into the design and development of a system, often partly unconsciously or unintentionally.[68] Choices made in the development of the systems may have ripple effects for everything from the use of resources in the health service to the payment of financial benefits to individuals.

Doctors exercise discretion when evaluating the patients who enter the ward or office. While an automatic, digital first line can provide a very accurate diagnosis and assessment of certain conditions, this can also make it more difficult to

[68] van den Hoven (2007).

approach the health service when someone has rarer, diffuse, complicated or complex ailments which cannot be categorised as easily by a robot without discretion.

On the other hand, like all human beings, doctors also have unconscious prejudices. This can also impact the help and treatment that different patient groups receive. A digital first line can therefore also counteract discrimination. The risk of discrimination therefore needs to be assessed for each individual system that is adopted.

THE PATIENT IS GIVEN MORE RESPONSIBILITY, BUT LESS POWER

A digital first line must be extremely user-friendly. However, irrespective of how user-friendly it is, a proportion of the population will not be able to make use of such a solution. Not everyone has a smartphone or PC, and not everyone will be able to use digital solutions. A digital first line can therefore never be the only interface for patients. The question is how many resources are assigned to the various first lines as digital solutions become more widespread. If the digital channels are prioritised, this may result in poorer outcomes for those who already had the least resources.

There are also major differences among those who are generally able to use a digital first line. For example, different patients have very different ways of describing and explaining the same symptoms. A doctor will consider the patient and know how to formulate questions about symptoms in order to get the patient to explain these as best as possible. A digital system will typically be far more standardised. If it is based on the processing of natural speech, it will also have to take into consideration that humans communicate very differently about the same thing. The sensitivity to the population groups the system is trained on will therefore also be extremely high. Medical expertise and digital medical expertise are not evenly distributed among the population, and it is important to ensure that the digital first line is accessible to everyone.[69] A more self-service type of system may end up placing more responsibility on the patient, because how the patient describes his/her symptoms will become more important.

Another effect of decision support systems is that they centralise power. Important decisions regarding the patient's health are transferred to a greater or

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[69] Le et al. (2021).

lesser extent to a central system. If the first line of the health service is governed even more by quantitative data, the patient, and the patient's doctor, may have less of a say. When these types of systems are designed, both unconscious and conscious choices are made that can affect how patients and diagnoses are prioritized.

DISCRIMINATORY ALGORITHMS

Machine learning allows machines to relatively accurately classify or predict outcomes, however the predictions can only be as reliable and neutral as the data they are based on. If there is already inequality, exclusion or other traces of discrimination throughout history, this will also be reflected in the data. This may negatively impact groups that have historically been assigned lesser priority in medical research, such as women and minorities.[70]

This can result in the algorithms believing that they *should* be treated differently. This means that the algorithms could perpetuate, and in some cases even reinforce, discrimination.

Furthermore, a large proportion of the machine learning is based on datasets from Western countries (and partly from China), and with a predominance of men. There is no certainty that the results are transferable between population groups. This may mean that the tools work less well for women and for people of other ethnic backgrounds. Artificial intelligence may therefore contribute to reinforcing differences that already exist in the health service, both nationally and globally.

When algorithms gain more power, it becomes all the more important to have good, and preferably open, processes for detecting and correcting discrepancies in the algorithms throughout the entire life cycle of the models. It may therefore be problematic that the development of AI is typified by a small number of major players who can control developments and keep their cards close to their chests. One incident that recently attracted a great deal of interest was Google's dismissal of Timnit Gebru, an expert on, among other things, discriminatory algorithms. Gebru was a member of the management group for Google's "Ethical A.I Team", and had been warning for several years about the dangers of one

[70] R. Thomas (2021).

of Google's major language models being trained using historical texts with biases related to, for example, ethnicity and gender.[71]

However, algorithms and artificial intelligence can also *prevent* discrimination. A computer system fed with your symptoms and personal medical history can precisely make a neutral assessment of the probable diagnosis and sensible treatment, without being influenced by a human's tendency to have prejudices against people based on gender, ethnicity, appearance etc.

However, biases in data sets are both easier to detect and manage than *inadequate* data. We know that there are a number of disorders for which we simply lack reliable research and reliable data. This may be because the conditions are rare, but also because the conditions have historically been assigned low priority, which is the case for, among other things, disorders that typically affect women.[72]

This can also be a self-reinforcing effect: The development of artificial intelligence requires a great deal of data. When the tools are adopted, they produce new data. This increases the biases between health conditions for which we have traditionally collected a lot of data, and conditions that researchers have not been focussing on.

[71] Metz and Wakabayashi (2020).
[72] Quora (2018).

2: HEALTH PERSONNEL ARE GIVEN DIGITAL ASSISTANTS

Virtual health assistants can help health personnel make diagnoses, find the best treatment, or monitor a patient and alert him/her of possible complications.

The production of knowledge in the field of medicine is increasing at a very rapid pace. In 2010, it took 3.5 years to double the amount of medical knowledge, while in 2020 it will only take 73 days. Without good tools, it would be difficult, if not impossible, for health personnel to acquire all of this knowledge and remain up-to-date.[73] In addition to the medical research literature, there are significant amounts of structured and unstructured patient data in patient records, other medical computer systems, and held by the patients themselves in the form of own readings, for example from smart watches or other wearable sensors. These sources have traditionally been difficult to use in the treatment, because it has been cumbersome process or impossible to find the relevant information at the correct time.

[73] Densen (2011).

Artificial intelligence can become a tool for providing health personnel with the information that is needed, when it is needed. By using Natural Language Processing (NLP) techniques, systems can search through, interpret and analyse medical literature, such as reference works, textbooks and clinical trials, and construct a model of the medical knowledge in a field.[74]

With the assistance of NLP, unstructured information from patient records, for example, notes from a doctor or nurse, can also be interpreted automatically. This could open up entirely new opportunities for using data from patient records for research, and for helping other patients with similar conditions. At the same time, this challenges traditional data protection rules that personal health data must only be used for the purpose for which it is collected, which is to help the patient being treated.

Both data from medical literature and data from patient records can form the basis for chatbots, software that doctors and other health personnel can send written or oral questions to, and receive advice regarding the patient who they have in front of them.

The digital assistants can also be integrated into the health personnel's equipment. For example, a modern stethoscope may have advanced software that analyses patterns in the sounds that it captures.[75]

However, virtual assistants can be more than just advisors. They can also assist directly in the treatment situation. For example, a system can monitor combined data from, for example, blood tests, blood pressure readings, heart rate or the like. When the system detects an anomaly, an alarm may go off warning health personnel that they need to examine the patient more closely.

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[74] Google has prepared a knowledge graph that they offer in Google searches in some countries, see Google (2021). Other examples are IBM Watson, Ada Health and Babylon Health.
[75] M3dicine (2021).

MORE ACCURATE BREAST CANCER SCREENING IN HALF THE TIME

Detecting the spread of cancer cells (metastasized cancer cells) is a process that is time-consuming, difficult and prone to error. Deep learning models such as LYNA (Lymph Node Assistant) can assist pathologists with interpreting images more quickly and accurately. One study showed that pathologists who had the support of this type of system became more accurate than without this support, however were also more accurate than what the algorithm could do on its own. The time spent per image also decreased, particularly for images depicting metastases, for which the time spent was halved.[76]

WILL PREDICT WHICH CHILDREN WILL REQUIRE HELP DURING BIRTH

Every year, about three million infants die during childbirth within the first 24 hours after they are born. SaferBirths is a project in which the University of Stavanger and Stavanger University Hospital collaborate with two hospitals in Tanzania to improve maternity care. Machine learning is used together with other statistical methods to analyse data sources, such as fetal heartbeat. The goal is to help doctors predict which babies will require help during birth, for example, cesarean sections or oxygen supply.[77]

EARLIER DETECTION OF ACUTE CONDITIONS

Blood poisoning, or sepsis in the technical language, is currently diagnosed based on symptoms and blood tests. In a 2021 study, researchers developed a machine learning model that utilises both structured data (such as readings of blood pressure, heart rate, oxygen saturation, body temperature, etc.) and unstructured data (typically notes from patient records) to predict which patients are at high risk of sepsis.

In the study, the model provided more accurate warnings of sepsis at an earlier stage than traditional methods, while also reducing the number of false positive alerts. At the same time, the authors of the study emphasised that they envisaged that the model would primarily assist doctors and health personnel in their

[76] Steiner et al. (2018).
[77] University of Stavanger (2019).

work, for example, to avoid possible sepsis cases being overlooked during a hectic hospital day, and would not be a substitute for the doctors' assessments.[78]

MACHINE LEARNING ANALYSES THE LUNGS OF COVID-19 PATIENTS

Following the coronavirus outbreak, many hospitals and academic institutions have collaborated to collect data and develop algorithms that can combat COVID-19 in various ways. One of the most successful areas has been the analysis of images of the lungs to better understand how the disease affects the lungs, and how the disease can be diagnosed and treated.

In April, a system that analyses CT images of the lungs was certified with a CE-label. The system can specify the percentages of the different regions of the lungs that are damaged. Such automatic quantification provides consistent and objective assessments of the lungs and can assist radiologists with risk-based triage of patients with moderate to severe symptoms.[79]

WILL DETECT POSTOPERATIVE DELIRIUM WITH TEXT ANALYSIS

Postoperative delirium is a state of confusion that can have serious consequences. The condition can occur after surgery, particularly in elderly patients, however often remains undetected and undiagnosed. In collaboration with the University of Northern Norway and the Norwegian Centre for E-health Research, a doctoral thesis at the University of Tromsø developed a machine learning algorithm that, among other things, uses free text data from the patient's medical record to predict postoperative delirium.[80]

WHAT COULD THAT MEAN?

HEALTHCARE BECOMES LESS DEPENDENT ON THE EXPERIENCE OF THE INDIVIDUAL DOCTOR.

With the help of virtual assistants, doctors can obtain easier access to experiences from both research literature and former patients. Electronic patient records contain experiences from a multitude of patients; many more than a doctor

[78] Goh et al. (2021).
[79] Icometrix (2020).
[80] Mikalsen et al. (2017); Johnsen (2019).

will encounter during his/her career. These experiences have significant value, particularly for understanding the health situation and prognoses for patients who have similar conditions. Not least, it becomes easier to find experiences from similar cases when encountering rare diagnoses.

This enables the doctor to make faster and more accurate diagnoses, or prepare better and more adapted treatment programmes based on the latest available knowledge and a similar illness progression.

In this manner, the assistants can contribute to making the healthcare much less dependent on the specific experience of the individual doctor. It can also make it easier to maintain good diagnostic and treatment services at smaller locations where there is a low frequency of certain diagnoses.

PERSONALISED DIAGNOSIS AND TREATMENT BECOME POSSIBLE

New technologies and research have resulted in the amount of information doctors are able to access about individual patients having multiplied in the past 20 years. One example is the so-called sequencing of the genetic material, the genome, of the patient, which contains about three billion codes. Other examples are physical measurements, such as heart rate and blood pressure, unstructured information such as in patient records, or the records of all other patients with a similar diagnosis.

It is no longer possible for a human to take into account all information that is of importance to the individual patient. One of the biggest advantages of machine learning is precisely that it is possible to analyse very large quantities of information. Machine learning can thus become the key to a greater level of precision in all parts of the health service, i.e. more targeted prevention, more refined diagnoses, more accurate treatment and better follow-up.

The hope is that the oncologist can, as an example, use artificial intelligence to assess which treatments may be the most effective, based on data about the tumour's molecular characteristics, information about how aggressive the cancer is or calculations of the probability of the cancer spreading.

Another hope is that genetic testing and analysis using artificial intelligence can provide much more precise medication, since our genes determine how well we can utilise the active ingredients.

TASK SHIFTING AND BETTER UTILISATION OF HEALTH PERSONNEL

Digital assistants increase the level of help each health worker can provide. A GP can make decisions that were previously reserved for specialists. A nurse can carry out treatment that was previously the domain of doctors. In short, each health worker is given tools that expand his/her area of application. This also frees up time for specialists to work more with demanding and complex patient pathways.

The more people in the health service who are capable of performing a task, the greater the probability that the help the patient needs is available where and when it is needed. The fewer specialised health personnel required to perform the tasks, the easier it will be to organise the health service as a whole. This may be especially important in the years ahead, when the demand for health services and health personnel could increase sharply as a result of demographic changes.

The greater the impact we have from technology that requires less specialized health personnel, the greater the implications this will have on the structure of the health service itself. The division of tasks between GPs, outpatient clinics, local hospitals, central hospitals etc. may also need to be reassessed. However, the development may also go in the other direction. New, advanced AI tools may also require greater expertise or entail high investment costs, such that the most rational course of action is further specialization.

OPPORTUNITIES FOR THE NORWEGIAN HEALTH SECTOR

Norway has many prerequisites for developing a new health sector based on artificial intelligence in healthcare. These prerequisites include health registries - both treatment-oriented registries and quality registries, as well as biobanks, which can be used to train models. Norway also has academic communities with a high level of both health-related and technological expertise. The health service is of a high quality and has a high level of trust among the population, who have a high level of digital literacy and a willingness to participate in research and trials.[81] It is also important for the Norwegian health service that there is specialised AI expertise within healthcare in Norway. This particularly applies when Norwegian health trusts are to adopt the use of solutions developed elsewhere and based on other populations, and then adapt these to Norwegian conditions.

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[81] Ministry of Trade, Industry and Fisheries (2019).

The challenge for Norway will be to correctly prioritise resources. Should we contribute to filling in the gaps for rare diseases, should we prioritize diseases that are more common in Norway than elsewhere, or should we prioritize the most serious diseases, such as the cancers which have the poorest prognosis for survival?

CHALLENGES

HEALTH DATA MUST BE MADE AVAILABLE WITHOUT SACRIFICING DATA PROTECTION

Access to rich, large and representative data sets — both from the public and private sectors — is a prerequisite for machine learning being able to contribute towards better healthcare. Protecting each individual's sensitive data is crucial to maintaining trust in the system. The more data that is shared, the greater the risk of sensitive data going astray. Furthermore, as more intelligent machine learning develops, it will be possible to derive more information from existing data. When data sets that individually have good data protection are linked together, this can still lead to:

- *anonymised data sets becoming identifiable*. Anonymised data sets can presently be used freely. Researchers believe that 15 pieces of demographic data are sufficient for identifying 99.98 per cent of Americans based on open, anonymized data sets.[82]
- *non-sensitive data becoming sensitive*. New data relationships that are not generally sensitive can nevertheless reveal sensitive information. Among other things, Facebook can infer sexual orientation, anxiety and risk of suicide based on the online activity of users.[83]

Machine learning can also reveal more refined diagnoses and completely new diagnoses. New definitions and thresholds for diagnosis may have consequences for individual rights and obligations. It may also result in a new type of stigma or discrimination if one finds oneself in a new category.

No one should be discriminated against or have their rights restricted as a result of them contributing their data to the development of systems with artificial

[82] Rocher, Hendrickx, and de Montjoye (2019).
[83] Wachter and Mittelstadt (2019).

intelligence. At the same time, many will want, or even expect, that data collected about their health condition is used to provide better healthcare for both themselves and others.

WEAKNESSES IN ARTIFICIAL INTELLIGENCE RESEARCH

Machine learning and artificial intelligence are receiving a great deal of attention, and new findings are constantly being reported in technology magazines and research journals. However, it has transpired that many of the tools being developed cannot be applied to populations and data sets other than those they are developed for, i.e. that the results do not apply on a general basis, but only under special conditions, for example, at a specific hospital.[84]

Small variations in how each health institution performs its measurements can have such an effect that a model which works in one hospital cannot be used in another. It is therefore absolutely crucial that AI models are verified by each of the institutions that adopts their use. A review demonstrated that medical applications of AI approved by the US FDA were often tested at only very few locations, and further investigations revealed that accuracy could be much lower elsewhere.[85]

This has led to a debate about whether the many research articles on artificial intelligence meet the research's basic requirements for reproducibility.[86] The problem is that research articles, which are often published by employees of some of the largest technology companies such as Google, do not include enough details for other researchers to be able to attempt to replicate the results.[87] This makes it neither possible to determine whether these are generally valid, nor to build on the results in other research.

In September 2020, new standards for clinical trials involving the use of artificial intelligence were launched in the leading medical journals Nature Medicine, The British Medical Journal and The Lancet. The goal is that this will make it easier to more credibly assess the quality of the experiments.[88]

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[84] Heaven (2020a).
[85] Andrews (2021).
[86] Haibe-Kains et al. (2020).
[87] Heaven (2020c).
[88] Heaven (2020b).

HOW WILL HEALTH PERSONNEL KNOW WHEN THE SYSTEM MAKES AN ERROR?

In principle, we can distinguish between a system that makes an autonomous decision and a system in which a human makes the final decision, and where the assessment by the system is included as part of the decision-making basis.

It is more difficult to make such a sharp distinction in practice. When the system makes good predictions in the vast majority of cases, it also becomes more difficult for a human to know exactly when to override the system. One factor is that present-day doctors have extensive experience in making these types of assessments themselves, and are thus well-trained to evaluate when the system makes an unreasonable recommendation. But what about the doctors of the future, who do not have this experience? When should they train their assessment skills if the system still makes the decisions in the vast majority of cases?

There are clear parallels between this issue and self-driving cars: The less often the driver has to intervene, the more difficult it will become once this is necessary.

In this context, *explainable AI* is often referred to as a possible solution. If the system could also explain how or why a particular recommendation is made, this could make it easier for health personnel to assess whether the decision appears sensible. However, translating a decision made by an algorithm into an explanation humans can understand is not a trivial matter, especially when deep learning is applied.

The discussion of when an explanation is actually required, and what this explanation should consist of, is now taking place in the academic communities. In some instances, it may be more important that the solutions have proven over time that they provide good results, rather than that they explain exactly why. A strict requirement for an explanation may mean that in some cases software or equipment will be rejected in favour of solutions that may be less accurate, but which in return may provide an explanation of what lies behind an answer or recommendation.

FALSE POSITIVES — RISK OF OVERTREATMENT

One challenge with all studies conducted in the health service is how to balance so-called "false positives" and "false negatives". False positives are patients who are sent on for treatment without this being necessary. False negatives are patients who should in fact have been examined, but who are not detected by the system. This is a dilemma in all health assessments: If the biggest fear is not detecting someone who requires help, this also increases the chance of healthy people receiving unnecessary treatment.

For new systems, the danger is typically the greatest for overtreatment, i.e. sending a patient for further follow-up too often rather than not sending him/her enough. This may sound harmless, however it can have negative consequences both for the individual and for society. Unnecessary treatment has an adverse affect on one's health. It may also entail that the burden on the health service is not reduced, but rather shifted from the current first line to the specialist health service.

3: DIAGNOSIS AND TREATMENT MERGE TOGETHER

Artificial intelligence can be used to collate relevant information from many different sources, and allows doctors to make diagnoses faster and more accurately. This contributes to ensuring that the various steps can be brought together in time and space, such that examination, diagnosis and treatment can take place at one and the same visit to the doctor.

Diagnosis in the health service can be a complex process, where several types of experts carry out tests, examinations and assessments. The process can involve both the primary care service and various departments in the specialist health service. Images (such as X-ray, CT, MRI or ultrasound) and samples of tissue or blood are often taken. [89,90] Specialized and expensive equipment is often required.

Photos and test results are analysed by experts. Finally, the doctor ends up with the most probable diagnosis(es), and can hopefully make a diagnosis. There

[89] Cross-sectional images using X-ray.
[90] Images of internal organs using magnetic fields and radio waves.

may be a long assessment period, which includes both waiting time and travel time for the patient.

The images and test results are already largely digital, and machines and computer programmes have been assisting doctors with interpreting these for many years. However, artificial intelligence and machine learning open up new opportunities for assisting health personnel with performing diagnostic tasks faster and more accurately, with fewer resources and with less risk.

Machine learning can make it possible to detect and classify findings much faster than before. For example, it may be possible to assess whether a tumour is malignant or benign on sight, and it can thus be diagnosed and removed in the same operation. Some of the diagnostic tools have also demonstrated that they can detect findings that specialists overlook.[91]

Artificial intelligence can make it technically possible to provide the patient with a simpler and more seamless path through assessment, diagnosis and treatment. However, the work processes in the health service must be changed in order to derive benefit from these opportunities. In order to succeed, it is equally as important to work for good patient pathways and patient experiences as it is to have the right tools available.

SIGNALS

IMMEDIATE ANALYSIS OF BRAIN TUMOUR SHORTENS THE OPERATION TIME

Before a tumour is operated on, there needs to be an analysis of a tissue sample of the tumour. The result determines whether or not the tumour should be operated on. Currently, the bottleneck for taking images of tissue samples is from freezing and preparing the tissue section, which takes up to 30 minutes. A new technique, *Stimulated Raman histology*, can produce images of tissue samples of the brain almost instantly, and combined with machine learning, the analysis time can be reduced to 2.5 minutes, with a level of accuracy that is better than

[91] Ardila et al. (2019), Shetty (2020).

current methods.[92] This means that surgeons can immediately operate and remove a malignant tumour in the brain and have the cranium open for significantly less time, thus reducing the risk of complications and increasing the probability of a successful operation.

FEWER UNNECESSARY OPERATIONS FOR BENIGN POLYPS

A colonoscopy is an important tool used for bowel cancer. The threshold for not operating on a suspicious polyp is very high, which means that many surgeries are performed despite these not actually being necessary. This exposes the patient to unnecessary risk. A 2018 study showed that a computer system could determine more accurately than both graduates and experts whether tumours in the intestine were benign.[93] Several commercial players have now launched image analysis equipment for use in, among other things, endoscopy, that alerts the doctor immediately of possible findings of polyps or other anomalies.[94,95]

INCREASES THE ACCURACY OF CANCER TREATMENT BY 62 PER CENT

Rapid cancer diagnosis with a high level of accuracy is important for giving patients correct treatment as early as possible. DoMore is a Norwegian research project that has developed a machine learning model from 3D images of tissue samples that can detect and assess the size and aggressiveness of a tumour in three minutes. It provides the patient with a prognosis that helps the specialists select the correct treatment, which can increase the accuracy of the treatment by 62 per cent.[96, 97]The marker that has been developed, which is known as DoMore-v1-CRC, can also determine whether or not a patient who has had a tumour removed requires additional chemotherapy. Avoiding unnecessary chemotherapy saves both the patient from major inconvenience and the health service from major costs.[98]

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[92] Hollon et al. (2020).
[93] Mori et al. (2018).
[94] Olympus (undated).
[95] Fujifilm (2020).
[96] DoMore (2020).
[97] Skrede et al. (2020).
[98] Moe (2021).

ASSISTANCE WITH MANAGING COMPLEX INFORMATION ABOUT THE PATIENT

In hospitals, weekly meetings are normally held by so-called multidisciplinary teams to organise the treatment for the individual patients. The ever-increasing amount of information also means an increase in the complexity and number of participants at these meetings. In the future, digital assistants with artificial intelligence could simplify these meetings by proposing a treatment plan adapted to the patient that is based on as much available information as possible. The BiGMED project at Oslo University Hospital is studying the possibilities of these types of solutions.[99]

WHAT COULD THAT MEAN?

FASTER TREATMENT LEADS TO LOWER RISK AND RESOURCE USE

Machine learning enables the actual process of making a diagnosis from an image or other data to proceed much faster. It can also be easier to perform multiple parallel tasks. This reduces the time spent on the actual diagnostic work. However, the truly profound effect is achieved in the instances in which the diagnosis can be made on site, without sending the patient home, and treatment can be started immediately. Diagnosis and treatment can therefore merge into a seamless pathway.

When done correctly, such seamless patient pathways can save health personnel the time spent on administration and information exchange, which is time they can then devote to other tasks or patients. This also reduces the risk of misunderstanding and loss of information during the process.

Time is precious for the patient. Earlier diagnosis and faster treatment can increase the probability of recovery. Health personnel who have more time for clinical attendance, empathy and communication can provide greater trust between patient and practitioner, and better healthcare for patients.[100] An immediate diagnosis also reduces the mental burden of having to wait for a test result.

[99] Vallevik et al. (2021).
[100] NHS (2019).

In addition, the patient avoids the specific travel time spent on the round trip to the treatment location.

The risk to the patient is also lowered by being able to reduce the number of procedures for the same condition. The time spent on the actual procedure can also be reduced, such as when tissue samples from the brain can be analysed in virtually real time, thus allowing surgeons to make an immediate decision on whether to operate. This increases both the quality of the procedure and patient safety.

ORGANISATIONAL DISTINCTIONS ARE ERASED

When new tools are used, it is important that they actually work in the specific treatment situation. Both the workflow and the method in which different groups of practitioners within the healthcare institution collaborate can be influenced by new tools. This often receives less attention than the technological solution itself, however is equally important to the patient actually having a better outcome.[101]

If diagnosis and treatment merge together, this also entails that the health service needs to rethink its organisation. For example, different types of health personnel may work in parallel to make complicated diagnoses.[102] In other instances, different professions have to work more closely together than what they previously were used to. For example, in the operating rooms of the future, the distinction between the radiology department and the surgical department may be erased, which is something they are experimenting with at the Intervention Centre at Oslo University Hospital.[103]

The organisational changes offer opportunities for improving efficiency and providing better services, but also present challenges. For example, there will still be a need for traditional, specialised departments for many disorders, while the conditions for which the technology results in the merging of diagnosis and treatment will benefit from more multidisciplinary teams.

Good user-friendliness is also important for patient safety. The information must be presented in the correct manner, at the correct time, to the correct person. It is important, for example, that alerts are communicated in a manner that

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[101] Elish and Watkins (2020).
[102] Viz.ai (2020).
[103] Fosse (2019).

makes it easy to react to them. Furthermore, there must not be such a high number of alerts that health personnel experience "alert fatigue", i.e. that they are unable to differentiate between important alerts and less important alerts.

FEWER UNNECESSARY TREATMENTS

Virtually all treatments also come with side-effects or risks. There are of course specific physical procedures that carry a risk of, for example, errors or infections. However, it is also mentally stressful to receive, for example, a cancer diagnosis. An important consequence of more accurate diagnoses is that unnecessary procedures and treatments can be avoided. It is also possible to better predict which patients will benefit from which treatment. This enables the health service to save resources, while at the same time avoiding patients being exposed to overtreatment.

It is uncertain as to whether the introduction of new systems will result in fewer unnecessary treatments, or to more treatments (as described under the previous trend). This should be carefully assessed both before and after the systems have been introduced.

LESS INVASIVE EXAMINATIONS

It may also be possible to replace invasive examinations with examinations that are less burdensome for the patient. For example, blood tests can replace traditional tissue samples, ECG[104] can replace blood samples, ultrasound can replace more extensive MRI or CT scans, and a pill camera can replace a colonoscopy.

With the help of deep learning techniques, more gentle examinations can be as accurate as current methods, and may eventually replace examinations that involve more risk or discomfort for the patient.

Simpler examinations, such as ultrasound, are typically performed with small, portable and affordable equipment, and are thus more accessible to several types of health workers, for example, GPs or nurses. More types of examinations may therefore become more accessible in the primary care service.

[104] Electrocardiogram, measurement of heart rhythm.

AUTOMATION MAKES IT DIFFICULT TO ASSIGN RESPONSIBILITY

The clinical systems for artificial intelligence that we discuss in this report are primarily systems that make recommendations, not systems that make independent decisions regarding patient treatment. However, the boundaries for what tasks machines can solve and what decisions they can make are constantly being moved. Despite the system only making a recommendation regarding diagnosis or treatment, the reality is that it can be difficult for a doctor to disregard this recommendation. This particularly applies in situations where a diagnosis needs to be immediately followed by treatment, and there is thus greater time pressure.

This raises the question of who should be held liable if the system recommends not removing a tumour, when, in reality, it is malignant. Is it the practitioner who followed the recommendation? Or is it the manufacturer of the equipment, the developer of the software, the provider of the training data used for training the model, the dealer who sold the equipment to the hospital or the hospital that put it into service?

According to current EU legislation, decision-making systems cannot in themselves be held liable for actions that result in harm to third parties, and liability must be able to be traced back to a person who could or should have foreseen that the harm could occur, and possibly could have averted it. However, autonomous systems are, by their very nature, unpredictable, because they themselves make decisions. There is thus no certainty that any human could have foreseen or averted harm, and it may therefore be problematic to assign liability. Therefore, one discussion that has taken place in the EU system is whether such liability should regardless and always be assigned to the people who use the systems.

Another alternative that has been discussed is to introduce compulsory insurance similar to that for motor vehicles, so that anyone who suffers harm from decisions made by a system with artificial intelligence can always seek compensation for such harm, irrespective of whether or not a specific person can be held liable.[105] In Norway, this could, for example, be part of the scheme for patient injury compensation.

The legal discussions regarding liability for the decisions and actions of artificial intelligence systems are in full swing within the EU system. While there appears to be broad consensus that those who are harmed by artificial intelligence should receive compensation for this, several countries are focussed on avoiding that the rules are so strict or dissuasive that they prevent the development of new solutions.[106]

A LONG WAY FROM LAB TO CLINIC

While AI algorithms can demonstrate good results in the research laboratories, considerable work remains with regard to understanding how machine learning can and should be adopted in everyday clinical practice in hospitals and doctor surgeries, such that it actually results in better and more efficient health services. A study in the medical journal *The Lancet* from February 2020 concluded that less than 0.1 per cent of studies in the field of artificial intelligence and medical diagnoses were of sufficient methodological quality to be used in clinical practice (14 out of 20,000 studies).[107] The systems also need to be suited to everyday practice and workflow in the health service. In order for the technology to produce better results for the patient, changes need to be made to processes and organisational structure, and in some cases, perhaps also organisational culture.

ARTIFICIAL INTELLIGENCE NEEDS TO BE INCLUDED IN HEALTHCARE EDUCATION AND TRAINING

When AI-based equipment enters the clinics, the health personnel must be trained in how to use this. This of course applies not only to the use of the equipment, but also to a deep understanding of the limitations of technology when given the particular risks associated with artificial intelligence as described elsewhere in this report.

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[105] European Parliament (2017).
[106] Bertolini (2020).
[107] Denniston et al. (2019).

If multiple departments and professions are to work more closely together, it is important that they share the same knowledge about the technical systems, and that they use these in the same manner.

There appears to be a broad consensus that artificial intelligence should be included to a greater extent in medical training and other health education and training. However, opinions are divided on how this should be effectuated. Some will want it to be a separate specialisation, while others will be of the view that it should be included across all other specialisations, because it is general technology. Another approach is that the technologists and engineers who develop artificial intelligence can specialise in the application of this technology within healthcare. The most probable solution will be a combination of all these approaches.

4: EVERYONE CAN MONITOR THEIR OWN HEALTH

Home sensors have become commonplace, and can record everything from heart rate to tone of voice. Artificial intelligence interprets the data and provides users with continual information about their physical and mental health.

A huge number of people now have a smartphone that can collect and interpret large quantities of data. Smartphones have a built-in camera, flash and accelerometer. In addition, they can easily be connected to extra equipment. There is a wide selection of sensors that measure blood pressure, heart rate, blood sugar, muscle activity etc. An increasing number of these types of sensors are being incorporated into other wearable technology, such as smart watches, intelligent "patches", and even smart bathroom mirrors.[108]

New consumer-oriented services are constantly being developed based on all these available readings, and often in the form of apps. Some of the solutions provide quality-assured medical care, for example, sensors and associated apps

[108] Andreu et al. (2016).

that help diabetics control their blood sugar. Others are only intended to contribute to a better lifestyle in general, for example, apps that measure the user's level of activity or sleep quality, with tips and advice for improvements.

The prevalence of sensors and associated software provides completely new opportunities for monitoring one's own health status. It also provides new opportunities for remotely monitoring a patient's health, without the patient needing to visit a doctor or hospital.[109]

SIGNALS

YOUR WATCH MONITORS YOUR HEART RATE, BLOOD COUNTS AND MOOD

Smartwatches have been on the market for a number of years. Early variants were watches with pedometers, such as the first editions of Fitbit, or GPS watches used for exercise. Additional equipment such as a chest strap was often needed to measure heart rate. Wrist-worn heart rate monitors are now standard in most watches. Watches are also being developed with continually more advanced monitors. The latest Apple Watch measures your blood oxygen levels, as well as all the "usual" readings of activity, heart rate, sleep quality and more.[110] Among other things, Amazon's *Halo* fitness band measures body temperature and uses voice recordings to assess the user's state of mind.[111]

MOBILE ECG CONTINUOUSLY DETECTS RISKS

Electrocardiography (ECG) is the recording of the heart's electrical activity. The technique is used to diagnose, among other things, heart attacks and to detect arrhythmias (rhythmic disturbances of the heart). An ECG device usually has 12 points, and has been most commonly found in hospitals. There are now more basic ECG devices, with 2 and 6 points, that can be connected to smartphones and watches. Readings can be taken and interpreted at home, either continuously, at regular intervals or when one feels something is wrong with the heart

[109] See, for example, Norwegian Directorate of Health (2021b).
[110] Shein (2020).
[111] Phelan (2020).

rate. Studies have shown that these more basic ECG devices can replace the 12-point ECG for multiple clinical applications.[112]

Kardia is a supplier that offers ECG devices that can be connected to a smartphone, which then conducts the analyses. Among other things, the 2-point devices can detect atrial fibrillation. The 6-point devices also provide the doctor with a more detailed insight into other cardiac arrhythmias, which may be indicators of cardiovascular disease.[113]

SENSORS AND HOME TESTS PROVIDED RELIEF DURING THE CORONAVIRUS CRISIS

New sensors and home tests have made it possible to monitor patients in their own homes. This went from a possibility to a necessity during the coronavirus pandemic. In countries where the pressure on the health services was far greater than in Norway, for example, the United Kingdom, telemedicine was in some cases the only alternative for overburdened hospitals. For example, British heart patients had their blood pressure and heart rate measured at home, while their doctor monitored this remotely.

However, it is also increasingly more common in Norway for patients to be monitored digitally at home. Ten per cent of the municipalities report that they have implemented digital home follow-up of residents in the risk groups in connection with the corona pandemic. One example is the municipality of Larvik, which has followed up patients with severe symptoms or underlying illnesses with the help of a thermometer and pulse oximeter. The results of the readings are automatically monitored, and if the system detects conditions that are considered serious, health personnel are connected via telephone or video consultation.[114]

Another example is the company BioIntelliSense, which has developed a coin-sized "button" that can be placed directly on the body and monitors the patient's vital signs for up to three months. Among other things, the system is now being used to monitor healthcare workers who have received the COVID-19 vaccine in Colorado, USA.[115]

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[112] Madias (2003).
[113] AliveCor (2021).
[114] Norwegian Directorate of Health (2021a).
[115] UCHealth (2020).

VIRTUAL HEALTH ASSISTANTS PROVIDE PERSONALISED HEALTH ADVICE

A continuous flow of health data does not always make sense to the individual directly, and needs to be interpreted. There are now a number of digital health assistants available to ordinary users. Some examples are Doc.ai [116], Babylon Health[117], YourMD[118], Sense.ly[119] and Ada Health[120]. These apps can typically store and monitor a user's health, activity, and results from various examinations. The apps help the user assess symptoms and can signal potential risk of illness. The assistants help users better understand their health situation and provide personal recommendations for preventing illness. If permitted, these apps will also, in future, download data from patient records in the health service, thus making the health picture more complete. Conversely, the health service could also upload and use data from private health apps to establish a better picture of the patient's health.

WHAT COULD THAT MEAN?

BREAKTHROUGH FOR TELEMEDICINE

It was previously the case that the doctor visited people at home. We have more or less moved away from this in modern times. In order for doctors and other specialists to use their time more efficiently, patients need to travel to the treatment location. However, we are now seeing the emergence of new technology that can enable each of us to monitor our own health at home. Tools that measure heart and lung sounds are becoming digital, mobile and more affordable. They will also be augmented with machine learning, thus enabling them to continuously analyse the data. Stethoscopes and ECG devices that make diagnoses as accurately as specialists can help less specialised health personnel, as well as citizens themselves, detect abnormal sounds and make diagnoses.

The development of more affordable equipment and digital readings also means that patients can, to a greater extent, be monitored in their own homes, by a doctor who is at a completely different location. This may mean fewer visits to

[116] Doc.ai (2018).
[117] Babylon Health (2021).
[118] Your.MD (2021).
[119] Sensely (2021).
[120] O'Hear (2017).

the doctor and fewer days spent in hospital, as well as better ongoing follow-up. A ripple effect of this is that more data is collected about patients and illness progression, which can potentially be used for research and development of new or improved solutions.

Dr. Eyal Zimlichman at Sheba, Israel's largest hospital, predicts that within a decade, 70 per cent of hospital visits will take place in the patient's own home through the use of telemedicine.[121]

Digital home monitoring is growing, including in Norway. According to the Norwegian Directorate of eHealth, there is major potential for further development of this type of technology.[122] The National Health and Hospital Plan 2020-2023 expresses a clear goal that services which previously required physical attendance will, in future, be provided via video consultations, patient-reported data, sensor technology and web-based treatment programmes.[123]

EASIER LIFE FOR PEOPLE WITH CHRONIC ILLNESSES

Equipment and sensors that can be used at home have become very affordable and accessible. This is particularly good news for chronically ill patients. Better and more continual monitoring of their own condition better enables chronically ill patients to manage their own illness. One example is the "patch" that continuously monitors the blood sugar levels of people with diabetes and administers the correct doses of insulin. It improves the daily quality of life while at the same time reducing the risk of complications.

EARLIER DETECTION OF DISEASE AND RISK

Diagnostic health apps and other home devices may contribute to more people having the opportunity to detect illness and the risk of illness at an earlier stage and start prevention or treatment more quickly. Some of the burden on the health service can be relieved by people performing part of the diagnosis themselves and treatment can be simpler, more affordable and less extensive. The ability to interpret signals such as heart and lung sounds will become more standardised and accessible, and more people will receive a diagnosis and treatment at an earlier stage. For example, many wearables such as Apple Watch or

[121] Medved (2020).
[122] Norwegian Directorate of eHealth (2021c).
[123] Ministry of Health and Care Services (2019b).

FitBit will be able to monitor your heart rate and notify you if something unusual is detected.

CITIZENS CAN HAVE FULL CONTROL OVER THEIR OWN HEALTH DATA

Citizens can now collect health and activity data in various apps that can provide recommendations regarding exercise, diet, prevention and treatment of illness. These can be created in such a way that neither data nor predictions are shared with others. If citizens are also permitted to access data from the health service and transfer this to the apps, citizens can obtain a complete picture of their health situation. In doing so, this can further improve predictions and health advice.

CHALLENGES

THE RISK OF OVERTREATMENT AND HEALTH ANXIETY

Continuous monitoring of one's own health can contribute towards detecting potential health problems at an earlier stage and receiving better and more adapted help. However it can also, paradoxically, result in poorer health. A virtual assistant that constantly monitors your health can quickly become a little too concerned, and a little too accessible.

For all medical examinations, one must decide what preferably to avoid: False positives, i.e. alerts that turn out not to be an illness, or false negatives, i.e. not reporting something that actually turned out to be dangerous. The goal is of course to avoid both, however, in practice, a choice has to be made about what is to be assigned the most importance.

When introducing systems for monitoring one's own health, it is not difficult to assume that those who intend to use these would prefer that alerts are issued too often rather than not often enough. However, it can, on the whole, result in both pointless visits to the doctor and unfounded concerns on the part of the individual. In the worst case, unnecessary treatment is carried out, which can be directly harmful. It should also be taken into consideration that many global healthcare actors have commercial interests in increasing the demand for treatment. It is important that financial incentives linked to the new technological solutions are properly disclosed.

Increased self-monitoring will also result in more people who are always monitoring and checking their symptoms wanting to obtain an assessment of whether they require healthcare. It is already a known fact that when laypeople research their own symptoms online, this can contribute to increased health anxiety.[124] For example, if one conducts a search for relatively innocent, but perhaps somewhat diffuse symptoms, one may get answers indicating that these symptoms *could* be due to serious illnesses. Therefore, symptoms that would previously not have resulted in someone visiting the doctor could result in both greater concern about one's own health and greater strain on the health service because more people are contacting their doctors.

There is, not least, a risk that people who already have a tendency to being overly concerned about their own health will become "triggered" by these types of systems. Some people may simply develop a morbid curiosity with keeping track of all the possible data that is produced.

CAN WE RELY TOO MUCH ON THE TECHNOLOGY?

People are sometimes too quick to attribute more qualities to technology than it actually has. The manufacturers of technology can also benefit from the impression being created that an app or a monitor can help us avoid illness and become both fitter and healthier. However, the impression that the technology can solve more than what has actually proven to be the case can also be formed when the manufacturer does not communicate the product's limitations in a clear enough manner.

One example is that many people believe new smartwatches, such as the Apple Watch, can detect a heart attack. This is not true.[125] It is correct that a larger study based on users of the watch demonstrated that the watch can in fact detect disturbances in the heart rate.[126] However, this is still rather different to the watch actually giving notice of a heart attack.

It is also not realistic to believe that every patient is capable of conducting quality controls of new digital tools — whether in terms of their effect or in terms of other aspects, such as data security and privacy. These are among the reasons for why the Norwegian Directorate of Health, the Norwegian Directorate of

[124] Zuccon, Koopman, and Palotti (2015).
[125] Pearson (2019).
[126] Park (2019).

eHealth and the Norwegian Health Network are assessing how the authorities can facilitate quality control for health apps.[127]

TWO-TIERED HEALTH SERVICE

Access to advanced equipment for monitoring one's own health is not evenly distributed among the population, either nationally or globally. Resourceful population groups have access to the most advanced technology. Wearables are typically still something people purchase privately in the commercial market. However, even if the equipment was to be available through the public health service, it usually requires considerable effort on the part of the individual to use and understand this equipment. It is not difficult to envisage that the groups with the highest socioeconomic status will also be those who best utilise these new opportunities.

There is thus a risk that the increased prevalence of tools for monitoring one's own health will result in greater disparities, and that those who already have the best prerequisites for good health can access even better help, while those with poorer prerequisites fall even further behind.

THE COMMERCIAL WINNERS TAKE IT ALL

Commercial investments could mean that new solutions are actually used in the health services in a manner that is to the benefit of patients. However, it could also mean that a small number of global players are left with both the data and the profits. One result may be undesirable market concentration, which in turn may hinder further growth and development.

The tech giants, such as Amazon and Apple, work hard to collect health data from their users, and generally do not have incentives to share this either with other private actors or with independent research communities. Private individuals have little benefit or interest in having their health data used for purposes other than helping themselves, and they often have little awareness about the use (and misuse) of their health data.

If the individual has all of the rights to decide over his/her own health data, this also brings with it a great responsibility to investigate whether the apps that we share our health data with are safe. For example, a review of mental health apps

[127] Norwegian Directorate of Health, Norwegian Directorate of eHealth, and Norsk Helsenett (2021).

showed that 92% sent data to third parties such as Facebook and Google for use in data analysis or marketing.[128]

Extensive use of private solutions for monitoring one's own health may therefore present challenges to data protection. However, it could also result in the commercial players running away with the profits, instead of health data which originates from citizens benefiting the wider community.[129] It is therefore a significant challenge to create platforms for sharing health data, including data that originates from private solutions and services.

[128] Huckvale, Torous, and Larsen (2019).
[129] Norwegian Board of Technology (2018).

5: EQUIPMENT IS CONSTANTLY IMPROVING ITSELF

By using artificial intelligence, software in medical devices can learn from a continuous stream of data. The equipment can therefore continuously improve and update itself.

Software is now an important component in most medical devices. The advantage of software is that it can be updated as required, without needing to replace the physical equipment. Medical devices, including the software, have traditionally been approved once before being launched on the market. They then function in more or less the same manner for as long as they are in use.

The difference for products that use machine learning when compared with traditional software is that they can be continuously updated and improved by continually learning from a stream of data. This is called dynamic, or continuous, learning. Well-known examples of dynamic learning are how the streaming service Netflix or the retail giant Amazon continuously adapt their models with data they collect from the use of the solutions, and can thus provide increasingly more accurate recommendations to users.

Continuous learning resembles more the human way of learning, i.e. every time we experience, see, or learn something new, we adapt the models we use to interpret the world around us. We therefore learn from a stream of information.

Traditional machine learning algorithms, on the other hand, learn from a given and final set of "training data", before the resulting model is applied to the world around it. However, there are several techniques for ensuring that machine learning models can learn from continual new data. The first is to include the new data in the set of training data, run the entire learning algorithm once more, and update the model that is used. This is not a problem for small data sets, however the present-day data volumes may require large computing capacity, and cost time, money and energy. Other methods involve using the new data to adjust the model that is already in place. This is much simpler, however, in some cases has resulted in the new data acquiring disproportionate weight, so that the model "forgets" things it had actually learned from before.

Not all machine learning systems make use of dynamic learning, but are instead "locked" upon their launch. This has largely been the case for the medical applications of artificial intelligence that have been adopted thus far. One reason is that the regulatory regime for medical devices does not take into account that the equipment may change function or character along the way. An adjustment of the model will mean that the entire solution will have to be approved once more.

Dynamic learning introduces new risks. However, such dynamic learning processes can be useful, especially in cases where it is important that the model quickly adapts to changes in its surroundings.[130] An ongoing pandemic outbreak, such as the COVID-19 pandemic, in which the disease itself can also develop and change, may be an example.

SIGNALS

PERSONALISED MEDICATION DOSAGE THAT IS UPDATED CONTINUOUSLY

Each year the incorrect dosing of medications results in many unnecessary deaths in hospitals and to other complications. It is common to adjust the dosage based on demographic and physical variables, such as gender, age, weight etc. The problem is that these categories are often too broad, and do not provide

[130] For an in-depth review of dynamic/continuous machine learning in healthcare, see, for example Xavier Health Organization (2018) or Lee and Lee (2020).

a well-adapted recommendation. A study from the Massachusetts Institute of Technology (MIT) used patient data collected continuously from the patient to adjust the recommended dose of medication during the process. The procedure produces better results than alternative models that do not take current data into account, and also better results than when health personnel determine the dose of medication.[131]

A CONTINUAL LEARNING ALGORITHM FOR MONITORING DEMENTIA PATIENTS

Researchers at the University of Surrey have developed a method for continuous learning from current data in order to recognise and send alerts for several different events and conditions. The method is applied to a data stream from patients with dementia. Patients are monitored at home using various sensors. The data consists of physiological data, such as body temperature, blood pressure and sleep patterns. This is compared with other data from the home, such as whether doors and windows are open or closed.

The system's task is to provide alerts of various conditions that require closer inspection, for example, detection of high blood pressure, urinary tract infection (a common cause of hospitalisations in dementia patients) or changes in behaviour that the system perceives as providing cause for concern.[132]

CONTINUOUS LEARNING DURING THE CORONAVIRUS PANDEMIC

Dynamic learning can make models more accurate and better adapted to changing environments. The prevalence of pandemics and infectious diseases is an example of an area in which knowledge may initially be limited, and one is forced to continuously learn from experience in order to be able to determine the correct diagnoses and treatments.

Time is critical, and machine learning may be beneficial for being able to quickly discern patterns from all the new infectious cases. Researchers at Lancaster University have trained a model using CT images from Brazilian patients to distinguish between those who are infected with COVID-19 and those who are not.[133] The model can continuously learn from new images, for example, from

[131] Ghassemi et al. (2018).
[132] Li et al. (2015).
[133] Soares et al. (2020).

CT images from Norwegian patients, and gradually become more accurate and better adapted to the Norwegian population.[134]

WHAT COULD THAT MEAN?

FASTER IMPROVEMENTS IN HEALTHCARE

The fact that the equipment is updated continuously means that there is not a long wait until, for example, the next product cycle, before there is access to better equipment. It improves itself along the way.

This can be particularly beneficial in rapidly changing health situations, such as during the ongoing coronavirus pandemic. Dynamic equipment makes it possible to learn from the experiences of the pandemic and quickly bring the new knowledge into the clinic. This is especially useful for dealing with a virus that can also alter its characteristics through mutations.

BETTER ACCURACY FOR LOCAL CONDITIONS

Dynamic machine learning models which adapt to new data and changing environments, can be useful for obtaining more precise algorithms that are better adapted to local conditions. It is a known problem that the existing data sets used to develop new AI solutions are typically collected from a small proportion of the world's population (primarily Western and Chinese populations). The possibility of dynamic learning can contribute to counteracting the problem of skewed data sets.

For example, an algorithm that analyses mammograms and makes recommendations regarding breast cancer could be primarily trained on data from white, Western women. If so, it would be a major advantage if it could be updated as more data from European women of African descent becomes available, because breast tissue varies in terms of ethnicity.[135]

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[134] If a new image resembles one of the categories defined by previous CT images, the new image is classified accordingly. If not, a new category is created and the new image is placed there.
[135] Cohen et al. (2020).

NEW RISKS ARISE ALONG THE WAY

Both the EU and its member states have legislation to protect users when the use of new medical devices is adopted. In Norway, medical devices are regulated, among other things, by the Regulations relating to medical devices. [136] The objective is to ensure that medical devices do not pose a danger to the safety of patients, users and anyone else in connection with the production, sale and use of these devices. While current legislation also regulates instances in which the product changes "significantly" after it is launched, it is primarily designed to assess safety risks at the point in time at which a product enters the market. When products contain software that can be updated continuously, this also means that new risks can arise at any time during the product's life cycle.

When the health service adopts the use of medical devices based on dynamic learning, it becomes more important to regulate the actual development process, and to monitor, identify and manage risks associated with these algorithms throughout the entire lifecycle.[137] This particularly applies to situations in which the equipment does not change significantly in one step, but rather changes gradually and in small increments over time.[138]

Both US and European regulators appear to acknowledge that dynamic systems require updated regulation. The United States Food and Drug Administration (FDA) has developed a life-cycle based regulatory framework for products that contain machine learning.

The purpose of the framework is to make it possible to make continuous changes based on real-world learning and adaptations, while ensuring that the safety and effectiveness of the medical device software are maintained.

One method of solving this in the health service is to introduce a digital twin of all patient data. One can then use a "frozen" algorithm in the day-to-day treatment, while the learning algorithm is able to develop in the digital twin. The further developed algorithm can then be tested and approved before replacing

[136]See, for example, Norwegian Directorate of eHealth (2019).
[137] Cohen et al. (2020).
[138] Ordish, Murfet, and Hall (2019).

the "frozen" algorithm. This satisfies both the need for predictability and dynamic development of relevant data.

The European Commission has conducted a review of the requirements in order to adjust or clarify current legislation in selected areas, for example, liability and security.[139] This is not specifically focussed on applications within healthcare, but addresses how matters pertaining to safety and liability are influenced when artificial intelligence is adopted more generally. The current legislation primarily assesses security risks at the point in time at which a product is launched in the market. Since products that use software, including machine learning, can change their functionality throughout their entire lifecycle, new risks may emerge that did not exist when the product was launched.

[139] European Commission (2020c).

6: PREVENTION IS TAILORED

By using machine learning, the health service can become better at finding people who are at greater risk of illness, and implementing preventive measures that actually have an effect.

Health services are largely about treating illnesses that have already occurred. This is despite it appearing as if "everyone" agrees that it is better for the individual and more affordable for society to prevent illness and injury from occurring. The problem is that prevention is difficult, because we usually do not know who is going to get sick.

There are two ways of approaching this problem: We can either attempt to initiate measures that have the widest possible scope, preferably the entire population as a whole. Or we can attempt, using different techniques, to cover the groups that are most likely to be impacted by a particular illness.

Preventive health at the population level may, for example, involve preparing and disseminating national advice on diet, physical activity, mental health etc. This advice should be as general as possible in order for it to reach the entire population. For example, the dietary advice from the Norwegian Directorate of

Health should be suitable for "the majority of people: adults, children, adolescents, women who are pregnant and lactating, and the elderly". [140]

The process of placing people in different categories for further follow-up based on their risk of developing an illness is known as *risk stratification*.[141] The traditional approach has been to create statistical models based on relatively few factors, such as gender and age. These factors have typically been handpicked, which is a laborious task, and the most important factors have not necessarily been determined.

When this type of risk assessment is conducted for the population as a whole, and large groups are selected for preventive examinations and/or treatments, this is often referred to as *screening*. Examples include cancer screening programmes such as the Mammography Programme, the Cervical Screening Programme and the National Screening Programme for Colorectal Cancer.[142]

Machine learning algorithms have the ability to calculate risk both more accurately and based on a broader set of possible variables. The algorithms may be able to identify other, perhaps unexpected, factors that could have greater predictive value, i.e. are better at predicting future health. The algorithms are also better suited for analysing how interactions between many different factors can affect risk. They also do not require any clear advance hypothesis about which variables or combinations will have the greatest effect. This may, in turn, mean that people who are actually at risk are more likely to be identified, and that this can occur at an earlier stage.

SIGNALS

EARLIER DETECTION OF DEMENTIA AND ALZHEIMER'S DISEASE.

Machine learning can detect details and patterns that humans cannot find. One example is a machine learning algorithm that has been able to identify signs of Alzheimer's disease six years earlier than when a patient would normally be diagnosed through analysis of PET images[143] of the brain. These results could

[140] Helsenorge.no (2019).
[141] Norwegian Directorate of Health (2018a).
[142] Ministry of Health and Care Services (2018).
[143] Abbreviation for Positron Emission Tomography, an advanced brain imaging technique.

open up new ways of understanding, and possibly treating or delaying, the progression of the disease.

An algorithm based on UK medical records identifies existing and new risk factors for developing dementia. The algorithm achieved a sensitivity and specificity of 84.5 per cent and 86.7 per cent respectively. This means that it could be possible to identify the risk of dementia simply by using data routinely collected by the GP.[144] This can make it easier, more affordable and faster to diagnose dementia in the primary care service and thus enable those with a heightened risk to obtain assistance with facilitation and potential treatment at an earlier stage.

Research is also being conducted into how digital personal assistants can help with diagnosing cognitive defects by listening to the conversations and analysing changes in different patterns such as voice or repetition of tasks. A conversational tool asks specifically designed and cognitively demanding questions to elderly people to test brain functions such as memory, speech and concentration. Voice and speech are also analysed to detect patterns.[145] These types of techniques can assist in diagnosing dementia at an earlier stage, even before family and friends notice the symptoms. For close contacts, it can typically be difficult to distinguish between dementia and natural forgetfulness.

AI CHOOSES WHO IS CALLED IN FOR BREAST CANCER SCREENING

Many routine examinations were cancelled or postponed during the coronavirus pandemic, including mammograms. A hospital in Massachusetts, USA, chose to use an algorithm to select the women who were presumed to have the highest risk of breast cancer, so that they could be better targeted for closer examination. The system reviews images from previous mammography examinations in combination with other health information. Of the people who the new system labelled as "high risk," 42 per cent actually developed breast cancer within five years, up from 23 per cent in the best model prior to this.[146]

DISCOVERED FIVE NEW SUBGROUPS OF TYPE 2 DIABETES

Diabetes has previously been categorized as type 1 or type 2. With the assistance of machine learning, Swedish researchers have discovered that type 2 diabetes

[144] Ding et al. (2018).
[145] Mirheidari et al. (2019).
[146] Knight (2021).

can be divided into five subgroups. These groups have different risks of sequelae, such as eye or kidney disease. With this knowledge, doctors can prescribe the treatment or lifestyle changes that will probably work best, and protect the patient from sequelae.[147]

However, it should nevertheless be mentioned that studies in which machine learning is used to detect subgroups of various diseases are the subject of some debate. A systematic review from 2021 warned that a very high number of the studies do not investigate or provide good enough responses to what the benefits to patients will be.[148]

WHAT COULD THAT MEAN?

SCREENING COULD BE REVOLUTIONISED

The current procedure is that participants in the screening programmes are typically selected based on a few well-known variables, such as gender and age. For example, all women over the age of 50 are offered the opportunity to participate in the mammography programme, because this group is considered to have the highest risk of breast cancer.

The benefit of some of the screening programmes has been debated, because it can be difficult to demonstrate that these programmes actually have a health-enhancing effect at population level. While screening for breast cancer results in more tumours being operated on and removed, meta-studies have shown that overall mortality for women has not been reduced by mammography programmes. This indicates that these types of screening programmes can just as easily result in unnecessary treatment, which in itself causes both physical and psychological harm.[149] Using the same arguments, the general screening of, for example, all men for prostate cancer, is also rejected. The testing of large groups does not appear to reduce overall mortality, however may lead to an increase in overtreatment with the associated side effects.[150]

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[147] Ahlqvist et al. (2018).
[148] Banerjee et al. (2021).
[149] NHI.no (2013).
[150] Johansen (2008).

Machine learning models can contribute to improving screening in two ways: Firstly, machine learning can be used to make a more targeted selection of who should be called in for screening, based on who is generally at higher risk. Secondly, they can analyse the images/measurements in the screening faster and more precisely, thereby increasing the accuracy when identifying who needs to proceed to treatment.

This then makes it possible to identify risk more accurately, faster and with fewer resources. Screening programmes can be made more targeted, with reduced costs and adapted to individual citizens, and more illnesses can be detected at an earlier stage.

NEW POSSIBILITIES FOR EARLY PREVENTION

In addition to improving current screening programmes through better selection or analysis, machine learning also offers completely new possibilities for prevention.

For most illnesses, it is easier, less expensive and there is a greater probability of successful intervention if the risk is detected early. Some illnesses are life-threatening if detected too late. Machine analyses of patient records and continuous readings of vital signs and activity can detect signs of adverse development more quickly and accurately than with current methods. For example, it could be that everyone over the age of 65 is given a small, portable sensor (for example a so-called "ECG patch")[151] that continuously measures heart rate. If a pattern of risk appears, the person in question is automatically called in for a more detailed check-up and follow-up by a cardiologist.

It is also conceivable that the preventive role of the GP office will increase significantly. Although GPs are already recommended to carry out systematic risk assessments of patients on their GP list, there is major potential for more preventive efforts. With the increased use of sensors at home, in combination with machine learning, GPs can continuously monitor the health status of patients on their list, and thereby detect risk or adverse developments. Perhaps this preventive work can be more fully automated or under the supervision of someone other than a GP.

[151] Nordic Semiconductor (2020).

WE CAN BE “NUDGED” TOWARDS BETTER HEALTH

Artificial intelligence can provide a better understanding of which type of prevention is most effective for health at the population level. Health information can be linked to information regarding living conditions, such that policy measures and grants can be implemented and allocated where they have the greatest impact.

Prevention under the auspices of the health authorities is currently carried out through general information campaigns that target the entire population. These campaigns reach many more people than those in the target group, which can lead to the wrong people following the advice. They also do not necessarily reach those who are actually in the target group.

A good example is the advice regarding exposure to the sun. A certain degree of sun exposure is healthy, however overexposure and sunburn increase the risk of skin cancer. Someone who likes to sunbathe will often interpret the message that "a little sun is good" as an argument for getting out the sunbed, while someone who is already very careful in the sun may place so much emphasis on the message of "avoiding too much sunbathing" that he/she ends up with a lack of vitamin D.

However, personalised advice which is based on the group one belongs to, increases the probability of getting the right message across to the right person. The recommendations can also be translated into careful little pushes in the right direction, also known as “nudging”. The essence of nudging is that everyone retains their freedom of choice, however it makes it easier to choose the alternative that is considered best for you. A well-known example is vaccination programmes in which one is summoned to an appointment automatically, and explicit notice has to be given if one does not want a vaccine.

There is a great deal of discussion about how artificial intelligence algorithms can be used to negatively manipulate both attitudes and actions, for example, through social media. Perhaps healthcare could be an area in which this can be turned into a positive influence. This requires extensive discussion of consent, responsibility and limits of influence. What is intended as well-meaning advice can quickly be perceived as intrusive, and in the worst case, diminish trust in the health authorities.

THE RIGHT TO AN EXPLANATION

Machines can identify new patterns and relationships in data sets, however they cannot necessarily explain causation. The models may not be very transparent and can be difficult to understand, something which is known as the *black box* problem.[152]

There may be several reasons for why systems appear to be black boxes. Sometimes it is a matter of deliberately restricting access to the algorithm due to commercial considerations, national security or privacy concerns. Other times, it is more about the algorithm simply being complicated and difficult to explain in terms that are understandable to humans.

Developments within machine learning have made the latter problem more prominent. Deep neural networks can have millions of connections, or "neurons," each of which makes a small contribution to the final decision. An example is the DeepPatient model, which can predict fluctuations in schizophrenia better than doctors, however does not provide a good explanation for how the model arrived at the predictions.[153] When a model cannot explain the results, information about what can be done to prevent the development of an illness can also be missed. However, if there is an understanding of why the prediction models arrive at a given result, it may also be possible to implement measures earlier for more patients.

For screening and long-term health prevention, this specifically means that the system may be telling you that you are in a risk group, however it does not necessarily have an explanation for *why*. Knowing that you are at an elevated risk of developing a more or less serious illness in the future, and receiving no better explanation for this than that it is a complicated combination of all the data registered about you will most probably be considered unsatisfactory, and perhaps even be directly harmful to your mental health.

[152] Norwegian Board of Technology (2018).
[153] Miotto et al. (2016).

Health personnel may also require an explanation for why the equipment they use arrives at these results, for example, in cases of doubt, or when the doctor does not agree with the assessment made by the artificial intelligence.

However, explainability is not an absolute requirement. There are very many types of technology that both laypeople and professionals use without us knowing exactly how this works. An alternative to an explanation may be that the equipment proves to be useful and reliable over time, and that there are good arrangements for quality assurance and control. A classic example is a car engine, which is something that few people have detailed knowledge about the workings of. However, we still trust that we can get into the car, and that it will, for the most part, take us predictably and safely to where we need to go.

WHO SHOULD KNOW ABOUT RISK:

With more advanced algorithms and access to more data, it will be possible to obtain intimate knowledge of both the current health situation and future risk. This raises questions about who should have access to information about risk and when an alert should be sent. Should it only be the person in question, his/her next of kin or someone in the health service? It is also not certain that everyone wants to be notified about a possible future illness if there is no treatment for this.

In some cases, the information can only be made available to the computer system. The system can warn of risk in accordance with specifically defined rules, for example if there are treatments or means of preventing illness.

However, in many cases, for example if a risk of serious illness is identified, there may be a need to be able to talk to a person, and not just receive a message from a computer system. This could be an argument for granting health personnel access to information about risk first, and be assigned responsibility for assessing whether the patient should be notified.

It may also be necessary to clarify what different external parties, for example, insurance companies or employers, should be allowed to request or obtain access to in terms of information about citizens' health.

SHOULD THERE BE CONSEQUENCES FOR DISREGARDING THE ADVICE?

Personalised prevention can make recommendations more targeted and include personalised recommendations. However, this also raises the issue of consequences if a person chooses not to follow the advice and becomes ill. Can they risk being assigned lower priority in the health queue, or do they have to pay more for the treatment?

There are already examples of how your own efforts impact whether you receive or lose treatment. For example, people with eating disorders may lose their place in a treatment programme if they do not follow the prescribed treatment regimen.[154] However, this is still currently the exception, not the norm.

Even if the deductibles in the healthcare system are not impacted by your own efforts, it is conceivable that insurance companies will have incentives to offer more affordable health insurance to people who commit to complying with preventive health advice. Similar schemes have been trialled for car insurance, where people who permit the insurance company to install a chip that monitors their driving patterns can receive a discount on their insurance.

UNCLEAR DISTINCTION BETWEEN RESEARCH AND HEALTHCARE

The legislation which regulates access to health data is based on the principle that data must only be used for the purpose for which it was collected. Artificial intelligence can, to a much greater extent than traditional medical research, make use of all kinds of data, including unstructured data, that were actually collected for the purpose of treating the individual patient.

Using patient data for a purpose other than for what it was originally intended does not come without problems, because health data is sensitive and must be well protected. However, part of the strength of machine learning is that it discerns patterns and relationships where humans cannot see these themselves. Therefore, strict requirements for the purpose having to be known in advance can make it more difficult to develop good AI tools.

Once a tool has been developed and used, data can be generated during the process, for example, data from the treatment of each individual patient can be used to further develop and improve the tool. It is therefore no longer possible to distinguish between research or development of the system on the one hand, and healthcare for the patient on the other.

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[154] Senneset (2018).

It is generally the case that most patients will probably want to contribute to ensuring that other patients receive the best possible treatment and that an illness is detected as early as possible. At the same time, there are good ethical and historical reasons for why people should not be able to be used for any type of research without their own consent. The question is therefore what rights patients should have to object to their data being used for research or further development of medical tools, and how consent or the option to opt-out should be managed in practice.

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