# Artificial Intelligence as a Driver of Value in Value-Based Health Care Systems

Martijn van der Meulen, MD

September 2019

Radboud University

Radboudumc university medical center

Health

# Table of Contents

# Overview

**Artificial Intelligence (AI) draws significant attention as a game-changer that can drive considerable value in health care. This report provides an abridged yet inclusive view of the value of AI in value-based health care systems, and explores the factors that inhibit the implementation AI in health care. This is done within the framework of the urgency of health care reform and the blueprint of the health care system redesign as formulated by business scholars Michael E. Porter and Thomas H. Lee.**

The major focus of this report is on the advantages that AI is able to offer to our health care system in this context. AI cannot solve the problems inherent to health care innovation, but it can greatly improve on issues health care systems face, by combating operational inefficiencies, lowering costs, automating workload and remedying a number of issues that both medical staff and patients deal with in their daily process of care delivery. As a result, embedding AI in the health care system can lead to vast improvements in health outcomes and cost reduction. That is, AI can be a significant driver to increase value by simultaneously improving on both sides of Porter and Lee's health care value equation:

$$Added\ value\ of\ AI\ in\ health\ care = \frac{Increased\ health\ outcomes\ by\ AI}{Decreased\ costs\ of\ delivering\ outcomes\ by\ AI}$$

The value-based health care system appeals to me as a clinician, as it is a reflection of patient-centered care, using the patient's health outcomes as the numerator. It appeals to my entrepreneurial side as well: putting the customer first is a solid principle in business. Is it important to note however, that while criticism[1] exists on the value-based health care model, exploration of its limitations and drawbacks falls outside the scope of this report.

This report is organized into 6 topics:

1. Exploring the need for health care reform
2. Value-based health care as a driver of health care reform
3. The added value of AI in a value-based health care system
4. The scientific fundamentals of artificial intelligence
5. AI requirements, costs and benefits
6. Factors that inhibit the adoption of AI in health care

The report includes also a concise technical overview of AI, to provide insights of AI to decision makers, especially those without a background in data science. The basic understanding of the AI fundamentals is essential to foster effective collaboration with subject matter experts on opportunities, requirements and potential pitfalls of using algorithms in the health care sector. As opportunism surrounds AI, it is important to be mindful of the limitations and misconceptions inherent to AI.

[1] Binder, 2014. Good News And Bad News About Value Based Healthcare. Source: https://www.forbes.com/sites/leahbinder/2014/10/01/good-news-and-bad-news-about-value-based-health-care

This report is based on my experience as medical doctor in the Netherlands as well as on my research, recently conducted in Toronto with the SE Health (Saint Elizabeth Healthcare)'s Futures Team, in the context of the Radboud University's Honours programme for Master students. Expertise of being both a medical doctor and working at the Radboud University Medical Center's REshape Center for Innovation has inspired me to examine the value of AI to make health care safer, more personalized and more cost-effective for the benefit of all of us.

This report has been written with the objective to inspire health care organizations, academia, private enterprises, insurance companies, governmental institutions and organisations representing patients to join efforts to formulate strategic health care reform plans and to implement AI in health care, on local, national and international levels. Additionally, the report strives to better prepare health care providers for the changes AI will bring to their field of work.

The report is intended for a broad range of stakeholders in health care innovation with AI as enabler. To ensure readability for such a wide audience, I omitted unnecessary jargon. Analogies and examples are used to describe key principles of AI and expose health care innovation issues. Furthermore, concise descriptions and explanations are provided to ensure common interpretation within a diversified audience.

# Chapter 1: The urgency for health care reform

**A number of issues that have been negatively affecting our health care system. These issues are reflected by escalating costs that we not only are unable to manage, but we cannot justify them from the point of view of the value in health care they provide either.**

Escalating health care costs are due to a number of factors. The most notable factors are aging populations, shortage of appropriate medical staff (right service, for the right patient, at the right time and place), operational inefficiencies, outdated reimbursement systems and increasing costs of new treatments development by the biomedical technology industry. These factors reinforce their negative impact on escalating health care costs resulting in a health care system that is no longer sustainable in its current structure and operating model.

As the challenges facing health care are well known, they are not thoroughly discussed in this report. However, for the completeness of this report, the main ones are briefly reviewed.

## Escalating costs due to demographic changes

Social changes that mark the beginning of the 21st century, have put health care issues on top of the political agenda in most Western economies. Western societies are growing old rapidly. This trend has a twofold impact on the health care system. On the one hand, it effects the health care contribution and cost structure, due to increase in care needs for chronic diseases typical in the elderly. On the other hand, aging patients expect more value and a different, more personalized health care experience.

Hence, demographic characteristics, such as growth of the population and proportion of the population above 65 years, due to increasing life expectancy[2], are important factors in healthcare inflation. An important effect of these demographic changes is the increase in quality of life and improvement of quality of care and medicines. Older citizens tend to utilize health care more, reflecting the increase in chronic incurable illnesses with age. Moreover, these elderly patients do not contribute to the workforce anymore, which makes for a compound effect of elderly on available tax base to finance healthcare services.

Rising societal costs of health care systems reflect the unsustainability of the current health care models. According to the Canadian Institute for Health Information (CIHI), Canada's healthcare system has surpassed expenditures of 11% of the Nation's Gross

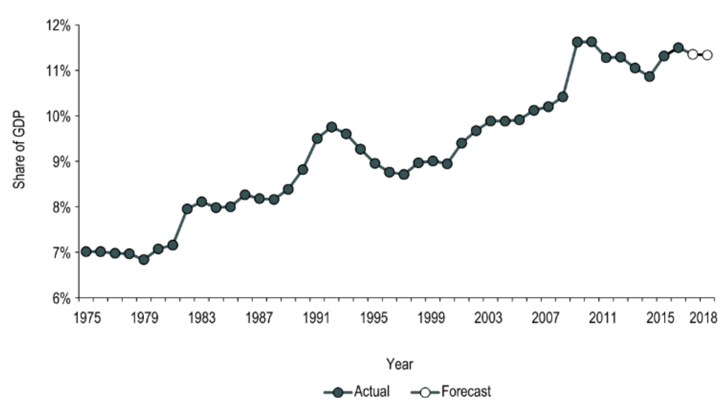



*Figure 1. Share of GDP spent on health care. Source: CIHI.ca*

[2] Willekens, 2014. Demographic transitions in Europe and the world. Source: https://www.demogr.mpg.de/papers/working/wp-2014-004.pdf

Domestic Product[3]. That is over 250 billion (Canadian) dollars in total, or almost $7,000 (Canadian) per citizen per year. More importantly, health spending is growing faster than the increase in gross domestic product.[4, 5] Between 2016 and 2031, health spending is projected to grow at 5.3 percent per annum on average.[6]

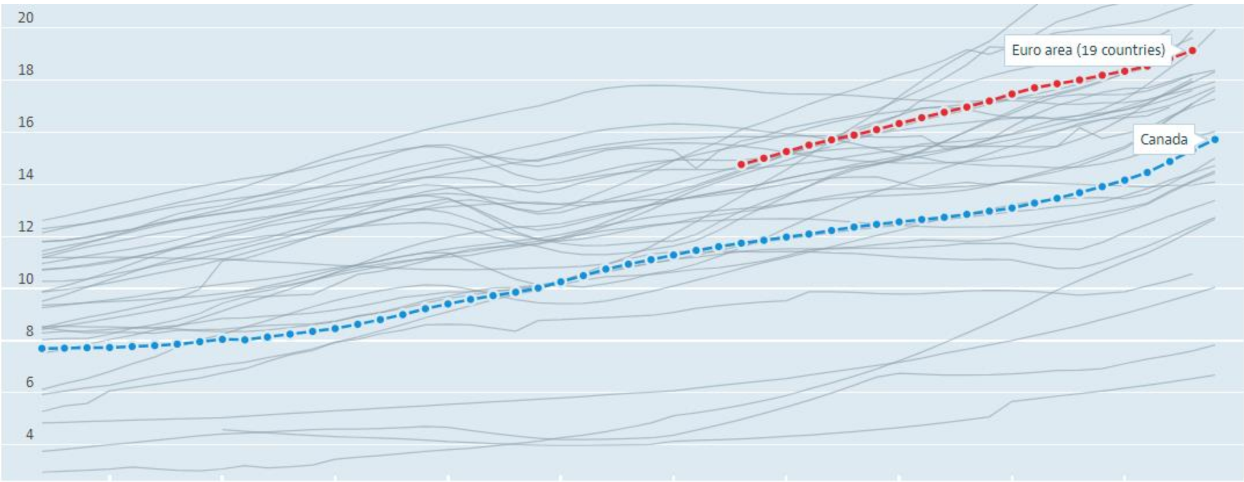



*Figure 2. Elderly population: Total, % of population, 1962 – 2014. The elderly population is defined as people aged 65 and over. Source: https://data.oecd.org/pop/elderly-population.htm#indicator-chart*

## Shortage of appropriate medical staff

The aforementioned demographic evolutions drive an increasing workload and shortages of appropriate medical personnel in most high-income countries. The Dutch National Institute for Public Health and the Environment (RIVM) of the Ministry of Health, Welfare and Sport of the Netherlands published a report in 2014 outlining performance of Dutch health care[7]. A key result was that one third of all care providers in the nursing and residential care sector reported in 2013 that insufficient staff was available to enable good-quality care, a figure that rose to 43% in residential elder care facilities and 53% in nursing homes in 2014.

A shortage of appropriate health care providers is one of the key drivers of high workload, rapidly becoming a bottleneck of our conventional health care system. Many other factors play a role as well, such as restrictive administrative environments and high administrative demands, the complexity of IT systems in workflow processes and a lack of IT skills in health care providers.

---

[3] Health Spending | Canadian Institute for Health Information (CIHI). Source: https://www.cihi.ca/en/health-spending

[4] Public spending on health: A closer look at global trends, WHO, 2018, https://apps.who.int/iris/bitstream/handle/10665/276728/WHO-HIS-HGF-HF-WorkingPaper-18.3-eng.pdf

[5] https://www.cihi.ca/en/health-spending/2018/national-health-expenditure-trends/how-has-health-spending-growth-changed-over-the-last-40-years

[6] https://www.fraserinstitute.org/sites/default/files/sustainability-of-health-care-spending-in-canada-2017.pdf

[7] Dutch Health Care Performance Report 2014. National Institute for Public Health and the Environment (RIVM), Bilthoven, The Netherlands. Original Dutch title: Zorgbalans 2014. De prestaties van de Nederlandse gezondheidszorg. https://www.rivm.nl/bibliotheek/rapporten/2015-0050.pdf

| | Doctors | | | | Nurses | | | |
|---|---|---|---|---|---|---|---|---|
| | Demand | Supply | Surplus/ shortage | Surplus/ shortage (as % of supply) | Demand | Supply | Surplus/ Shortage | Surplus/ Shortage (as % of Supply) |
| United States | 1,238,490 | 1,018,813 | −219,677 | −21.6 | 6,093,332 | 4,286,071 | −1,807,261 | −42.2 |
| Germany | 386,697 | 443,069 | 56,372 | 12.7 | 1,426,505 | 1,452,273 | 25,768 | 1.8 |
| France | 298,880 | 243,422 | −55,458 | −22.8 | 838,253 | 873,940 | 35,687 | 4.1 |
| United Kingdom | 217,588 | 233,897 | 16,309 | 7.0 | 824,163 | 727,291 | −96,872 | −13.3 |
| Mexico | 408,990 | 462,905 | 53,914 | 11.6 | 594,561 | 495,758 | −98,804 | −19.9 |
| Canada | 126,342 | 129,718 | 3376 | 2.6 | 564,304 | 446,703 | −117,600 | −26.3 |

[8]

The United Kingdom's National Health Service (NHS) anticipated in their 2017 Workforce Strategy to need 190,000 more staff by 2027, assuming demands on the health care system will stay the same.[9]

Finally, as society itself is changing, health care providers' expectations of a work-life balance and the role work plays in life is changing as well. Health care provider retention is declining. The NHS identified a number of reasons why providers are leaving. The most notable reasons are pressure of work, lack of flexibility, pay and limited career development opportunities. [10]

This acute situation, in addition to growing healthcare needs by the elderly care sector, demands modern and creative solutions.

## An outdated cost reimbursement system and operational inefficiencies

Volume-based health care, the approach of paying by the visit/pill/procedure, results in growing volumes while trying to maintaining margins[11]; it is no longer a sustainable reimbursement system. The costs are not being measured completely, and therefore they cannot be managed adequately. Moreover, cost obscurity impedes clear quality and value analyses.

Furthermore, according to a 2014 report from the Canadian Institute for Health Information[12], robust estimates show inefficiencies in care delivery varying between 18% and 35%, averaging at 27%. Three important determinants of inefficiencies are administrative, operational and clinical wastes.[13]

[8] Projecting shortages and surpluses of doctors and nurses in the OECD: what looms ahead, Scheffler et al, Jan 2018, https://www.cambridge.org/core/journals/health-economics-policy-and-law/article/projecting-shortages-and-surpluses-of-doctors-and-nurses-in-the-oecd-what-looms-ahead/493055A944EF9EC181D8C4C2D3C3247E

[9] Facing the Facts, Shaping the Future. A draft health and care workforce strategy for England to 2027. https://www.hee.nhs.uk/sites/default/files/documents/Facing%20the%20Facts,%20Shaping%20the%20Future%20%e2%80%93%20a%20draft%20health%20and%20care%20workforce%20strategy%20for%20England%20to%202027.pdf

[10] Facing the Facts, Shaping the Future. A draft health and care workforce strategy for England to 2027.

[11] Porter & Lee, 2013. The Strategy That Will Fix Healthcare. Harvard Business Review.

[12] Canadian Institute for Health Information. Measuring the Level and Determinants of Health System Efficiency in Canada. Ottawa, ON: CIHI; 2014.

[13] Albejaidi et al, 2017. Cost of Waste and Inefficiency – A Health Care System Perspective.

## These issues demand the restructuring of healthcare

In conclusion, continuously increasing healthcare expenditures in the current health care delivery models is not a sustainable long-term strategy. These increasing costs call for an entirely new health care model.

As such, there is a broad consensus that health care innovation is a necessary and urgent topic both from the financial point of view as from the point of view of administrative processes as well as from the point of view of value for patients.

According to groundwork of Michael Porter and Thomas Lee – Restructuring the Health Care System[1], a new model is needed for health care to become sustainable. Their proposal, value-based health care (VBHC), is based on measuring the performance of every health care process in a value-oriented way. Organising health care around value-based has the potential to become a key driver of implementing sustainable health care. There are six key topics on which changes are needed to shift health care to a value-based model. They are further explicated in chapter 2.

## Chapter summary

The present operating model of the health care systems in our Western economies appear to be outdated and it does not satisfy needs of its stakeholders. Both the organizational structure, unnecessary complexity of the core processes and the costs reimbursement method, based on a volume-based health care model, are not sustainable in the 21st century. It results in escalating costs that are not justifiable from the societal or any other perspective.

Instead of incremental changes, many scholars and thought leaders have proposed alternative models from the volume-based, fee-for-service approach to healthcare design, delivery and financing. Among them, the model that has garnered the most international interest has been that of Porter and Lee who suggest restructuring the health care model to a value-based health care (VBHC) model, in which process performance is measure in a value-oriented way, focusing on patient health outcomes. Implementation of the new system of cost accounting, formulated by Kaplan, should become an integral part of health care reorganization.

# Chapter 2: A Blueprint for Health Care Reform: The Value-Based Health Care (VBHC) model

A unique process of deterioration of health care delivery compared to outcomes expected by patients has been occurring already for some time. Yet the dominant position of key shareholders, based on political and historical domination, outdated cost calculations and payment models have stayed intact, inhibiting the necessary changes. This underlying, hidden structure of the health care ecosystem is complex and leads to vulnerability due to impeding innovation. That directly affects the patients and health care providers as well.

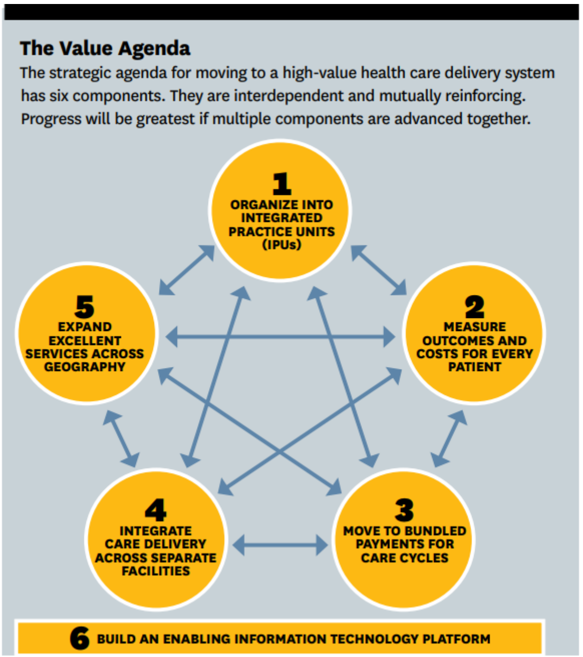
As outlined in chapter 1, changing the delivery and reimbursement models of health care is of paramount importance to guarantee health care's sustainability.

## The Strategy for Value Transformation

Porter and Lee created the blueprint to move to a value-based health care system through organizational change in a six-step model. The goal of the value-based model is to increase value for patients, defined as follows:

$$Value = \frac{Health\ outcomes}{Costs\ of\ delivering\ the\ outcomes}$$

The strategic agenda for moving to a high-value health care delivery system comprises of six interdependent components: organizing around patients' medical conditions rather than physicians' medical specialties, measuring costs and outcomes for each patient, developing bundled prices for the full care cycle, integrating care across separate facilities, expanding geographic reach, and building an enabling IT platform.




### Integrated Practice Units (IPUs)

Currently, health care is organized around medical specializations, instead of around patient's care pathways. As conditions often require multiple specializations, this delivery structure is inefficient and leaves the patient in a care path that is scattered across multiple separate departments that have no direct communication between them. Furthermore, as they are not specialized in the full care cycle of the most common conditions, quality of care and costs associated are not optimized either.

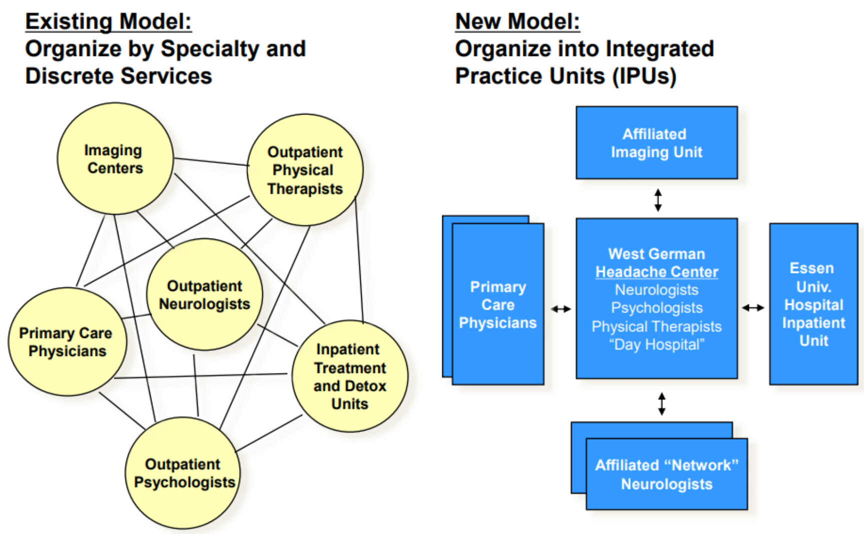



*Figure 3. A side-by-side comparison of the existing care model and the integrated practice unit model for the West German Headache Center. Source: Value-Based Health Care Delivery, Porter, May 2012.*
*https://www.hbs.edu/faculty/Publication%20Files/2012%205%208_EM*

Porter and Lee propose a new way of organizing health care delivery, by creating integrated practice units (IPUs) that combine all health care providers in a single practice unit for a specific care path. For diabetes, this means offering the full range of health care services needed to treat the commonly occurring related conditions as well, such as eye care for diabetic retinopathy, behavioural psychologists and dieticians for losing weight and physiotherapy for increasing exercise. In order to be efficient, you need volume. The volume gives you the capacity to create a high-value structure.[14] Implementing this new health care model leads to the optimization of the healthcare over the full process cycle of care per patient. This optimization results in increasing value of care for patients and simultaneously lowers the costs of healthcare.

For patients, outcomes improve as quality of care increases in specialized practice units with a lot of experience in dealing with these full care cycles. Furthermore, evaluation of quality of care of the entire care cycle becomes easier. Health care providers can optimize their workflows around these commonly occurring care cycles, reducing workload. Finally, costs go down by reducing overhead and increasing efficiency.

### Measure outcomes and cost for every patient

Outcomes and cost measurement are still undervalued indicators in health care. Moreover, the metrics that *are* tracked are usually not those that relate to the perceived value for patients. Instead, they track guideline adherence or compliance. Without rigorous measurement of value-driving outcomes, cost accounting and comparison of best practices cannot directly drive improvement.

Measuring value-driving outcomes for entire care pathways, such as for diabetes as a whole instead of solely measuring for one speciality or intervention, performance comparisons and improvement possibilities in quality of care and cost control become much more transparent. This way, patients get the information they need to decide what outcomes they value most and what

[14] Source: Porter, Michael E., Clemens Guth, and Elisa Dannemiller, The West German Headache Center: Integrated Migraine Care, Harvard Business School Case 9-707-559, September 13, 2007

practice unit offers the best care based on those outcomes. Furthermore, it helps health care providers measure and improve on value-driving outcomes.

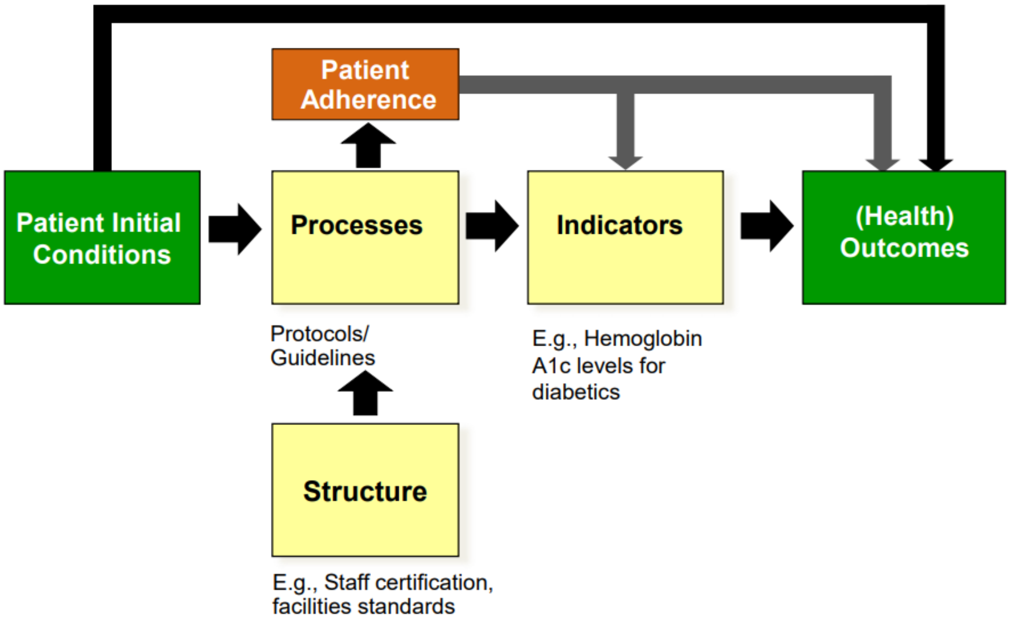



*Figure 4. Measuring Outcomes and Cost for Every Patient. Source:* [https://www.hbs.edu/faculty/Publication%20Files/2012%205%208_EMS_APA%20Deck%20(for%20May%208th)_final_4decf537-b307-4a6e-a52a-c25da319568a.pdf](https://www.hbs.edu/faculty/Publication%20Files/2012%205%208_EMS_APA%20Deck%20(for%20May%208th)_final_4decf537-b307-4a6e-a52a-c25da319568a.pdf)

### Moving to bundled payments for care cycles

As payment models in health care are not directly coupled to value, there are no direct financial incentives to increase value. Hence, health care providers are not rewarded to improve on both cost and health outcomes. Rather, they are merely incentivized to increase their volume and compete with similar facilities.

Bundled payments for the entire care cycle forces health care providers to increase outcomes and decrease costs across the entire care cycle. This prevents situations in which single care points can be excellent, but the overall outcome is bad. For example, a great internal medicine specialist could treat diabetes excellently in terms of medication, but if diabetic retinopathy is diagnosed too late, the patient can go blind regardless. As such, health care providers are made responsible for value of the entire care path, from diagnosis to rehabilitation.

### Integrate Care Delivery Systems

Nowadays, most hospitals are members of so-called multisite care delivery organizations. These however, are fragmented and offer duplicate care pathways. Porter and Lee suggest changing these organizations in order to integrate systems more efficiently by choosing either of four alternatives:

1. Defining the scope of services, which results in the reduction or elimination of care pathways of which health care providers cannot achieve high value;
2. Concentrating volume in fewer locations, an essential step to form integrated practice units and the subsequent improvement of outcome measurement.
3. Choosing the right location for each service, moving less complex and routine care pathways into low-cost facilities, increasing value by focusing health care provider skills and experience.
4. Integrating care across locations. As integrated practice units manage the entire care pathway, primary processes that do not require specialists of which there are few such as physiotherapy or psychology can be delivered in a decentralized way, close to the patient's home.

### Expand Geographic Reach

Geographic expansion allows for the concentration of complex care pathways that require many specialists, whereas more common processes with a higher patient throughput can be decentralized to allow for visits nearby the patient's home. Porter and Lee propose a model in which satellite facilities for which responsibility of cost and quality lies with the integrated practice unit are established to allow for care delivery close to the patient, while delivering focused care in a centralized way.

This way, patients can get expert care delivered by specialists at a hub location, while getting the mainstay of their treatments closer to home.

### Building an Enabling Information Technology Platform

An important requirement of these components is the availability of a comprehensive IT platform, that allows for exchange of patient data and continuous tracking of metrics. Porter and Lee describe six essential elements of such a platform:

1. Centered on patients, following them across the entire care pathway.
2. Using common data definitions, enabling data analysis and preventing duplication of data.
3. Encompassing all types of patient data, to allow for a comprehensive view.
4. Accessibility of the medical record to all parties involved in care.
5. Including templates and expert systems for each medical condition.
6. System architecture allowing for easy extraction of information to measure outcomes and track costs.

This allows for embedding AI algorithms that require many different data sources, without having to invest heavily in creating connections between medical record systems.

## A different way of measuring costs: Time-Driven Activity Based Costing (TD-ABC)

To determine value, we need an accurate system to measure outcomes and the costs associated. To drive the organizational

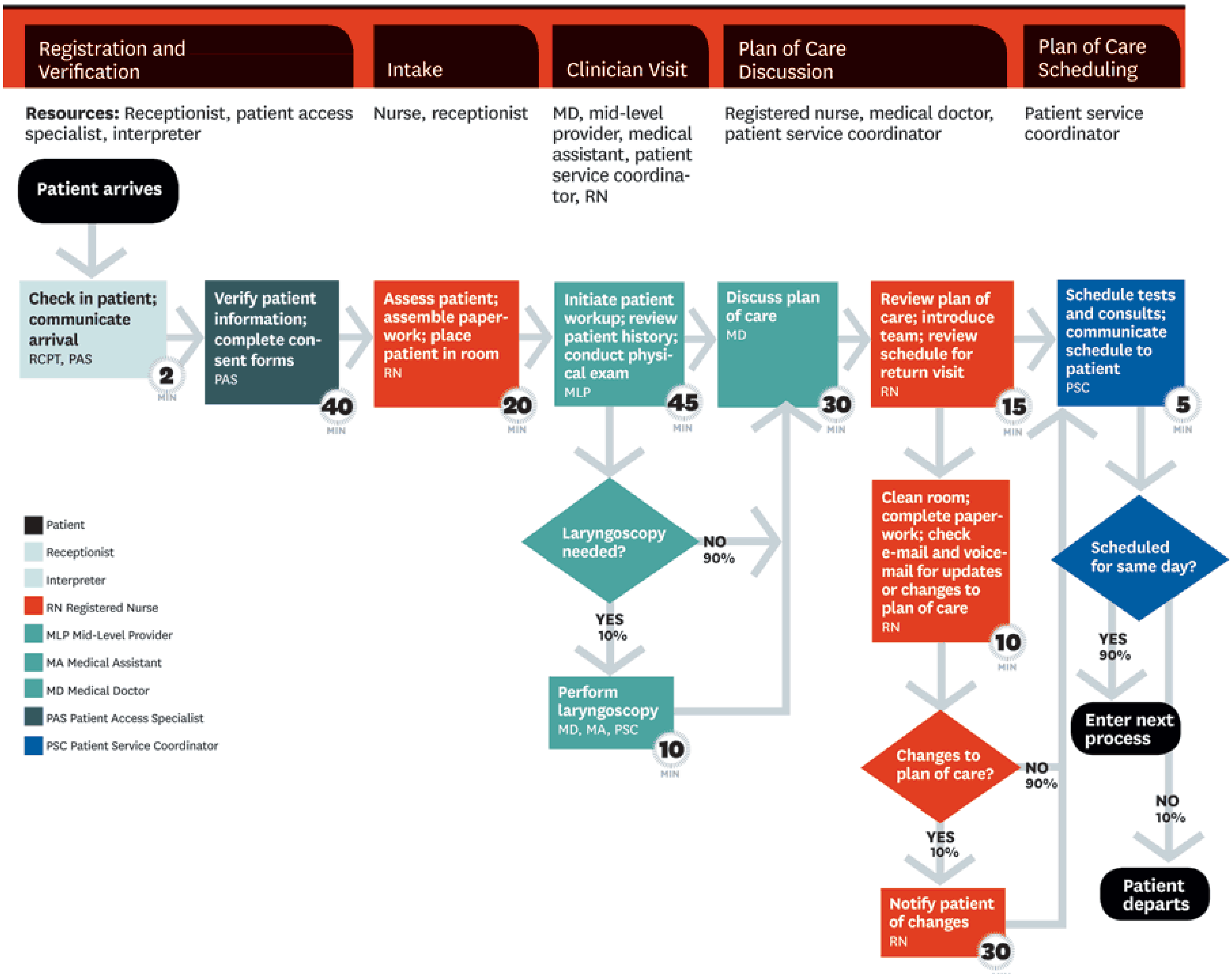



*Figure 5 - New-Patient Process Map. This process map describes a segment of the patient care cycle at MD Anderson Head and Neck Center. Process maps show the resources required for each activity and often reveal immediate opportunities for process improvement and cost reduction. Source: https://hbr.org/2011/09/how-to-solve-the-cost-crisis-in-health-care*

changes needed, Porter and Lee propose an alternative way of measuring costs, using the time-driven activity based costing (TD-ABC) model. Kaplan's TD-ABC model seems to offer the right solution to measure cost and manage them in order to decrease them. Hence, it is considered to be an inherent part of the value-based health care model.

A key feature of the TD-ABC model is uncovering costs from redundant administrative and clinical processes. As clinical processes become more transparent, departments are stimulated to work together and integrate care across specialties.[15]

TD-ABC requires an estimate of two parameters:

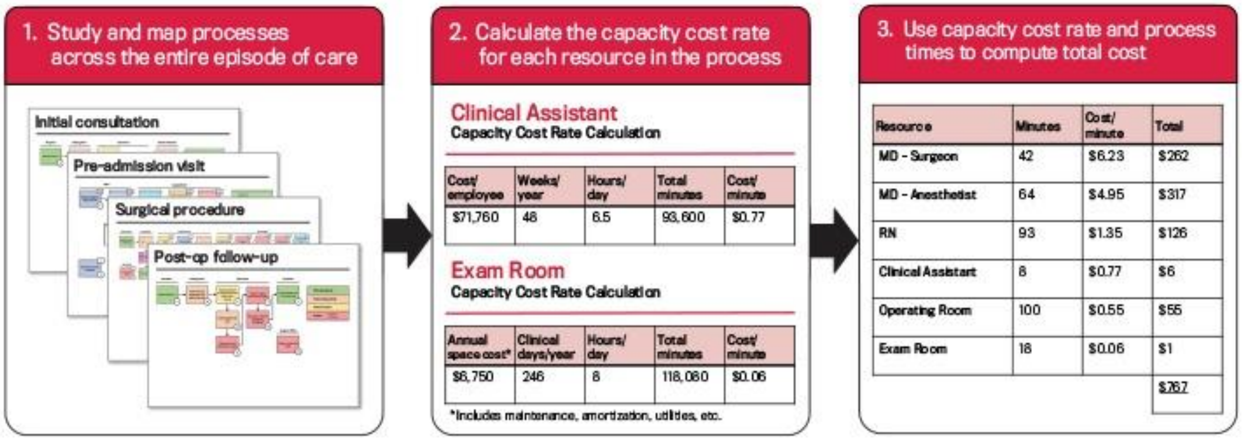
1. The unit cost of supplying capacity.
2. The time required to perform a transaction or an activity.

Kaplan describes a seven-step process to implement the TD-ABC model:

1. Select the medical condition, defining the beginning and end of a care cycle, or for chronic conditions, a care cycle for a period of time such as a year.
2. Define the care delivery value chain (CDVC), which charts the principal activities involved in the care cycle along with their locations.
3. Develop detailed process maps of each activity that encompass the paths patients may follow as they move through their care cycle in the care delivery value chain. These maps should include all the capacity-supplying resources (personnel, facilities, and equipment) involved at each process along the path, both those directly used by the patient and those required to make the primary resources available.
4. Obtain time estimates for each process. When a process requires multiple resources, estimate the time required by each one.
5. Estimate the cost of supplying patient care resources: the direct costs of each resource involved in caring for patients. This includes compensation for employees, depreciation or leasing of equipment, supplies, or other operating expenses. Account for the time that medical staff spends teaching and doing research in addition to their clinical responsibilities. Kaplan recommends estimating the percentage of time that a physician spends on clinical activities and then multiplying the physician's compensation by this percentage to obtain the amount of pay accounted for by the physician's clinical work. The remaining compensation should be assigned to teaching and research activities.
6. Estimate the capacity of each resource, and calculate the capacity cost rate. The capacity cost rate equation requires three time estimates:
    a. The total number of days that each employee actually works each year.
    b. The total number of hours per day that the employee is available for work.
    c. The average number of hours per workday used for nonpatient-related work, such as breaks, training, education, and administrative meetings.

[15] The Big Idea: How to Solve the Cost Crisis in Health Care Robert S. Kaplan and Michael E. Porter, HBR September 2011 Issue

7. Finally, calculate the total cost of patient care.



[16]

## Artificial intelligence is the ideal driver to improve value in health care

Artificial intelligence has the potential to improve value drastically in health care systems. AI cannot solve the problems inherent to health care innovation, but by embedding AI in clinical workflows and other related processes, it can greatly improve on issues health care systems face, by lowering costs and automating workload.

As quantifiable value of health care for the patient is the centerpiece of value-based health care, and the value of predictive algorithms is economically quantifiable as well, the true impact of AI in health care might be in improving care in a value-based health care model. This economic perspective of predictive algorithms is further explicated in chapter 5.

## Chapter summary

Porter and Lee's value-based health care model seems to be an ideal candidate for restructuring health care. In their model, process performance is measured in a value-oriented way. Value is defined as health outcomes over the cost of reaching those health outcomes. Its goal is to increase value for patients, while decreasing costs where possible.

The value-based health care model's strategic agenda for implementation encompasses six key steps to move towards value-oriented system: organizing around patients' medical condition rather than physicians' medical specialty, measuring costs and outcomes for each patient, developing bundled prices for the full care cycle, integrating care across separate facilities, expanding geographic reach, and building an enabling IT platform.

---

[16] The Big Idea: How to Solve the Cost Crisis in Health Care [Robert S. Kaplan] and [Michael E. Porter]. HBR September 2011 Issue

# Chapter 3: The scientific fundamentals of artificial intelligence

**In order to fully grasp the benefits and pitfalls of AI in health care, it is important to have a basic understanding of the fundamentals of AI. Moreover, by reviewing the inner workings of machine learning, the strengths and limitations of AI in health care become apparent. Hence, this chapter outlines of the relevant aspects and technical fundamentals of AI.**

Defining artificial intelligence is difficult. According to some definitions, any computer program that display intelligent humanlike behavior is a form of AI:

*"The art of creating machines that perform functions that require intelligence when performed by people."* [17]

As almost every human action requires intelligence, it is hard to define limits to the scope in which AI can be of use: from predicting the weather to driving cars.

A description more revealing of the specific workings of AI is as follows: AI is a set of analytics techniques that leverage large datasets, both structured and unstructured, to offer accurate predictions by finding patterns or classifying data.

## What is an algorithm?

Algorithms are the building blocks of AI. Algorithms describe processes and divide tasks into three parts:


1. Input.
2. Process: the logic or rules that use the input to come up with the output.
3. Output.

AI techniques can be categorised into three groups:

1. Classic machine learning (ML) techniques.
2. More recent deep learning (DL) techniques.
3. Natural Language Processing (NLP) methods.

| Input | Process | Output |
|---|---|---|
| Ingredients | Recipe | Cake |
| Blocks | Sorting by height | Sorted set of blocks |
| Earnings | Tax rules | Tax payment |

[17] A definition of AI according to Ray Kurzweil. Source: Artificial Intelligence A Modern Approach Third Edition Stuart J. Russell and Peter Norvig, 3rd edition, 2009

## Classic machine learning (ML)

Classic machine learning techniques constructs algorithms to extract features from data. Input includes patient 'traits' or key indicators of value, such as mortality or survival rates. Patient traits include data such as age, medical history and gender. Disease-specific or care cycle specific data such as symptoms, imaging and sequencing results are used as well.

### How does machine learning work?

Similar to the way humans apply memories and experience to improve the accuracy of their expectations, machine learning algorithms apply methods such as Bayesian statistics and linear regression to datasets to find patterns. Imagine plotting temperature versus ice cream sales. If there is a correlation, it might allow you to estimate ice cream sales at a given temperature. Many other variables influence ice cream sales, but a rough estimation can be made nonetheless. As such, it is important to have enough data, to make an accurate estimate.

### Categories of machine learning

Machine learning methods can be divided into three categories:

1. Supervised learning
2. Unsupervised learning
3. Reinforcement learning

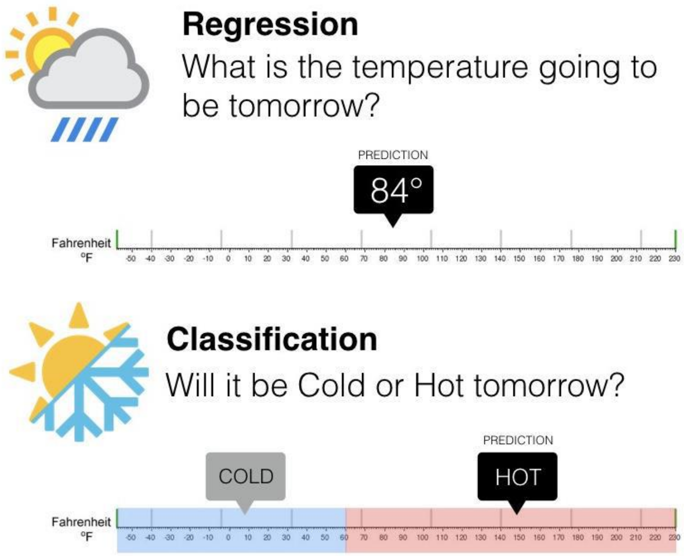
### Supervised learning

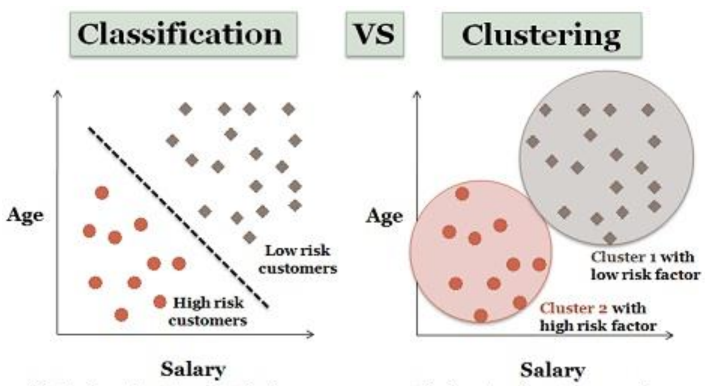
Supervised learning algorithms learn from specific input-output pairs. There are two main supervised learning methods:

| Input | Process | Output |
|---|---|---|
| Traffic reports of the past five years | Machine learning | An overview of traffic patterns |
| Location of reported crimes | Machine learning | Crime hotpots and patterns |
| Records of stroke patients and healthy controls | Machine learning | Risk factors related to stroke |

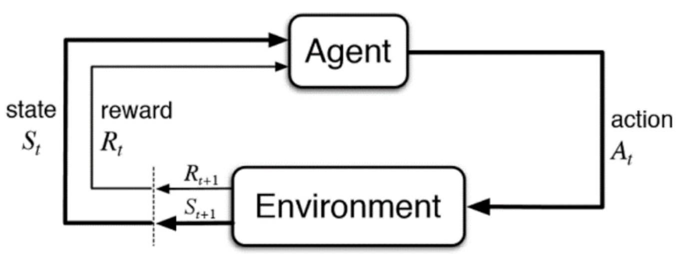
1. Classification predicts a category the data belongs to, such as spam detection, churn prediction, sentiment analysis & dog breed detection.
2. Regression predicts a numerical value based on previous observed data, such as house price prediction, stock price prediction & height-weight prediction.

Hence, supervised learning is similar to regular, widely used methods in statistics, in which we try to find answers to hypotheses such as 'is drug A better than drug B?', or 'does life expectancy increase with dosage of drug C?'.




Risk classification for the loan payees on the basis of customer salary




[18]

## Unsupervised learning

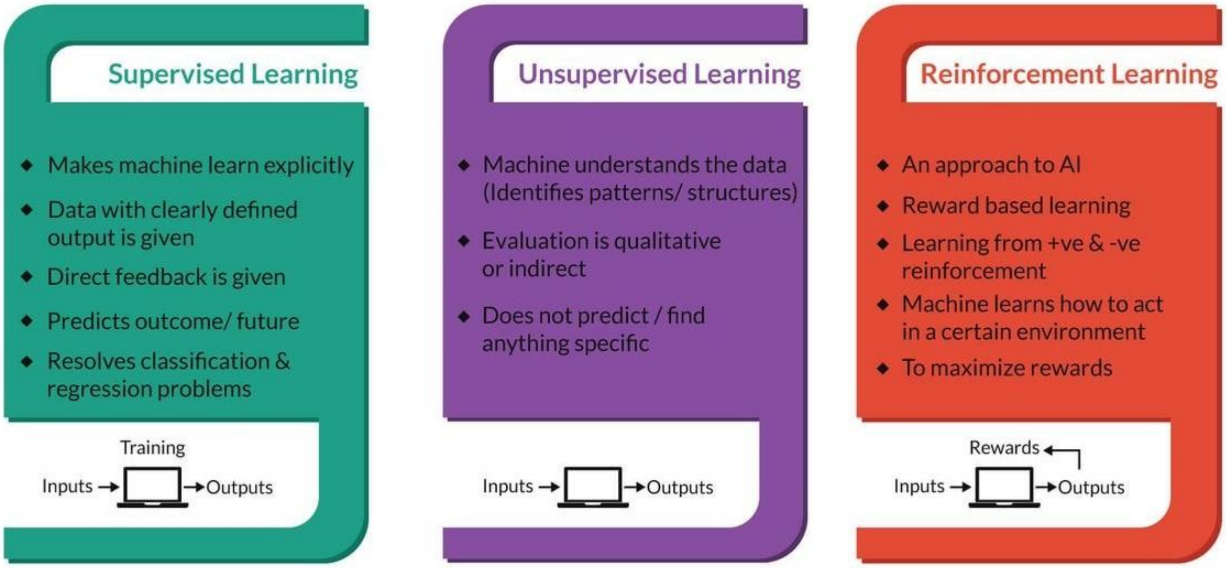
We can perform machine learning on datasets in the absence of labels, or rather without explicit feedback. One of the most commonly used unsupervised learning methods is clustering: separating data into groups based on some distinction. An example would be an algorithm that tries to find a cut-off point between patients that respond to a certain treatment – and patient that do not respond to the treatment. We can ask the algorithm to come up with the best grouping in which to cluster the data.

Oftentimes, a mix of methods is used, aptly called 'semi-supervised learning'. This allows for machine learning to correct for inaccuracies and errors in reporting, by using both labeled data and unlabeled data in conjunction.

## Reinforcement learning

Reinforcement learning works by giving rewards or punishments for every action, to train the algorithm to optimize its chances of winning. This type of learning is often used to teach an algorithm how to play a game: the better the algorithm plays the game – the more points or rewards it gets. It's free to try different strategies to find the most rewarding one.

[18] https://techdifferences.com/difference-between-classification-and-clustering.html




[19]

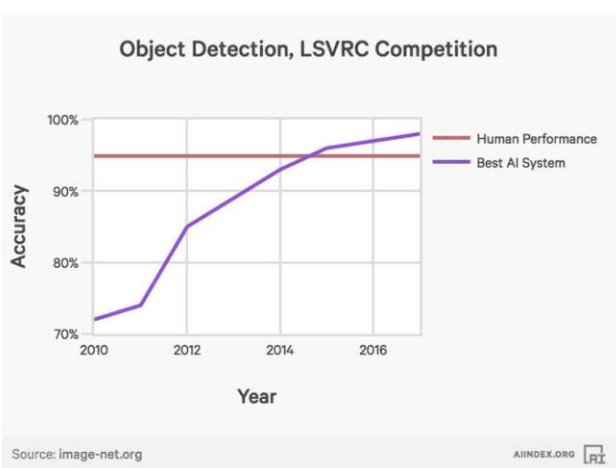
## Deep learning (DL)

Deep learning is a relatively new method of machine learning that uses layers of neurons in a network to find hidden patterns in complicated datasets, such as images.

Deep learning is seen as the next step in machine learning, and holds the promise of creating algorithms that solve some of the most difficult challenges in AI such as computer vision and speech recognition, by allowing for the training of algorithms that perform in real-time with very high accuracy. Deep learning algorithms use so-called 'Artificial Neural Networks' to learn patterns, not unlike our brain's neurons do.

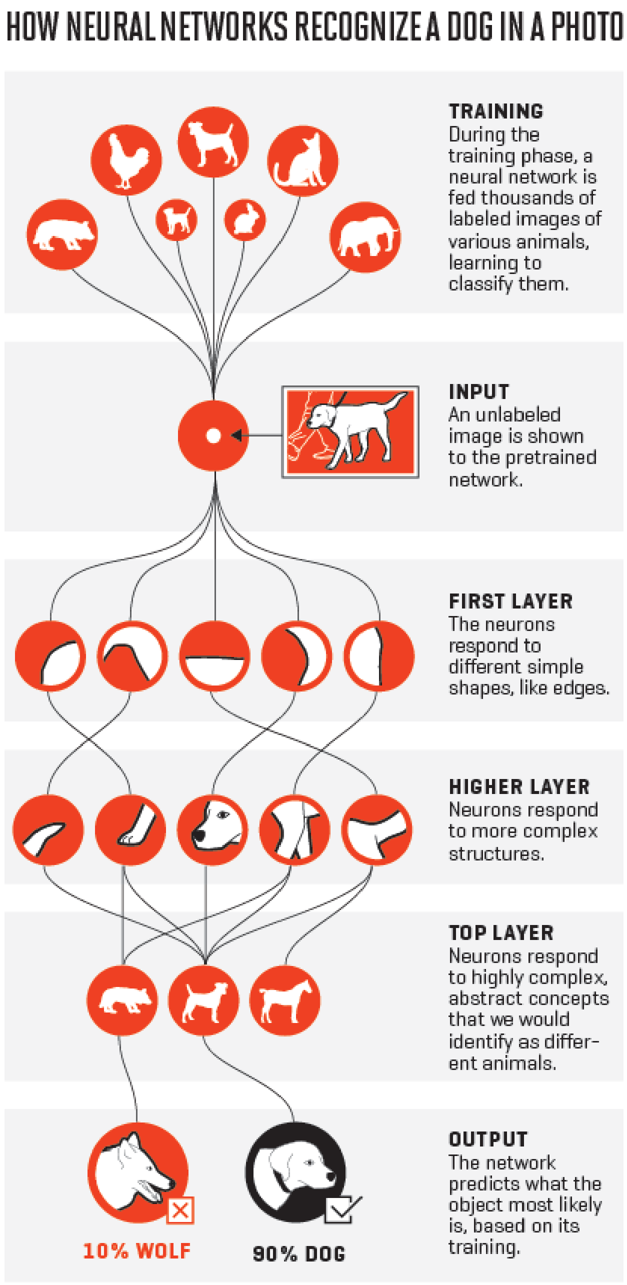
### Artificial neural networks

In an artificial neural network, layers of mathematical processing to make sense of the information it's fed.




In the case of Computer Vision, an artificial neural network is able to weigh the importance of individual (groups of) pixels or shapes in an image to determine which object (or objects) is most likely in

[19] Types of machine learning. Source: https://www.analyticsvidhya.com/blog/2016/12/artificial-intelligence-demystified/




the image. For the artificial neural network to be able to find all of these pixels and shapes, it needs a very large 'training set' of examples.

The majority of neural networks are fully connected from one layer to another. These connections are weighted; the higher the number the greater influence one unit has on another, similar to a human brain. As the data goes through each unit the network is learning more about the data. On the other side of the network is the output units, and this is where the network responds to the data that it was given and processed.

Deep learning is expert in supervised learning and great at absorbing huge amounts of labeled data, such as CT scans and pathology images.

Thanks to artificial neural networks, AI was able to beat humans at accurately label objects in images for the first time in 2015. Just like winning from Gary Kasparov in 1997 in chess, this is an important milestone that demonstrates the potential power of artifcial intelligence in tasks we didn't believe computers would surpass humans for a long time to come.

## Natural Language Processing (NLP)

Natural Language Processing (NLP) techniques leverage AI to analyze large volumes of textual data to interpret language. In NLP, syntactic and semantic analysis methods analyze text according to grammatical rules and the actual meaning of the text, respectively. NLP algorithms use unstructured data such as clinical notes or text from books or research articles.

## Chapter summary

AI is a collection of techniques that can be used to create algorithms to leverage large datasets for prediction. AI is often categorized in three categories of techniques: classic machine learning (ML), the more recent deep learning (DL) and natural language processing (NLP). In machine learning, training can be done supervised, unsupervised, semi-supervised or through reinforcement learning.

# Chapter 4: Understanding the Value of AI for Value-Based Health Care

The waves of implementation of IT in the health care sector have automated standard and repetitive administrative tasks, proceeding into full digitalization, just like in other sectors. Artificial Intelligence is a relatively new technology (in terms of implementation in daily life or practice), with growing applications in almost every sector due to availability of more and better data, and better computer processing power. AI can offer a considerable increase in value, a necessity to remedy issues health care systems face, as outlined in the first three chapters of this report.

## Societal impact of artificial intelligence

It is difficult to underestimate the impact of AI for society – without asking for credit, AI influences many aspects of our day-to-day life already. New articles demonstrate the value of AI every day. The accuracy and speed at which AI algorithms can process language, images and big data is changing industries. Comparable to our seemingly sudden dependency on smartphones – daily tasks such as navigation (Maps[20]), ordering services (Uber[21], Foodora[22]) and e-commerce (Amazon[23]) rely heavily on these new forms of AI. The broad consensus is that AI will fundamentally change the health care system in many aspects and processes. [24,25,26]

## Artificial intelligence as a driver of value in health care

As mentioned in chapter 3, we can describe AI *as a set of analytics techniques that can leverage large datasets to offer accurate predictions*. The AI analytics techniques, called algorithms, search for patterns in data. It can use both structured and unstructured forms of data. In chapter 3, the scientific fundamentals of AI are further explicated.

The accuracy of these algorithms is or will soon be able to successfully compete with human clinical practice, with accuracy of diagnostic algorithms reaching over 79% and in some cases over 90%.[27]

---

[20] https://www.theverge.com/2018/5/10/17340004/google-ai-maps-news-secret-weapon-remaking-old-apps-products-io-2018

[21] https://www.forbes.com/sites/johnkoetsier/2018/08/22/uber-might-be-the-first-ai-first-company-which-is-why-they-dont-even-think-about-it-anymore/#32f4ecba5b62

[22] https://futuresstudies.nl/en/2017/11/27/the-impact-of-ai-in-every-company-division-part-5-of-the-series-perspectives-on-artificial-intelligence/

[23] https://www.forbes.com/sites/blakemorgan/2018/07/16/how-amazon-has-re-organized-around-artificial-intelligence-and-machine-learning/#4ed5d5a57361

[24] Forbes Insights, 2019. AI And Healthcare: A Giant Opportunity. Source: https://www.forbes.com/sites/insights-intelai/2019/02/11/ai-and-healthcare-a-giant-opportunity/#27d3267a4c68

[25] PWC, 2017. What doctor? Why AI and robotics will define New Health. Source: https://www.pwc.com/gx/en/industries/healthcare/publications/ai-robotics-new-health/ai-robotics-new-health.pdf

[26] Moody, 2019. Accenture Blog: AI in Healthcare – A Key to Industry Evolution. Source: https://www.accenture.com/us-en/blogs/blogs-ai-healthcare-key-to-industry-evolution

[27] Rasmi, 2019. China has produced another study showing the potential of AI in medical diagnosis. Source: https://qz.com/1548524/china-has-produced-another-study-showing-the-potential-of-ai-in-medical-diagnosis/

## Perspectives of the impact of AI on value-based health care

Both value-based health care and AI improve value from multiple perspectives:

1. **The societal perspective**, to remedy the financial burden for the society. Financial perspective concerns national budgets, insurance companies and patients.
2. **The patient perspective**, empowering and enabling patients with personalized care systems (example - hospital at home and enabling smart home monitoring devices).
3. **The health care provider perspective**, automating repetitive tasks and leveraging information to create decision-making support systems and streamlining workflow and increasing efficiency of the work processes.

As health care processes are by nature data-intensive, use cases of AI for the compound increase in health care's value are abundant, as applications of AI have the potential to increase health outcomes while decreasing costs at the same time.

$$Added\ value\ of\ AI\ in\ health\ care = \frac{Increased\ health\ outcomes\ by\ AI}{Decreased\ costs\ of\ delivering\ outcomes\ by\ AI}$$

AI shows all the features required to play a role as a driver in improving value in health care considerably, as it automates and scales tasks that were previously only possible by highly skilled personnel.

The key issue is achieving alignment of workflows of health care providers, financing, procedures and information infrastructure to enable value-based health care. As such, changing to a value-based health care model requires transparency and accountability in the entire healthcare delivery chain. AI can also play a key role in cost accounting, as algorithms can help expose the value of resources used in health care processes.

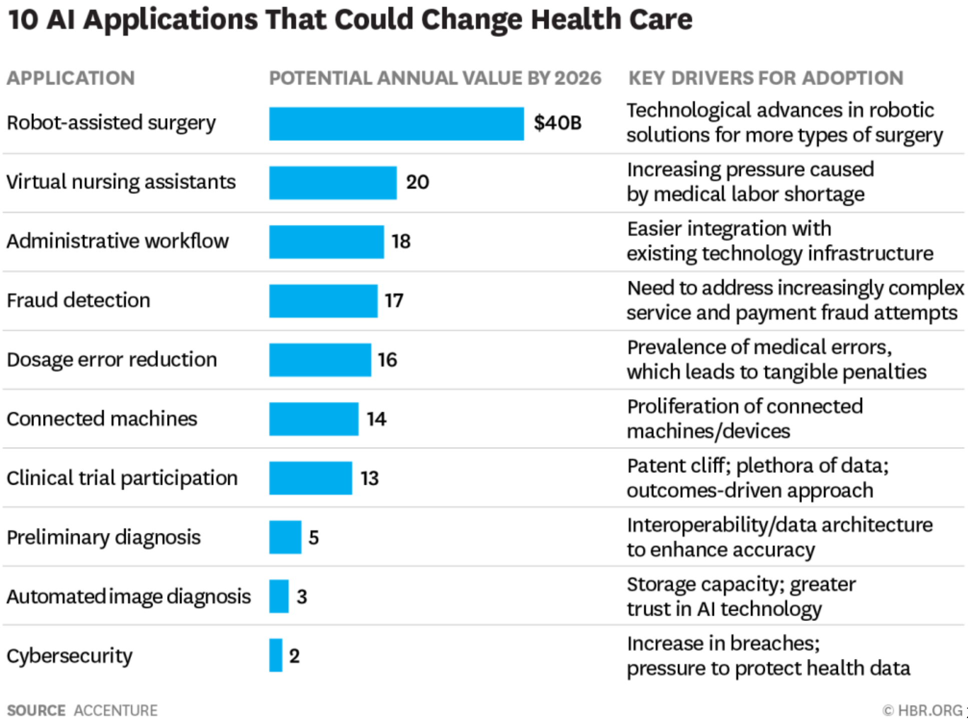
## Use cases for AI applications in health care

Successful implementation of AI applications requires access to huge amounts of data, cheap and reliable computing power, and data storage. According to a 2018 Philips AI report[28], the essential ingredients for the implementation of AI in health care are now in place:

1. There is mounting pressure to increase value in health care.
2. Exponential increase in available health data.
3. Advances in computing power and data science methods allow for the development of health care algorithms.

None of these components of AI pose a constraint to rapid nation-wide implementation.

[28] Using AI to meet operational clinical goals, February 2018, Philips



[29]

The following use cases are categorized on the basis of either mainly improving health outcomes or on decreasing health care costs. Most of these applications provide both benefits: increasing health outcomes while decreasing costs.

## Improving health outcomes

As AI has the ability to duplicate (and in some cases, exceed) the human cognitive function of prediction, it has the potential to fundamentally transform work processes, considerably improving the way value in health care is being created. Thanks to the accuracy of these advanced analytics techniques, AI can even outperform the accuracy of human diagnostic capabilities. Many different use cases exist in leveraging big data to personalize health care and increase quality of care across the board. Many of these solutions leverage the simultaneous emergence of Internet of Things (IoT) devices that function as sensors that can gather some form of health data, and AI algorithms as the systems needed to interpret the data. These solutions are also democratizing access to health care: as they are cheap and scalable, and omit (or significantly reduce) the need for a health care provider. They also drive the consumerization of health care, as these IoT devices do not require the intervention of health care providers.

Well-trained algorithms are a key part of delivering personalized health care of high quality: these algorithms have the potential to learn and tailor specific and personalized responses on a case-by-case basis.

[29] Accenture, An overview of AI applications in health care. Source: https://hbr.org/2018/05/10-promising-ai-applications-in-health-care

AI benefits in health care diagnostics have been demonstrated in a number of areas, such as neurology[30,31,32,33], cardiology[34], oncology[35,36,37], radiology[38], psychiatry[39], dermatology[40] and ophthalmology[41,42].

## Continuous Monitoring and Decentralized Diagnostics, Improving Accuracy and Speed

Continuous Monitoring (CM) is the whole spectrum of devices and sensors that enable remote and continuous monitoring. These devices gather health data such as saturation, heartrate variability and glucose level to feed AI algorithms in real-time that can function as early warning systems. These algorithms detect abnormalities, such as atrial fibrillation in patients that suffer from heartrate irregularities, and give advice, such as the required dosage of insulin in diabetics based on their current glucose level.

The Radboud University Medical Center in Nijmegen, The Netherlands, is currently running the Radboudumc Forecast pilot, in which CM devices are training an algorithm to enhance the prediction of Early Warning Scores (EWS).

Another important use case of CM-devices is the remote monitoring of patients. This allows for patients to recover at home while being monitored by a healthcare organization, such as a hospital or an elderly care facility. Medical devices that are used to monitor and treat most chronic disease become widely available to consumers. From ingestible sensors that track medication usage to smart inhalers that give feedback on inhalation technique: the potential of pairing medical devices with AI is considerable. These devices use AI to process the continuous streams of data and triage the workload of health care providers.

---

[30] Bouton CE, Shaikhouni A, Annetta NV, et al. Restoring cortical control of functional movement in a human with quadriplegia. Nature 2016;533:247–50.

[31] Farina D, Vujaklija I, Sartori M, et al. Man/machine interface based on the discharge timings of spinal motor neurons after targeted muscle reinnervation. Nat Biomed Eng 2017;1:0025

[32] Hirschauer TJ, Adeli H, Buford JA. Computer-Aided diagnosis of Parkinson's Disease Using Enhanced Probabilistic Neural Network. J Med Syst 2015;39:179.

[33] Khedher L, Ramirez J, Garriz JM, et al. Early diagnosis of Alzheimer's disease based on partial least squares, principal component analysis and support vector machine using segmented MRI images. Neurocomputing 2015;151:139–50.

[34] Dilsizian SE, Siegel EL. Artificial intelligence in medicine and cardiac imaging: harnessing big data and advanced computing to provide personalized medical diagnosis and treatment. Curr Cardiol Rep 2014;16:441.

[35] Somashekhar SP, Kumarc R, Rauthan A, et al. Abstract S6-07: double blinded validation study to assess performance of IBM artificial intelligence platform, Watson for oncology in comparison with manipal multidisciplinary tumour board ? first study of 638 breast Cancer cases. Cancer Res 2017;77(4 Suppl):S6-07

[36] Khan J, Wei JS, Ringnér M, et al. Classification and diagnostic prediction of cancers using gene expression profiling and artificial neural networks. Nat Med 2001;7:673–9.

[37] Sweilam NH, Tharwat AA, Abdel Moniem NK, Moniem NKA. Support vector machine for diagnosis Cancer disease: a comparative study. Egyptian Informatics Journal 2010;11:81–92.

[38] Dheeba J, Albert Singh N, Tamil Selvi S. Computer-aided detection of breast Cancer on mammograms: a swarm intelligence optimized wavelet neural network approach. J Biomed Inform 2014;49:45–52.

[39] Orrù G, Pettersson-Yeo W, Marquand AF, et al. Using support Vector Machine to identify imaging biomarkers of neurological and psychiatric disease: a critical review. Neurosci Biobehav Rev 2012;36:1140–52.

[40] Andre Esteva, Brett Kuprel, Roberto A. Novoa et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature 2017; 542:115–118

[41] Ting DSW, Pasquale LR, Peng L, et al Artificial intelligence and deep learning in ophthalmology. British Journal of Ophthalmology 2019;103:167-175.

[42] Wong TY, Bressler NM. Artificial Intelligence With Deep Learning Technology Looks Into Diabetic Retinopathy Screening. JAMA. 2016;316(22):2366–2367. doi:10.1001/jama.2016.17563

Furthermore, these algorithms can automate the decision-making of health care providers in certain scenarios, and only ask for human guidance when the algorithm is unsure of what course of action to suggest.

Similar to Continuous Monitoring are Decentralized Diagnostics (DD) devices that allow for remote diagnosis and do not need human interpretation of diagnostic health data. Examples are test kits that patients can use to diagnose urinary tract infections at home or diagnose skin disease with a smartphone, which can improve diagnostic accuracy or enable faster and more convenient treatment, as the patient doesn't need to visit a health care provider anymore.

*Figure 6 - Source: Eversense Diabetes. Source: https://ous.eversensediabetes.com/mediakit/*

### Virtual Assistants

Integrating AI into Virtual Assistants allows for many use cases in the fields of helping and advising both patients and health care providers.

The UK's NHS has given the status of General Practitioner to Babylon[43], a British AI start-up's Virtual Assistant that can triage complaints and give personalized health advice with the accuracy of a human GP. Through the Babylon app, citizens can ask health related questions and get machine-tailored information.[44]

Virtual Assistants aid health care providers by leveraging Natural Language Processing algorithms to transcribe patient consults and summarize key information in both conversations and medical records.

Due to the widespread adoption of consumer virtual assistant devices, such as the Amazon Echo and Google Home, health applications can be scaled and distributed on a massive scale. Using voice instead of text has more upsides, as it allows for sentiment analysis[45] and is a faster input source than typing[46]. Hence, mental (e-)health applications and lifestyle management coaches can leverage these data sources to better provide scalable forms of therapy and interventions. Personal robots are seen as the culmination of robotics and AI, combining both worlds to become the ultimate 'virtual' assistant.

[43] Iacobucci, 2019. Babylon's GP at Hand gets green light to form single primary care network. DOI: https://doi.org/10.1136/bmj.l2384
[44] https://www.babylonhealth.com
[45] Kleber, 2018. 3 Ways AI Is Getting More Emotional. Source: https://hbr.org/2018/07/3-ways-ai-is-getting-more-emotional
[46] Carey, 2016. Smartphone speech recognition can write text messages three times faster than human typing. Source: https://news.stanford.edu/2016/08/24/stanford-study-speech-recognition-faster-texting

### Epidemiology and Clinical Research

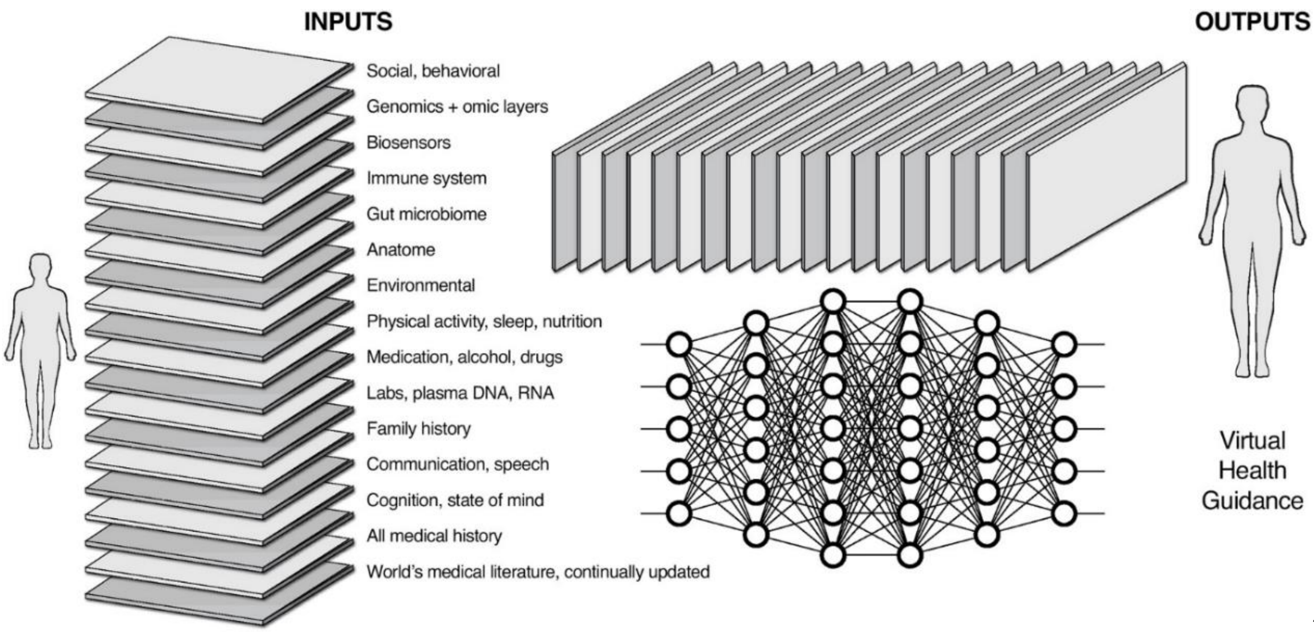
As AI thrives in finding correlations and analysing very large datasets, information from previously unused data sources such as social media and Google searches can function as sources of public health information. Algorithms can be trained to predict disease outbreaks and environmental problems that need early government intervention.[47] Such algorithms are usually called 'predictive analytics' algorithms, leveraging datasets to predict future events.

Furthermore, combining these data sources with conventional health data sources, such as General Practitioner's medical records systems could increase the accuracy of these algorithms. These algorithms can also track and predict large-scale treatment effectiveness to speed up clinical research.

## Combining datasets unlocks the true impact of AI on health outcomes

These aforementioned potential use cases of AI in health care reveal that the combination of data sources has a compound effect on the possibilities and potential impact of AI on improving health outcomes. As data sources are combined, the algorithm has the potential to find more (hidden) relationships in data, which can lead to new insights and increase the potential impact of these algorithms.

Hence, truly personalized health can be achieved by combining all of these datasets: training algorithms on *omics (genomics, metabolomics, etc.) datasets together with medical IoT sensor data and other data sources can drastically change health care.




[48]

---

[47] Wong et al., 2019. Artificial Intelligence for infectious disease Big Data Analytics. DOI: https://doi.org/10.1016/j.idh.2018.10.002

[48] A schematic of a deep neural network with all of a person's data inputted, along with the medical literature, to provide the output of health coaching. Source: Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again, Topol, 2018

## Cost Reduction

### Improving health care logistics

The low-hanging fruit of AI in health care is in its potential to improve on the logistics of health care delivery. By optimizing health care through the improvement of logistical inefficiencies, we can drive cost-effectiveness of many processes involved in patient care without interfering with direct patient care processes. Furthermore, a wealth of experience with logistical algorithms already exists in other industries. These best practices are equally usable to improve on health care process flows as well. At the Radboud University Medical Center, data science pilots are run to personalize and improve the use OR and endoscopy timeslots, potentially leading to substantial improvements in efficiency.

### Reducing administrative burden and optimizing workflow

AI applications such as speech to text, sentiment analysis and natural language processing can drastically decrease the administrative burden of health care providers. AI will lead to workflow optimization and result in cost reduction as selected tasks can be assigned to AI devices. As a consequence, this will result in increased efficiency of health care processes, because it will allow for medical staff to spend more time with patients, leading to better patient-provider relationships. In turn, this can potentially reduce staff shortages and decrease burnout rates.

Next to that, smart electronic medical records can optimize health care provider workflows by predicting what information the provider likely needs at a specific point in the clinical workflow.

### Decision support for health care providers, increasing safety and decreasing the workload

Decision support systems with embedded AI can help to reduce diagnostic and therapeutic errors that are inevitable in the human clinical practice[49,50], such as prescribing wrong medication or dosages, and advising on the correct step forward.

Medication adherence optimization offers yet another benefit: AI can help personalize medication schedules to fit personal lifestyles better, increasing medication adherence.

Additionally, decision support systems using AI algorithms can be programmed to send health risk alerts and make medical staff aware of likely health outcome predictions.[51] An AI system can also assist physicians by providing up-to-date medical information from journals, textbooks and clinical practices to inform them of the latest guidelines and best practices.

### Automating clinical processes

Using AI to directly automate clinical processes is a field that is in rapid development. Both radiology and pathology contain well-defined core clinical processes that are automatable through AI. These core clinical processes revolve around pattern recognition.

---

[49] Dilsizian SE, Siegel EL. Artificial intelligence in medicine and cardiac imaging: harnessing big data and advanced computing to provide personalized medical diagnosis and treatment. Curr Cardiol Rep 2014;16:441

[50] Patel VL, Shortliffe EH, Stefanelli M, et al. The coming of age of artificial intelligence in medicine. Artif Intell Med 2009;46:5–17

[51] Neill DB. Using artificial intelligence to improve hospital inpatient care. IEEE Intell Syst 2013;28:92–5

Popular examples are finding breast cancer tissue in biopsies and lung cancer in X-rays. A suggested workflow change would be to allow AI to 'triage' images: allow the algorithm to decide if it's sure of the diagnosis, to free up time for the specialist so they can focus on only reviewing images in which the algorithm is unsure of the diagnosis. A lot of focus is being put towards the use of AI in radiology and pathology: algorithms can help diagnose 'easy' cases, which frees up the specialist to spend more time analyzing the difficult cases.

## Chapter summary

AI can be of great benefit in impacting both the numerator (improving health outcomes) and denominator (decreasing cost) of the value-based health care equation, resulting in a compound increase in value. As multiple stakeholders can benefit from these applications, the potential impact is far-reaching. The computing power and data storage are components that pose absolutely no constraints to wide and rapid implementation of AI in health care.

Continuous Monitoring devices and Decentralized Diagnostics devices can work in tandem to allow for decentralized health care delivery. They drive easier diagnosis and monitoring of patients at home.

AI offers multiple benefits ranging from directly decreasing societal costs by optimizing workflows, decreasing workload to potentially lower burnout rates, empowering patients and delivering truly personalized health care. Health care providers are advised to focus and prioritize their efforts on the low-hanging fruits of AI: low risk, small investment. Small wins will help foster the implementation of AI in health care.

# Chapter 5: Outline of requirements, costs and benefits of AI

**Embedding AI in our information and communication technology infrastructure on a national and international basis can be cost-effective, due to sharply decreased costs of the three main requirements for leveraging the capabilities of AI on a large scale. These three requirements are computing power, data storage and large datasets. Costs reduction due to the increase in workflow efficiency, the limiting of medical diagnostic errors, better prevention and the reduction workload of medical staff will certainly have considerable benefits.**

However, to maximize this health care cost reduction effect, implementation should be done in conjunction with implementation of the value-based healthcare as outlined in chapter 2 of this report.

## How Far has Artificial Intelligence Come?

AI was unable to create substantial impact until recently, because it lacked the ingredients needed to create and train highly accurate and meaningful algorithms.

Nevertheless, the concept of AI is not recent. Since the 1950's, humans have been experimenting with the creations of machines that mimic humanlike behavior. It's hard to define the starting point of a field that's born out of the crossroads of statistics, mathematics and computer science. Oftentimes, Alan Turing's question in 1950, "Can machines think?", is viewed as a starting point. In 1956, computer scientists came together to discuss a new field they called AI. Their ideas were not that different from the applications of AI we strive to create today: decision support for doctors, driverless cars and computer vision.

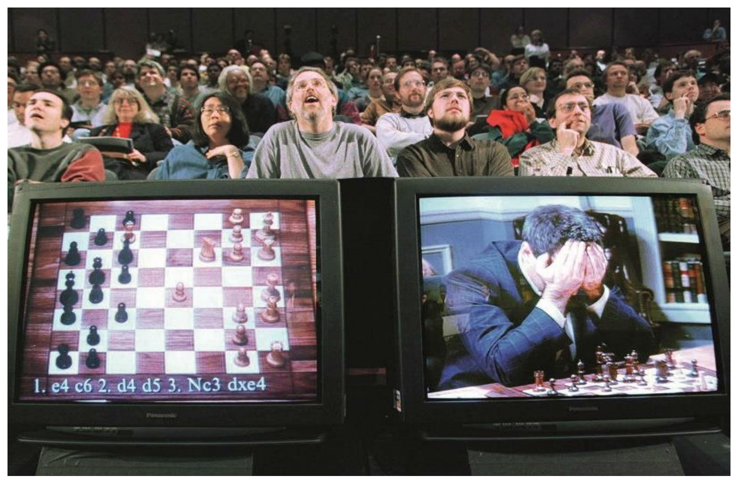
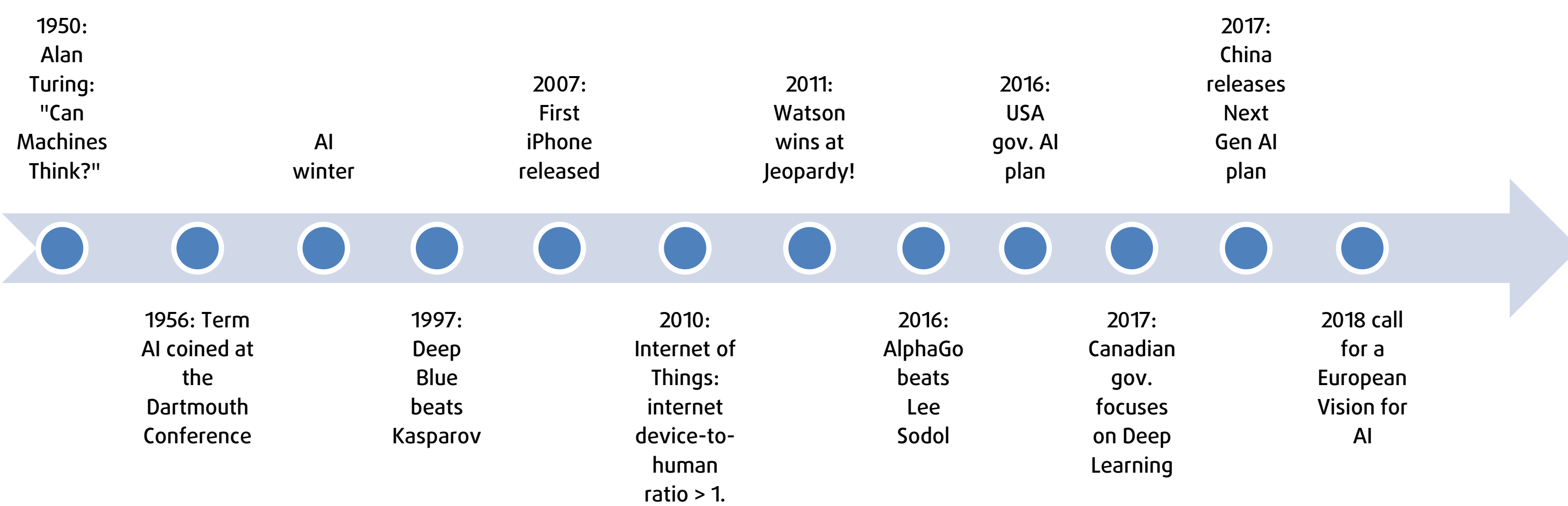



*Figure 7 - Kasparov losing from Deep Blue. Source: https://blog.prodir.com/en/2016/11/kasparovs-bolt-from-the-blue/*



However, due to the limited computing power of machines, limited data storage capabilities and a lack of funding, progress halted in the in the decades after, which we now refer to as the 'AI Winter'. Aside from some progress in the field of AI and robotics in this period, it wasn't until the 90's that IBM started investing in AI, which lead to beating the world's best Chess Grandmaster, Garry Kasparov in 1997.[52]

## AI needs computing power and data

Moore's Law describes the exponential increase in transistor counts on chips, which is a determinant of the constant increase of computing power.[53] Thanks to this constant increase, we now have computers that are fast enough to execute AI algorithms that have meaningful use in our society. [54]

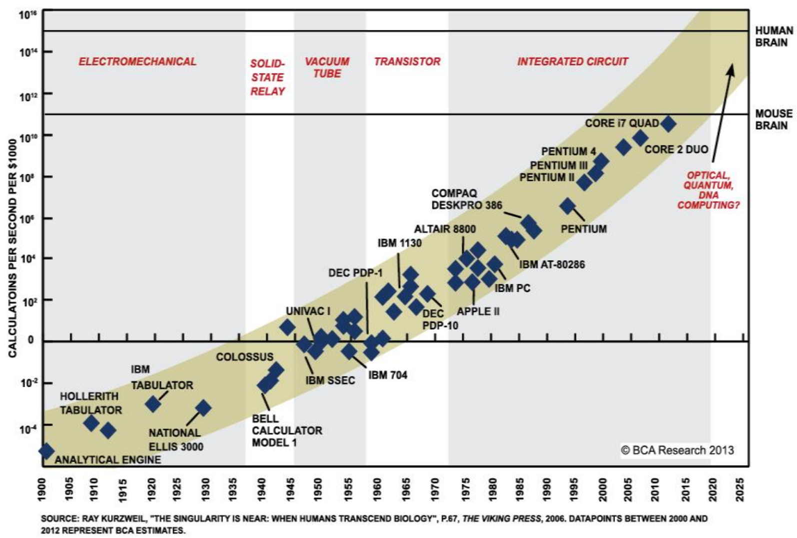



*Figure 8 - Moore's Law. Source: Kurzweil, "The Singularity Is Near".*

However, in order to train these algorithms accurately, we need a lot of (electronic) data as well. In the 21st century, where more devices are connected to the internet than there are humans – the internet of things, we are gathering enormous amounts of data to train these algorithms – from videos and images, to text and sensors.

An important requirement for data is data storage. Not unlike Moore's Law, the cost of data storage is exponentially decreasing, while the capacity per hard drive is exponentially increasing. This allows us to store seemingly unlimited amounts of information on servers, home PC's and smartphones.

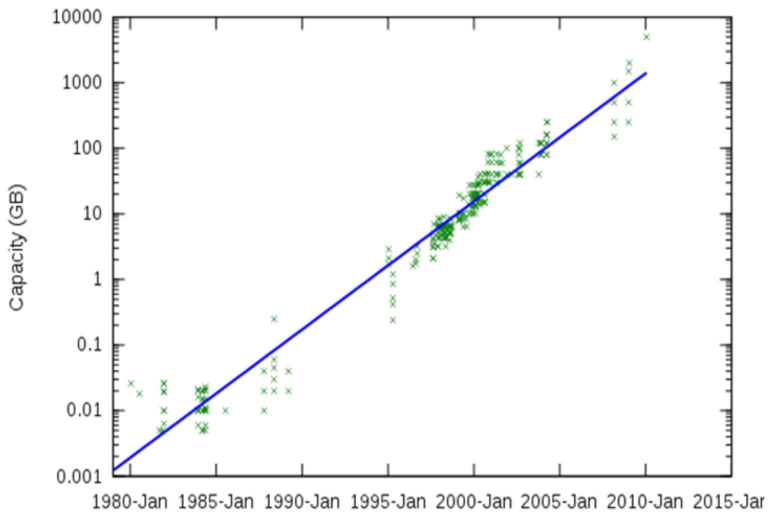



*Figure 9 - The exponential increase in storage capacity (Kryder's Law). Source: David Rosenthal.*

[52] Kasparov's bolt from the blue, https://blog.prodir.com/en/2016/11/kasparovs-bolt-from-the-blue/

[53] "Cramming more components onto integrated circuits", Moore, 1965, https://drive.google.com/file/d/0By83v5TWkGjvQkpBcXJKT1I1TTA/view

[54] Moore's Law. Source: Ray Kurzweil "The Singularity is Near", 2006

## Value of AI through the lens of economics

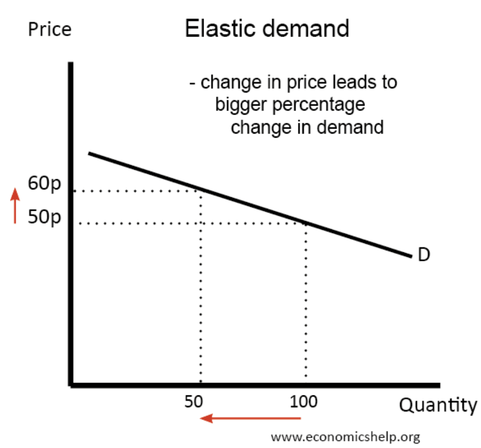
Late 2018, Gans, Goldfarb and Agrawal published the book Prediction Machines[55], in which they created an economic model that quantifies the commercial value of AI and its predictive capabilities. They argue that prediction can be viewed as any other good with a specific value. Consequently, laws of economics and trade can be applied to these prediction algorithms and their human counterparts. An example would be self-driving cars versus taxi drivers: the initial investment and operating costs of a self-driving car can be calculated and compared to a human driver.

The author's model describes three lessons from economics that are thusly applicable to prediction algorithms as well. This chapter will summarize these lessons and their implications for the adoption of AI.

### Price elasticity effect: As the price of coffee drops, we buy more coffee

This concept of macroeconomics is applicable to almost all goods: the price of a good is directly correlated with demand. This holds true for prediction as well. As the development of prediction by algorithms is becoming cheaper, two changes are happening:

Firstly, we are reframing decision-making problems as prediction problems to broaden the scope of application. As algorithms are infinitely scalable, deep learning algorithms with the prospects of computer vision or natural language processing have many potential use cases. Self-driving cars are made possible because we view driving as a solvable prediction problem.




Secondly, we are going to use more prediction through AI algorithms. As the development and implementation of algorithms is becoming cheaper, we're going to use more of them. Since the tools to create AI models are made freely available by companies such as Google and Microsoft, many startups race to find their business-to-business algorithm niche.

### Effect of the substitute: As we buy more coffee, we buy less tea

The direct consequence of using more computer prediction to solve societal problems, the prediction parts of work that humans used to do are being substituted by the more scalable – and eventually cheaper – computer algorithms.

[55] Gans et al, 2018

According to a 2018 OECD policy brief, 14 percent of the current workforce' tasks are highly automatable, mostly affecting jobs in the manufacturing industry and agriculture.[56] Predictive algorithms will likely be an important factor in this next wave of automation. According to a 2016 McKinsey study, data processing in health care is the most technically feasible automatable activity.

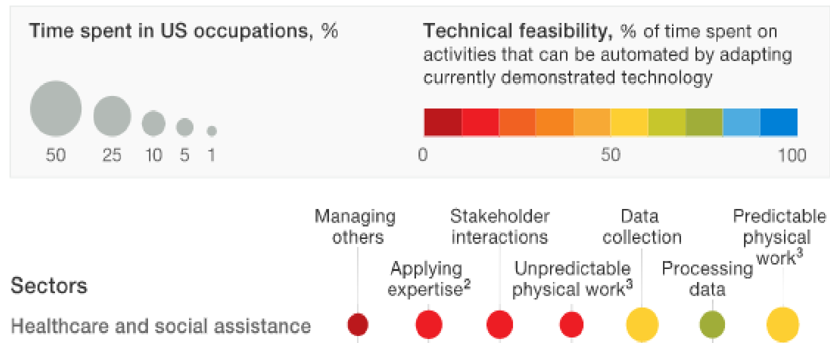



*Figure 10 - Automation is technically feasible for many types of activities in industry sectors, but some activities can be more affected than others (adapted). Source: https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Digital/Our%20Insights/Where%20machines%20could%20replace%20humans%20and%20where%20they%20cant/SVGZ-Sector-Automation-ex3.ashx*

In 2019, Lee published the book "AI Superpowers: China, Silicon Valley, and the New World Order", in which he describes how many of our current societies' jobs have prediction tasks. Lee suggests that these tasks will be automated, and depending on the percentage of tasks that are not predictable of automatable, will disappear. Lee describes four quadrants of labor, separated by two axes: social versus asocial and optimization-based versus creativity- or strategy-based. Lee theorizes that the easily optimizable jobs which create little social value are likely first to be fully automated. Radiology is often seen as a field that is likely to be among the first in health care to be disrupted by AI, either replacing radiologists outright or thoroughly changing their activities in the foreseeable future.[57]

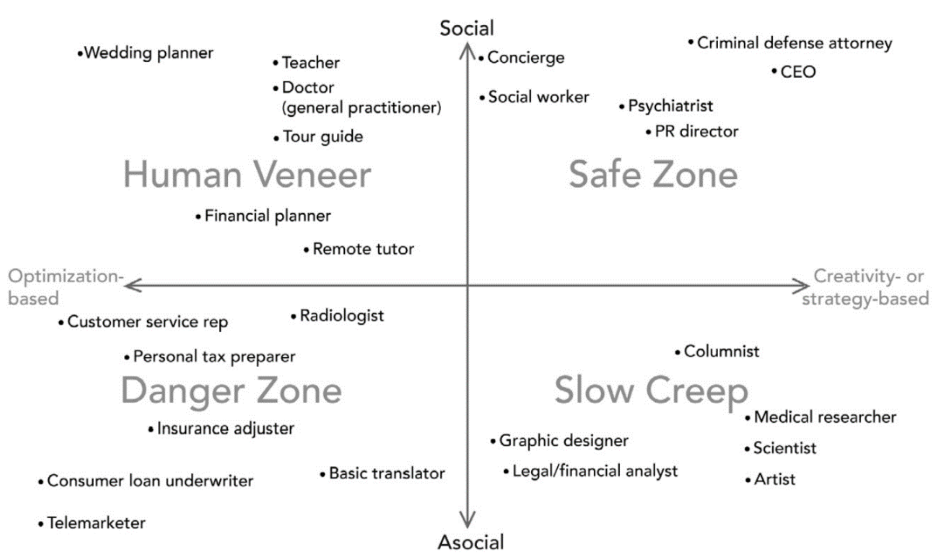



*Figure 11 - Risk of replacement for cognitive labor. Source: Lee, 2019, AI Superpowers.*

Alternatively, Lee also hypothesizes that it's possible for most jobs to be augmented of a human + AI combination, rather than

[56] https://www.oecd.org/employment/Automation-policy-brief-2018.pdf

[57] Davenport et al., 2018. AI Will Change Radiology, but It Won't Replace Radiologists. Source: https://hbr.org/2018/03/ai-will-change-radiology-but-it-wont-replace-radiologists

being substituted by AI and disappearing from the labor market. Furthermore, the development and implementation of AI prediction algorithms in society will likely create new jobs as well, akin to new jobs such as Social Media Managers and Search Engine Optimizers that emerged recently.[58]

**Complementary goods effect: As we buy more coffee, we buy more sugar & cream**

In many cases, prediction alone is not enough to make a decision. Gans et al outlined the complementary goods of decisions: judgement and data.

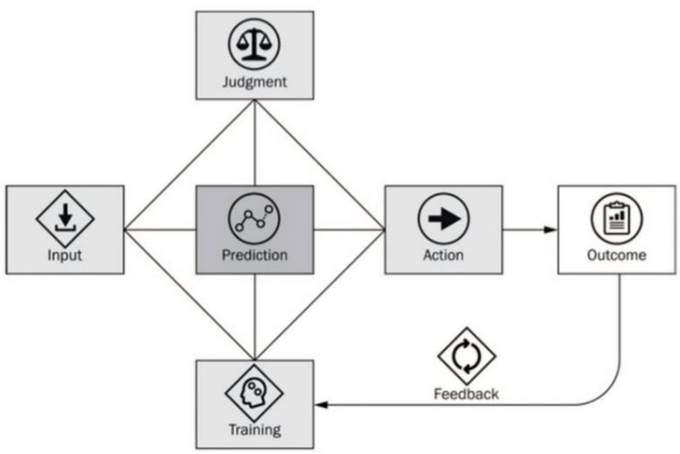
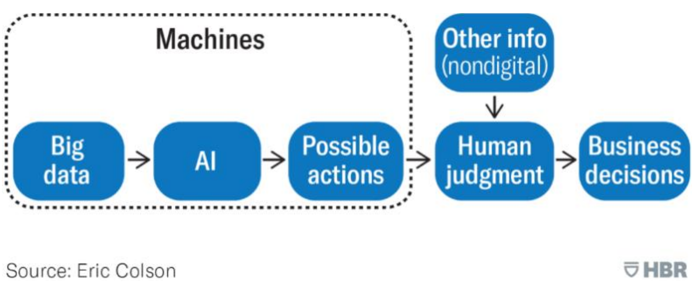



*Figure 12 – a model outlining the requirements needed for making a decision. Source: Gans et al., 2018, Prediction Machines*




Judgement plays an important role in deciding the best course of action, and that calls for a human thought process. At times, decisions need human judgement, for example in the form of an ethical consideration.

Furthermore, without enough data, the prediction cannot be accurate enough to be meaningful. In some cases, human senses are difficult to automate: we're unsure what data is related to good outcomes and rely on human intuition, or many different data sources are needed to train the algorithm. These types of decisions rely heavily on humans, as computers cannot learn intuition through AI techniques.[59]

## Artificial intelligence is shifting value in health care as a consequence of the broad implementation

A recent BCG report[60] proposes two scenarios in which value shifts between value pools in health care players and sectors. In these scenarios, there are four key health care players:

1. Biopharma
2. Health care providers
3. Payers
4. Med-tech

Furthermore, three primary categories of value pools exist:

[58] World Economic Forum, 2018. The Future of Jobs Report. Source: http://www3.weforum.org/docs/WEF_Future_of_Jobs_2018.pdf
[59] https://hbr.org/2019/07/what-ai-driven-decision-making-looks-like
[60] Chasing Value as AI Transforms Health Care. Aboshiha et al, BCG, March 2018.

1. Changes created by applications that will reduce cost, leading to additional value within that sector
2. Shifts yielded by applications within one health care sector that will threaten revenue or profits within other sectors
3. Shifts driven by applications within one of the four health care sectors that cause value to flow from that sector to either tech companies or consumers.

In scenario 1, most of the value unlocked by AI stays within the health care industry and the tech industry. Each player keeps the value unlocked in terms of their own efficiency gain. Consumers see improved outcomes but limited savings. In this scenario; tech, med-tech, providers and payers benefit the most.

In scenario 2, value is passed on to consumers. AI helps drive value-based health care, improving outcomes and lowering cost, which leads to lower premiums or out-of-pocket costs. In this scenario, the tech and med-tech industries also benefit significantly.

## Chapter summary

The ingredients needed for AI are data, storage and computing power. For the first time in history, they are all available in abundance and at low prices.

Predictive algorithms adhere to economic value and as with any other product: laws of macroeconomics are also applicable to AI. As algorithms become cheaper and more widespread, their potential use and impact increases. This is leading to an interesting phenomenon: to increase the application of AI algorithms, we reframe conventional problems to become prediction problems so that we can use AI to find ways of solving them at scale. This is already happening in the area of driverless cars.

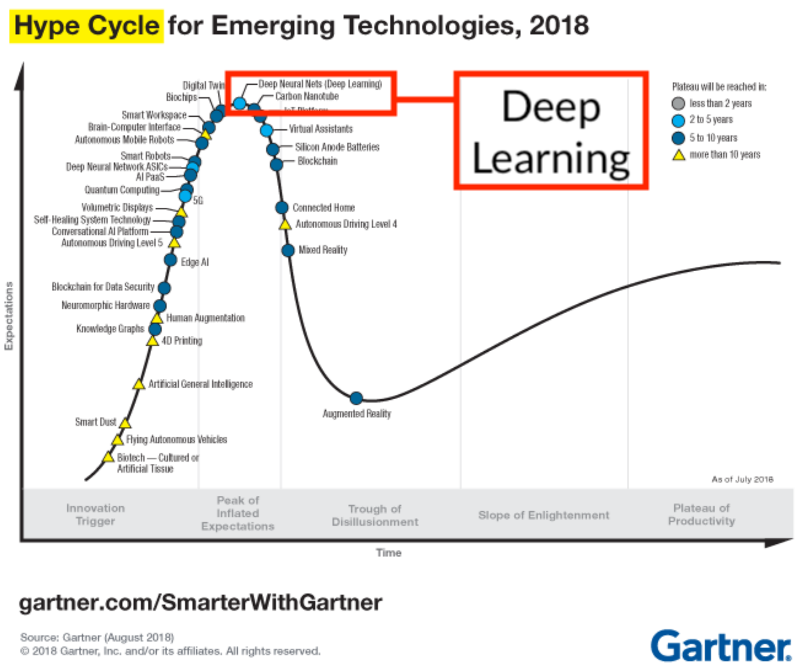
AI powered systems have already proven their value as tools supporting human diagnosticians. It’s also important to note that human prediction tasks will likely become too expensive as compared to AI prediction, and as such, we will make less use of those. AI has the potential to replace some of the repetitive analytic human tasks in the near future. Yet in complex decision making, human judgement will retain its value, as human intuition cannot be automated by the current methods used in the development of AI.

Finally, broad implementation of AI on a national and international basis might lead to a shift in the value distribution of health care. Hence, a value shift is likely to occur between players in the health care field, as it will either shift to tech and med-tech companies, or will be mostly passed on to consumers.

# Chapter 6: factors that inhibit the adoption of AI-powered, value-based health care

**The need for health care innovation is clear, and most impact of AI can be found in enabling value-based health care by leveraging automated prediction and decision-making. As many other industries already adopted AI algorithms in their core work processes to a great extent, health care is lagging behind tremendously in terms of adoption and implementation. In this chapter, we will explore the potential barriers AI faces in health care.**

Despite its great potential and best efforts, implementation of AI in health care is very slow. There is a number of challenges that all fields face implementing AI, and there are a number of specific challenges for the implementation of AI in health care. Moreover, some of these factors are common for every innovation in health care, in the public sector or even in any large organization.




As deep learning sits on top of the Gartner Hype Cycle, it is important to look to the future and find out what issues we can expect in the trough of disillusionment.

## Inhibiting factors in health care innovation in general

Many bottlenecks hamper the implementation of innovation in health care. Those issues have been analysed in the professional literature. Hence, they are only mentioned for the sake of completeness. These factors are oftentimes characteristics of the health care industry or the public sector in general:

- **Highly regulated industry**, leading to inertia and long approval times of systems changes.
- **Complex ecosystem**, with many stakeholders involved in most processes that sometimes have opposing interests.
- **Risk-averse culture,** due to a high-risk environment in Medicine and a mind set to follow Best Practices and focus on Evidence Based solutions. This oftentimes leads to “perfect” being the enemy of “good”.
- **Complacent mind set,** as key stakeholders experience no incentives for change.
- **Lack of feeling of urgency,** due to the reimbursement system offering safety for conventional work processes.
- **Little focus on post-pilot implementation,** as decisions are often driven by short-term goals.
- **Lack of personnel with skills in both medicine and IT,** leading to misunderstandings and wrong prioritization.

## Inhibiting factors specific to implementing AI in health care

There are additional barriers specific to the implementation of AI in health care. The importance of each barrier is highly variable and depending on the use case of each algorithm. For example, a fraud analysis algorithm is likely easier to implement than a clinical decision-support algorithm. Likewise, the negative impact of a mistaken prescriptive algorithm is lower than that of a wrong diagnostic algorithm.

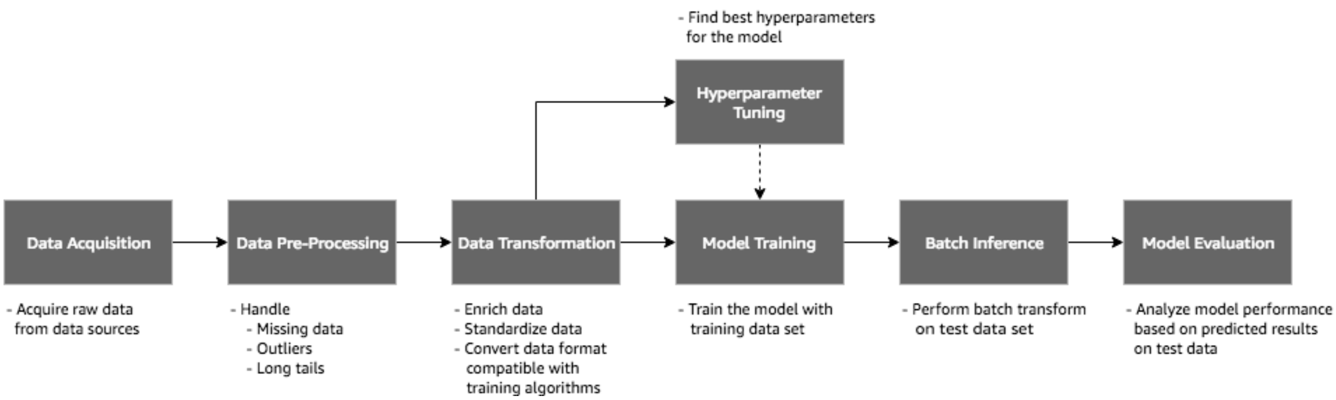
This overview is based on interviews with numerous stakeholders in the fields of AI, health care innovation and health care delivery.

### Data: Amount, Availability, Standards, Quality, Bias and Governance

Experts are often regarded as those who have a lot of experience in their respective fields. In health care, this means a lengthy exposure to the field. The more patients a provider has seen, the more likely they are to have seen, diagnosed and treated both common diseases and rare syndromes.

This is no different for algorithms. A large dataset is of paramount importance to train an algorithm correctly. The more edge cases there are in the dataset, the lower the degree of uncertainty is for those edge cases. This is analogous to the quality of AI algorithms used in self-driving cars: the more miles the algorithm has observed humans driving, the more likely it has seen how to respond in certain unique situations.

Another important factor is the quality of data. The quality of the algorithm directly depends on the quality of data. Training a model on mediocre data leads to algorithms that potentially make disastrous mistakes. These mistakes can be found in the labelling or the contents of the dataset itself.



[61]

[61] https://aws.amazon.com/blogs/machine-learning/build-end-to-end-machine-learning-workflows-with-amazon-sagemaker-and-apache-airflow/

As Electronic Medical Records (EMRs) are still the main modality of health care data used in patient care cycles, there is little structured and high-quality data to come by in many clinical workflows. As EMRs mostly rely on data input by humans, inaccuracies are bound to occur.

Moreover, both interoperability and standardisation of data are large issues that hamper the training of algorithms in health care. Even though standards such as SNOMED have been around for a while, they are rarely implemented across health care institutions.

Health care institutions should ideally share their datasets to increase the amount of patient cases and decrease the likelihood of underrepresentation. Analogous to medical trials: multicenter studies are generally regarded as a stronger form of evidence than single-center studies. However, most health care institutions hold their data on premise without accessibility or interoperability between health care institutions. In algorithm development across patient care cycle or Integrated Practice Units, this poses a great challenge. Split Learning is a novel machine technique that could be a potential solution, as it allows for distributed deep learning without sharing raw patient data.[62]

Bias in datasets is also an important factor to consider. As algorithm only learn off of the dataset they're trained on, patients or edge cases that are not represented or underrepresented in the dataset can lead to inaccurate predictions. This is especially important in high-impact use cases such as clinical treatment recommendations.

Data governance is the field responsible for maintaining data and ensuring quality. Unfortunately, a 2018 KPMG report revealed that data governance is not a priority for most health care institutions. [63]

### Ecosystem of health care

As many startups enter the playing field of AI in health care, the potential for training AI in a broad context of data sources decreases. For most narrow-context AI use cases, this is not an issue. These algorithms are trained on a single data source, potentially combined with open-source datasets.

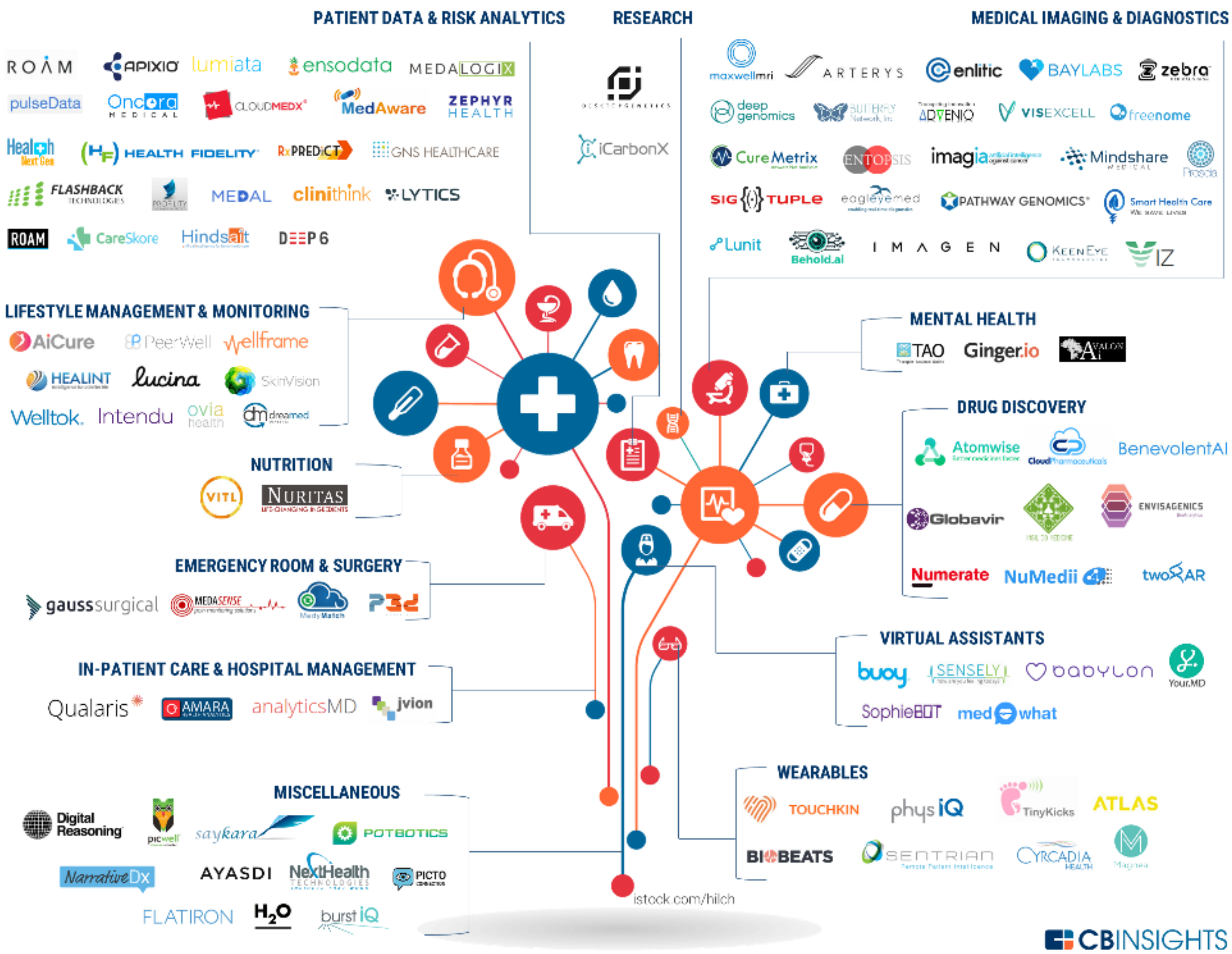
However, the most promising use cases are by definition use cases that are rich in context and need multiple data sources to add considerable value. In chapter 4, the impact of combining *omics data with IoT device data is explained.

---

[62] Split learning for health: Distributed deep learning without sharing raw patient data. 32nd Conference on Neural Information Processing Systems (NIPS 2018), Montr´eal, Canada.

[63] Lee et al., Data governance: Driving value in healthcare. 2018, KPMG. Source: https://home.kpmg/xx/en/home/insights/2018/06/data-governance-driving-value-in-health.html

As many different companies enter the health care AI field, proprietary algorithms are often the mainstay of the company's revenue models. Hence, they are not easily shared with other parties allowing for a rich-context algorithm.




[64]

[64] A myriad of startups are entering the health care AI field. "106 startups transforming healthcare with AI". Source: https://cbinsights.com/research/artificial-intelligence-startups-healthcare/

A few single, large companies gaining access to most data sources is potentially perilous as well: a monopoly position of these large firms on health care data could impede innovation and lead to unethical behavior, making them too powerful.

### Privacy, Accountability and Law in General

The European General Data Protection Regulation (GDPR) forces companies to allow their users to retrieve the personal data the company has stored about them at their discretion.[65] This could stimulate the creation of APIs that users can opt-in to, to exchange their data and allow third parties or government institutions to train algorithms on multiple data sources across institutions and companies.

It is important to note that GDPR mandates explanations to be on various educational levels, to ensure all end-users understand the ramifications of sharing their data. It can be difficult to provide a clear explanation in many use cases of AI, especially those in a rich context.

In terms of privacy, de-identified information is both under European law (GDPR) and under Canadian law no longer regarded as personal information. Such information may be used to train algorithms. However, the process of de-identification or anonymization may require explicit consent[66], which could induce bias in itself. After all, the data of those that do not give consent would not be used in the algorithm's training.

Currently, there is no explicit regulation for the use of AI algorithms in the Netherlands or Canada. Accountability for mistakes lies with the organization creating the algorithm – they are responsible for the use, misuse and effects of their algorithms.

### Ethics

A balance is needed between the opposing forces of innovation and evidence to allow for safe development and implementation of machine learning algorithms that improve patient care. There are many questions that lack unambiguous answers, most notably in the context of explain-ability. To what degree do we need explainable algorithms? Can we use highly accurate, yet inexplicable algorithms in health care? For example, an algorithm might be able to analyze CT-scans that uses less radiation. However, the consequence would be that the radiologist can't determine that the algorithm is correct in its diagnosis.

As the amount of data sources that are used to train algorithms increases, finding out how an algorithm actually came to a certain recommendation becomes increasingly more difficult. This is especially applicable to deep learning algorithms, in which many hidden layers are responsible for a prediction. This is especially a problem for algorithms that have clinical use cases in which trust in the quality of the outcome is key.

[65] EU data protection rules for business and organisations. European Commission. Source: https://ec.europa.eu/info/law/law-topic/data-protection/reform/rules-business-and-organisations_en

[66] https://iapp.org/news/a/does-anonymization-or-de-identification-require-consent-under-the-gdpr/

According to a 2019 discussion on interpretability of models at H2O.ai[67], the main drivers of adoption of explainable algorithms are:

1. The importance of explaining impact decision-making algorithms.
2. Regulatory compliance
3. Forensics for cyber attacks on algorithms
4. Auditing and remediating bias

Dr. Matt Turek from the Defense Advanced Research Projects Agency (DARPA) formulated six questions that need to be answerable for any high-stake algorithm. [68] These questions reflect the importance of transparency for integrity and accountability:

1. Why did you do that?
2. Why not something else?
3. When do you succeed?
4. When do you fail?
5. When can I trust you?
6. How do I correct an error?

Hence, the key is to find out which algorithms are important to be explainable using impact assessment methodologies.

Another issue mentioned earlier is underrepresentation: how do we handle groups that are not represented well in data, and potentially suffer biases from algorithms that aren't trained on their unique situations? These questions are important to consider when applying AI in a field such as health care.

### Shortage of skilled personnel

As industries are ramping up on their business intelligence and algorithm development, the labor market for data scientists has never been better. As such, public institutions such as health care organizations have difficulties finding enough skilled personnel needed to utilize fully the potential possibilities of AI in health care.

Furthermore, as AI development in health care requires multiple skillsets on the crossroads of health and IT, even less data scientists or software engineers will have the required backgrounds. Hence, additional training will likely be required, increasing the difficulties in finding skilled and affordable personnel even more.

[67] https://www.h2o.ai/blog/h2o-world-explainable-machine-learning-discussions-recap/
[68] Explainable Artificial Intelligence (XAI), Dr. Matt Turek, Defense Advanced Research Projects Agency (DARPA). Source: https://www.darpa.mil/program/explainable-artificial-intelligence

Finally, hype, false expectations and misunderstandings about the fundamentals and limitations of AI can lead to misuse of algorithms in health care. Implementing AI courses in medical curricula, reskilling health care providers and Whole System in the Room (WSR)[69] consultations that include data scientists and health care providers are ways to potentially mitigate misconceptions and find consensus between stakeholders involved in implementation of AI in health care.

## Chapter summary

In the implementation of AI in health care, there are many different barriers to overcome. Some of these challenges are inherent to health care, but require elegant solutions nonetheless. As AI descends into the Gartner Hype Cycle's trough of disillusionment, it's important to be aware of opportunism and misconceptions surrounding the fundamentals, possibilities and limitations of AI.

Specific to health care AI development, many factors surrounding data contribute to the difficulties of training algorithms: the amount, availability, lack of standards, quality, bias and governance are all aspects of data that should be considered when developing algorithms in health care.

The ecosystem of health care is a difficulty in itself, where data sources are spread across numerous institutions and companies, connecting these data sources will prove to be a difficult task on its own.

A balance is needed between the opposing forces of innovation and evidence to allow for safe development and implementation of machine learning algorithms that improve patient care.

[69] Huzzard et al. 2018. Whole System in the Room: Toward Systems Integration in Healthcare. Health Commun. 2018 Jul;33(7):800-808. doi: 10.1080/10410236.2017.1314854.

# Final Conclusions

**This report intends to outline the issues that play a key role in the complex world of the health care, and explore the advantages Artificial Intelligence has to offer to support the necessary change in the health care value chain.**

There is a broad consensus among all key stakeholders in health care that, due to a number of factors, our conventional health care systems that use a volume-based health care model, is no longer sustainable. Porter and Lee's value-based health care model seems to be an ideal candidate for restructuring health care. Instead of incremental changes, Porter and Lee suggest restructuring the health care model to a value-based health care (VBHC) model, in which process performance is measure in a value-oriented way. Its goal is to increase value for patients, while decreasing costs where possible.

The value-based health care model's strategic agenda for implementation encompasses six key steps to move towards value-oriented system: organizing around patients' medical condition rather than physicians' medical specialty, measuring costs and outcomes for each patient, developing bundled prices for the full care cycle, integrating care across separate facilities, expanding geographic reach, and building an enabling IT platform.

Kaplan's Time-Driven Activity Based Costing (TD-ABC) seems to be the right solution to measure costs in a value-based health care model. It requires estimates of the unit cost of supplying capacity and the time required to perform a transaction or an activity.

AI is the ideal driver to significantly improve value in a value-based health care model, as it can have a compound effect on both increasing health outcomes and reducing costs. As multiple stakeholders can benefit from the applications of AI in health care, the potential impact is far-reaching.

AI is a collection of statistics techniques in which algorithms leverage large datasets to produce an output in the form of accurate predictions that can support or automate conventional health care processes. Important examples of such processes are the diagnosis of disease and treatment recommendation systems. The input requirements needed for the training of AI algorithms are data, data storage and computing power. Nowadays, all of these requirements are available abundantly and their costs are decreasing. As the use of these algorithms becomes cheaper and more widespread, their applications will increase. In consequence, it is to be expected that the development of AI applications will continue by reframing conventional problems to prediction problems, to find ways of solving them at large scale, similar to the area of driverless vehicles. This trend will affect jobs where human prediction tasks are performed: humans will likely become too expensive compared to AI applications, and as such, we will tend to make less use of those. However, human judgement will become more important in decision-making processes and in personalized care. As such, human intuition and human care will be of considerable importance in health care processes, as clinicians work together with AI algorithms to deliver care. Continuous Monitoring devices and Decentralized

Diagnostics devices can work in tandem to allow for decentralized health care delivery leveraging medical Internet of Things (IoT) devices. They drive easier diagnosis and monitoring of patients at home.

The potential impact of AI is far-reaching and ranging from directly decreasing societal costs by optimizing workflows, decreasing workload of the medical staff leading to potentially lowering burnout rates, empowering patients and delivering truly personalized health care. This can shift the value creation in the entire health care system on a global level. Value will likely shift to tech and med-tech companies, or is mostly passed on to consumers.

Yet the implementation of value-based health care, powered by AI, requires overcoming a number of constraining factors. Some of these challenges are inherent to health care innovation, such as regulation, culture and lack of IT skills in medical personnel. The amount, availability, quality, and governance of data are important factors that can inhibit AI implementation in health care. Moreover, potential bias due to underrepresentation can be potentially devastating in high-impact algorithms. As Electronic Medical Records (EMRs) of different health care institutions do not yet use the same standards, algorithm training on these data sources can prove to be very difficult.

Furthermore, as many startups enter the playing field of AI in health care, the potential for training AI in a broad context of data sources decreases. Data is scattered across numerous players in the health care field that lack interoperability. As companies enter the health care AI field, business models disincentivize the sharing of algorithms and data between health care players. On the other hand, a monopoly position of large firms could impede innovation and lead to unethical behavior, making them too powerful.

The European General Data Protection Regulation (GDPR) forces companies to allow their users to retrieve the personal data the company has stored about them at their discretion. This could stimulate the creation of APIs that users can opt-in to, to exchange their data and allow third parties or government institutions to train algorithms on multiple data sources across institutions and companies. Currently, there is no explicit regulation for the use of AI algorithms in the Netherlands or Canada. Accountability for mistakes lies with the organization creating the algorithm – they are responsible for the use, misuse and effects of their algorithms.

A balance is needed between the opposing forces of innovation and evidence to allow for safe development and implementation of machine learning algorithms that improve patient care. There are many questions that lack unambiguous answers, most notably in the context of explain-ability. the main drivers of adoption of explainable algorithms are the importance of explaining impact decision-making algorithms, regulatory compliance, forensics for cyber attacks on algorithms and the auditing and remediation of bias.

Finally, a shortage of data scientists leads to difficulties for public institutions such as health care organizations to enough skilled personnel needed to utilize fully the potential possibilities of AI in health care.

A resilient leadership with courage, confidence and perseverance is critical to alleviate these challenges and pursue results by pioneering decision makers and stakeholder champions.

Health care providers should focus and prioritize their efforts on the low-hanging fruits of AI: low risk, small investment. Small wins will help foster the implementation of AI in health care.

## Special thanks

I would like to thank everyone for their help and making me feel at home during my stay in Toronto, especially Zayna Khayat, Mary Lou Ackerman and the rest of the team at SE Futures. I would also like to thank Zayna, Tom van de Belt (my research supervisor at the Radboudumc REshape Center in the Netherlands), and my mother for reviewing my report.

## Acknowledgements

Thanks to the following individuals for agreeing to be interviewed as part of the research for this report:

- Amos Adler, President, MEMOTEXT Personalized Adherence Solutions
- Kristina Bush, Account Associate Healthcare, Compugen
- Cheryl Chung, Lawyer, Société Professionnelle Cheryl Cheung Professional Corporation
- Laura Copeland, Chief Medical Information Officer, Healthtech Consultants
- Gillian Fischer, Global Manager of Customer Advocacy, Mindbridge.ai
- Pim Haselager, Associate Professor, Donders Institute for Brain, Cognition and Behaviour
- Peter Hung, Data Scientist in Clinical Research, University of Toronto
- Peter Jones, Industry Lead for Healthcare, Microsoft Canada
- Linda Kaleis, Lead Data Scientist, MEMOTEXT Personalized Adherence Solutions
- Mike Monteith, Co-Founder & CEO, ThoughtWire
- Alison Paprica, Vice President, Health Strategy and Partnerships, Vector Institute for Artificial Intelligence

# References


- Stuart J. Russell and Peter Norvig, 2009, Artificial Intelligence A Modern Approach Third Edition
- Ajay Agrawal, Avi Goldfarb, and Joshua Gans, 2018, Prediction Machines: The Simple Economics of Artificial Intelligence
- Kai-Fu Lee, 2018, AI Superpowers: China, Silicon Valley, and the New World Order
- Eric Topol, 2019, Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again
- Top health industry issues of 2019: The New Health Economy comes of age, PwC Health Research Institute, PriceWaterhouseCoopers
- Healthcare Challenges and Trends The Patient at the Heart of Care, 2013, CGI Group
- Stone et al., 2016, Artificial Intelligence and Life in 2030. One Hundred Year Study on Artificial Intelligence: Report of the 2015-2016 Study Panel, Stanford University. Source: http://ai100.stanford.edu/2016-report.
- Papanicolas et al, 2018, Health Care Spending in the United States and Other High-Income Countries. Source: https://jamanetwork.com/journals/jama/article-abstract/2674671
- KPMG, 2018, Growing Pains: Canadian CEO Outlook
- McKinsey, 2018, The promise and challenge of the age of artificial intelligence. Source: https://www.mckinsey.com/featured-insights/artificial-intelligence/the-promise-and-challenge-of-the-age-of-artificial-intelligence
- McKinsey, 2018, AI, automation, and the future of work: Ten things to solve for. Source: https://www.mckinsey.com/featured-insights/future-of-work/ai-automation-and-the-future-of-work-ten-things-to-solve-for
- McKinsey, 2014, Healthcare's digital future. Source: https://www.mckinsey.com/industries/healthcare-systems-and-services/our-insights/healthcares-digital-future
- CIFAR, 2019, Annual Report of the CIFAR Pan-Canadian AI Strategy
- Gartner, 2018, Build the AI Business Case
- PWC, 2018, AI predictions: 8 insights to shape business strategy
- Microsoft, 2018, Responsible bots: 10 guidelines for developers of conversational AI
- CIFAR, 2018, Building an AI world: Report on National and Regional AI Strategies
- Deloitte, 2015, Connected health: How digital technology is transforming health and social care
- AI Now Institute, 2019, Discriminating Systems: Gender, Race and Power in AI
- CIFAR, 2018, Accountability in AI: Promoting Greater Social Trust
- Gartner 2019, CIO Agenda: Secure the Foundation for Digital Business – Six key take-aways for a successful transformation
- NHS, 2019, The Topol Review: Preparing the healthcare workforce to deliver the digital future

- HealthPRO, 2015, Canada's Healthcare Innovation Challenge
- Cisco, 2011, The Internet of Things: How the Next Evolution of the Internet Is Changing Everything
- JAMA, 2019, Artificial Intelligence in Health Care Will the Value Match the Hype?
- Gartner, 2019, How AI Will Impact Jobs and Your Workforce
- Paprica, 2019, "Method" for partnership-based innovation in complex systems
- McKinsey, 2011, Big data: The next frontier for innovation, competition, and productivity
- Machine Intelligence Research Institute, 2012, How We're Predicting AI—or Failing To
- Executive Office of the President National Science and Technology Council Committee on Technology, 2016, Preparing for the Future of Artificial Intelligence
- PWC, 2019, Top health industry issues of 2019: The New Health Economy comes of age
- Fischer, 2019, AI Adoption Journey
- Microsoft, 2018, The Future Computed: Artificial Intelligence and its role in society
- Dilsizian SE, Siegel EL. Artificial intelligence in medicine and cardiac imaging: harnessing big data and advanced computing to provide personalized medical diagnosis and treatment. Curr Cardiol Rep 2014;16:441.
- Patel VL, Shortliffe EH, Stefanelli M, et al. The coming of age of artificial intelligence in medicine. Artif Intell Med 2009;46:5–17.
- Jha S, Topol EJ. Adapting to Artificial Intelligence: radiologists and pathologists as information specialists. JAMA 2016;316:2353–4
- Weingart SN, Wilson RM, Gibberd RW, et al. Epidemiology of medical error. BMJ 2000;320:774–7.
- Graber ML, Franklin N, Gordon R. Diagnostic error in internal medicine. Arch Intern Med 2005;165:1493–9.
- Winters B, Custer J, Galvagno SM, et al. Diagnostic errors in the intensive care unit: a systematic review of autopsy studies. BMJ Qual Saf 2012;21:894–902.
- Lee CS, Nagy PG, Weaver SJ, et al. Cognitive and system factors contributing to diagnostic errors in radiology. AJR Am J Roentgenol 2013;201:611–7.
- Neill DB. Using artificial intelligence to improve hospital inpatient care. IEEE Intell Syst 2013;28:92–5.
- Jiang F, Jiang Y, Zhi H, et al. Artificial intelligence in healthcare: past, present and future. Stroke and Vascular Neurology 2017;0: e000101. doi:10.1136/svn-2017-00010

## About the Author

Martijn van der Meulen (26) is a recently graduated MD, entrepreneur and software developer. During his studies, he worked for numerous departments of the Radboud University Medical Center and its REshape Innovation Center in The Netherlands implementing health care innovation. He participated in Singularity University's Exponential Medicine Conference and created the Tanzanian Treatment Guidelines app, which is used by over 5,000 clinicians in Tanzania.

He teaches e-health and the fundamentals of AI to undergraduate students in Medicine at the Radboud University. He is also the founder of Plexuz, an AI startup that helps Dutch medical students uncover their knowledge gaps.

In his spare time, Martijn is an avid field hockey player, deejay and home automation geek. He is a member of the Kairos Society for young entrepreneurs and global leaders, and recently joined WZ2025 (Healthcare2025), an initiative of young Dutch MDs to innovate in health care.

**E-mail:** martijn.vandermeulen@radboudumc.nl, martijn@doktermartijn.nl
**Website:** https://martijn.md
**LinkedIn:** https://www.linkedin.com/in/martijnvdmeulen/
**Twitter:** https://twitter.com/martijnmd