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3 The substitution of labor

From technological feasibility to other factors influencing the potential of job automation[1]

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1. Introduction

This chapter, which illustrates the potential of a number of technologies to replace labor, begins with a brief overview of digitalization and automation and the three primary technologies enabling job automation – artificial intelligence (AI); machine learning (ML) – a subcategory of AI; and robotics – in order to create a solid understanding of the concepts. We then proceed to discuss the distinct human capabilities that are required in the workplace and to what degree the three primary technologies can substitute these capabilities based on their current state of development. We then turn to a categorization of job tasks based on a commonly-used framework of routine vs. non-routine and cognitive vs. manual tasks and map the human capabilities in the workplace from the previous section onto this matrix. In the next section, we discuss the resulting automation potential of tasks, jobs and industries. We then turn to discuss a set of factors beyond technological feasibility that influence the pace and scope of job automation. The chapter concludes with a brief summary of the findings that support our prospects for the future of labor.

2. Brief overview of digitalization and automation

Before one can make a proper judgment on the substitution potential of specific tasks, or even complete jobs, it is essential to first develop a solid understanding of the processes and technologies that underlie this substitution. This section aims to create the first part of this understanding by exploring the definition and history of each of the involved technologies and processes.

First, it will touch upon the process of digitalization as it is technology-led and it arguably has had, and will continue to have, a significant influence on labor. We then turn to automation, which is the overarching concept describing the substitution of human labor by machines. Subsequently, artificial intelligence and its subfield of machine learning along with robotics will be discussed as these have been identified as the three most prevalent technological areas within automation.

2.1. Digitalization

2.1.1. Definition of digitalization

Of all the topics in this chapter, digitalization is arguably the broadest concept with the most dispersed definition. Concepts such as Internet of Things (IoT), big data, mobile applications, augmented reality, social media and many others all fall within the scope of digitalization.

In business, digitalization is generally used to describe the process of improving or changing business models and processes by leveraging digital technologies and digitized resources in order to create new sources of value creation.

At the core of this process lies the rise of data-driven, networked business models (Mäenpää and Korhonen, 2015), also known as digital businesses. Digitalization is also used to describe the wider global trend of adopting digital technologies and the effects of this adoption throughout all parts of society (I-Scoop, 2017).

The term digitalization is frequently used interchangeably with digitization and digital transformation. However, it is helpful to make a clear distinction between the three. In this study, digitization will refer solely to the process of transferring analogue data (like pictures, sounds, etc.) into a digital format, i.e., binary code (Khan, 2016; Oxford Dictionaries, 2018b; I-Scoop, 2017).

With digitalization, we will refer to the business process previously described. Lastly, digital transformation is both used to describe a company's journey to become a digital company as well as the larger effects of digitalization on society at large.

Digitalization is also occasionally confused with concepts like mechanization, automation, industrialization and robotization. However, these terms usually refer to improving existing processes, such as workflows, whereas digitalization refers to the development of new sources of value creation (Moore, 2015).

2.1.2. A brief history of digitalization

The history of digitalization began with the development of the modern binary system by Gottfried Wilhelm Leibniz in 1703. However, digitalization, as we refer to it today, started with the introduction of the first digital computers in the 1940s and accelerated with the widespread adoption of the personal computer in the second half of the century (Press, 2015; Vogelsang, 2010).

Digitalization surged with the establishment and development of the World Wide Web in the 1990s, which revolutionized the access to and diffusion of information around the world. Today, with the rapid development of digital technologies like Internet of Things, big data, and AI, this transformation is happening at an unprecedented pace. Though digitalization has caught the attention of both the public and private sector, most organizations are still insufficiently prepared for a digital future, according to IBM (Berman, Marshall and Leonelli, 2013).

2.2. Automation

2.2.1. Definition of automation

The term automation refers to the process of introducing technologies to automatically execute a task previously performed by a human or impossible to perform by a human (Grosz et al., 2016). The field is closely related to mechanization, which refers to the replacement of human labor by machines (Groover, 2018). This is different from systems operating *autonomously*, which relates to the achievement of a goal without predefined execution rules provided by humans. The term automation therefore suggests that the system follows a fixed set of rules to complete its goal (Sklar, 2015). Automated systems are typically made up of three building blocks (Groover, 2018):

1 Power sources. Power sources, such as electricity, are necessary to execute the required action. In general, power sources are used to execute two types of actions: processing, which relates to the mutation/transformation of an entity, and transfer and positioning, which relates to the movement of an entity.
2 Feedback control systems. Feedback control systems monitor whether the required action is performed correctly or not. An example is a thermostat, which monitors the temperature in a room to match a target temperature, and adjusts the heating element's output if this is not the case.
3 Machine programming. This comprises the programs and commands that determine the system's aspired output and the required execution steps. Typical methods for machine programming are using paper/steel cards, tapes, and computer software. Automation by computer-controlled-equipment is also known as computerization (Frey and Osborne, 2013).

One of the most prevalent use cases for automation is within manufacturing. Automation in this field is also known as industrial automation (PHC, 2016). There are three types of industrial automation (Groover, 2018):

1 Fixed automation. The equipment configuration is fixed and cannot be adapted to perform another process. Hence, the sequence of processing operations is permanent.
2 Programmable automation. The equipment can be reprogrammed to perform another process, but the reconfiguration takes time and requires human interference.
3 Flexible automation. The system is controlled by a central computer and can be reprogrammed automatically and instantly. Therefore, the system can perform different processes simultaneously.

Modern, complex automated systems comprise several technologies (Robinson, 2014). Consequently, developments in the field of automation are closely related to advances in these technological sub-fields. Examples are artificial intelligence, neural networks, and robotics (Chui, Manyika and Miremadi, 2016). These will be discussed later in the chapter.

2.2.2. A brief history of automation

The term automation was coined in 1946, but its history stretches back to the dawn of humanity. As mentioned previously, automated systems usually comprise three building blocks. The history of automation can be explained by the development of these three blocks (Groover, 2018):

The first large development in automation came with the invention of tools that utilized a power source other than human muscle. This development started in the early stages of humanity with the creation of tools that magnified human muscle power, like the cart wheel and the lever.

Subsequently, devices were invented that could operate in complete absence of human power by harnessing the energy of wind, water and steam.

In the nineteenth and twentieth centuries, stronger power sources, like electricity, were incorporated into the machines, which significantly increased their power.

The growing machine power gave rise to the need for control mechanisms to regulate the output. At first, human operators were needed to control the energy input to the machine. However, the invention of the first negative feedback system removed human involvement from the process. These systems monitor whether the output of the machine corresponds to the desired level and enable a machine to self-correct its input if the output is off. Developments in this field from the seventeenth century onwards gave rise to modern feedback control systems.

The third large development in the history of automation was the introduction of programmable machines. The first was developed by Joseph-Marie Jacquard in 1801, who used steel cards with different hole patterns to determine the output of his automatic loom. Nowadays, machines are programmed by using paper cards with whole patterns and computers.

The combination of these three developments ultimately led to the rise of automation. The introduction of electrical power enabled a surge in automation at the turn of the nineteenth century. During the second half of the twentieth century and the start of the twenty-first century, the capabilities of automated systems increased significantly following several technological advancements. Firstly, automated systems became much more sophisticated and faster after the introduction and incorporation of the digital computer. This increase in power accelerated following advances in computer science, programming language and storage technology. Meanwhile, the prices of these technologies decreased exponentially. Secondly, developments in mathematical control theory and sensor technologies amplified the capabilities and power of feedback control systems, increasing the systems' versatility and ability to operate autonomously in unstructured environments.

2.3. Artificial intelligence

2.3.1. Definition of artificial intelligence

Artificial intelligence (AI) is a technological field that arguably holds considerable potential for the future. It is such a broad field that it is hard to define precisely what it really is. A famous and useful definition made by Nils J. Nilsson (2010) reads, "*Artificial intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment*." In other words, AI is computers performing tasks that normally require human intelligence (Oxford Dictionaries, 2018a). However, "intelligence" is a complex phenomenon that has been studied in several different academic fields, including psychology, economics, biology, engineering, statistics and neuroscience. Over the years, advancements within each of these fields have benefitted AI significantly. For example, artificial neural networks were inspired by discoveries within biology and neuroscience (Grosz et al., 2016).

The field of AI research has grown significantly over the past few decades and it has been used for a variety of applications, from beating professionals in board games such as chess and Go to the navigation of self-driving cars (Marr, 2016a). Terms such as big data, machine learning, robotics and deep learning all fall within the scope of AI, alluding to the breadth of the technology.

There are several ways to divide and categorize the different methods, subsets, and applications within AI. One way is to distinguish between general and applied AI. Applied AI, also known as weak or narrow AI, is more common and refers to algorithms solving specific problems and programs completing specified tasks (Aeppel, 2017). For example, a computer may excel in one specific board game that is bounded by specific rules, but outside this task it is useless (MathWorks, 2018c). General AI, or strong AI, aims to build machines that can think and perform almost any task without being specifically programmed for it (Copeland, 2018). This means that the machine has a mind of its own and can make decisions, whereas under weak AI, the machine can only simulate human behavior and appear to be intelligent (Difference Wiki, 2017).

Another way of dividing AI is into research areas that are currently "hot". This is an appropriate division as AI arguably suffers from the "AI effect", or "odd paradox", which means that once people get accustomed to an AI technology, it is no longer perceived as AI. Today, "hot" research areas include large-scale machine learning, deep learning, reinforcement learning, neural networks, robotics, computer vision, natural language processing (NLP), collaborative systems, crowdsourcing and human computation, algorithmic game theory and computational social choice, Internet of things (IoT) and neuromorphic computing (Grosz et al., 2016).

Robotics, deep learning and machine learning are all discussed further on in this chapter; however, NLP is also a subset that has made substantial progress in the last few years. NLP applications attempt to understand natural human communication, written or spoken, and to reply with natural language (Marr, 2016b). The research in this field is shifting from reactiveness and stylized requests toward developing systems that can interact with people through dialogue (Grosz et al., 2016). The other subfields will not be discussed individually.

2.3.2. A brief history of artificial intelligence

The term artificial intelligence was first used by John McCarthy in 1956 at the Dartmouth Conference, the first conference in history on artificial intelligence (Childs, 2011). The goal of the conference was to discover ways in which machines could be made to simulate aspects of intelligence. Although this was the first conference on AI, the technical ideas that characterize AI existed long before. During the eighteenth century, the study on *probability* of events was born; in the nineteenth century, *logical reasoning* could be performed systematically, which is much the same as solving a system of equations; and by the twentieth century, the field of *statistics* had emerged, enabling inferences to be drawn rigorously from data (Grosz et al., 2016).

Despite its long history, AI has only recently begun to pick up speed in research advancements. Between the 1950s and 1970s, many focal areas within AI emerged, including natural language processing, machine learning, computer vision, mobile robotics and expert systems.

However, by the 1980s, no significant practical success had been achieved and the "AI winter" had arrived; interest in AI dropped and funding dried up.

A decade later, collection and storage of large amounts of data were enabled by the internet and advances in storing devices. Moreover, cheap and more reliable hardware had stimulated the adoption of industrial robotics and advances in software allowed for systems to operate on real-world data. As a confluence of these events, AI was reborn and became a "hot" research field once again (Grosz et al., 2016).

2.4. Machine learning

2.4.1. Definition of machine learning

A plethora of papers discuss machine learning (ML), but none truly succeed in explaining what it is or what subdivisions there are. As a result, the term machine learning is often misused and confused with artificial intelligence.

According to the Oxford Dictionary, ML is a subset of artificial intelligence and is defined as "*the capacity of a computer to learn from experience, i.e., to modify its processing on the basis of newly acquired information*" (Copeland, 2018). This definition describes what machine learning is, but it does not explicitly explain what the field encompasses. The following paragraphs attempt to explain what machine learning comprises.

Machine learning has grown into a fundamental research topic with several different approaches and algorithms to be used depending on the problem. One way of dividing the field is into supervised and unsupervised learning. In supervised learning, the answer is known (found in past or completed data), whereas in unsupervised learning it is not (Libesa, 2016). Supervised learning uses a known dataset (a training dataset that is a set of labeled objects) to make predictions for datasets in the future. Unsupervised learning, on the other hand, draws inferences from datasets where input data have no labelled response (MathWorks, 2018b).

Unsupervised learning allows computers to reason and plan ahead in the future, even for situations they have not yet encountered or for which they have been trained (Bengio, 2017).

For example, both types of ML can be used for image recognition, a common machine-learning problem in which the system has to classify objects based on their shape and color. If supervised learning is used, the computer has already been taught how to identify and cluster the objects. It will know that an octagon has eight sides and will hence cluster all eight-sided objects as octagons. Under unsupervised learning, the system does not follow a predefined set of clusters or object characteristics. The system must create these clusters itself by identifying logical patterns between the objects; it will notice that several objects have eight sides and cluster them if the characteristics are deemed prevalent (MathWorks, 2018a).

Supervised learning itself has two distinct categories of algorithms: (1) classification – used to separate data into different classes, and (2) regression – used for continuous response values (MathWorks, 2018d).

Unsupervised learning can also be divided into two different categories: (1) cluster analysis – used to find hidden patterns or groupings in data based on similarities or distances between them (MathWorks, 2018b), and (2) dimensionality reduction – where smaller subsets of original data are produced by removing duplicates or unnecessary variables (Ghahramani, 2004).

Supervised learning is the less complicated of the two since the output is known, and it is therefore more universally used. Nonetheless, unsupervised learning is currently one of the key focus areas for AI (Bengio, 2017).

One of the machine-learning techniques that has been widely covered the last few years is deep learning (Deng and Yu, 2014). Deep learning is used within both supervised and unsupervised learning and teaches computers to learn by example, something that comes naturally to humans. Deep learning uses deep neural networks, a network consisting of several layers of neurons loosely shaped after the brain, to recognize very complex patterns by first detecting and combining smaller, simpler patterns.

The technology can be used to recognize patterns in sound, images and other data. Deep learning, is, among others, used to predict the outcome of legal proceedings, for precision medicine (medicine genetically tailored to an individual's genome), and to transcribe words into English text with as little as a seven percent error rate (Marr, 2016b).

2.4.2. A brief history of machine learning

Arthur Samuel coined the term machine learning in 1959, three years after AI (Puget, 2016), but, just as for AI, the technical ideas around ML were developed long before. The two major events that enabled the breakthrough of machine learning were the realization that computers could possibly teach themselves, made by Arthur Samuel in 1959, and the rise of the internet, which increased the amount of digital information being generated, stored and made available for analysis.

The focus point within machine learning has changed over time. During the 1980s, the predominant theory was knowledge engineering with basic decision logic. Between the 1990s and 2000s, research focused on probability theory and classification, while in the early to mid-2010s, focus switched to neuroscience and probability. More precise image and voice-recognition technologies had been developed which made it easier. Memory neural networks, large-scale integration and reasoning over knowledge are currently the predominant research areas. The recent discoveries within these fields are what has brought services such as Amazon Echo and Google Home into scores of households, particularly within the US market (Marr, 2016a).

2.5. Robotics

2.5.1. Definition of robotics

The field of robotics comprises the science and technology of robots and aims to develop, operate and maintain robots by researching the connection between sensing and acting (Siciliano and Khatib, 2016; Grosz et al., 2016).

Robotics is a mix between several academic fields, including computer science, mechanical engineering and electrical engineering, and is one of the primary technologies used for automation (Groover, 2018). The field is strongly related to AI (Encyclopaedia Britannica, 2018) and particularly to the fields of machine learning, computer vision and natural language processing (Grosz et al., 2016).

Developing an overall definition for robots is difficult as robots differ widely in terms of purpose, level of intelligence and form (Wilson, 2015). The Oxford Dictionary defines a robot as "*a machine capable of carrying out a complex series of actions automatically, especially one programmable by a computer*" (Oxford Dictionaries, 2018c). The International Federation of Robotics (IFR) makes a distinction between two types of robots: industrial robots and service robots.

The IFR has aligned its definition for industrial robots with the definition of the International Organization for Standardization (ISO) and refers to them as "*automatically controlled, reprogrammable, multipurpose manipulators programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications*" (International Federation of Robotics, 2017, p. 2).

An example of an industrial robot is a robot arm used in a car manufacturer's production process. Service robots are defined as robots "*that perform useful tasks for humans or equipment excluding industrial automation applications*". The IFR further distinguishes between personal service robots and professional service robots. The first are service robots that are not used for commercial purposes, for instance a domestic vacuum-cleaning robot, while the latter include all service robots that are used for commercial purposes, such as delivery robots in hospitals and offices (International Federation of Robotics, 2017, p. 2).

Combining the previous definitions, Wilson (2015) defines robots as "*artificially created systems designed, built, and implemented to perform tasks or services for people*". Moreover, he expands the definition of robots to include cognitive computing, which refers to automated computer programs. In other words, physicality is not a requirement and many robots solely consist of software (Horton, 2015). Examples of this are Twitterbots and IPSoft's virtual assistant, Amelia.

For the purpose of this study, the term robot will refer to all artificially created systems that perform tasks and services for people, whether they have a physical state or not. We will also adhere to the split between industrial robots and service robots. In addition, while some authors distinguish between robots and automated vehicles, for the purpose of this study they will both fall under the umbrella of robotics.

2.5.2. A brief history of robotics

From Greek mythology to da Vinci's machine designs, humans have always fantasized about creating skilled and intelligent machines, but the word robot was only introduced in 1920 by Karel Čapek, a Czech playwright (Siciliano and Khatib, 2016). The first electronic autonomous robots were created in the 1950s and the first industrial robot was developed in 1959. Nevertheless, it took two more years until the first industrial robot was acquired and installed in a manufacturing process (International Federation of Robotics, 2017). From that moment, robotics became widespread in industrial, warehousing and military applications (Boston Consulting Group, 2014; Siciliano and Khatib, 2016).

The first generations of robots consisted of large, immobile machines with a narrow skillset and limited power to adapt to their surroundings (Latxague, 2013).

Over the past decade, the field of robotics has made a gigantic leap as advances in programming, sensors, AI and robotic systems have significantly increased the intelligence, senses and dexterity of robots (Decker, Fischer and Ott, 2017; Sander and Wolfgang, 2014; Manyika et al., 2013). This has resulted in robots that are more versatile (Decker, Fischer and Ott, 2017), smaller and better connected to each other. Consequently, it is much safer for robots and humans to work closely together and the range of applications for robots has increased significantly. For example, the technological advances have enabled robots to enter the realm of services, which was previously deemed impossible (Manyika et al., 2013). In the future, technological advances are expected to further increase the capabilities of robots and prices are expected to drop. As a result, the field of robotics is expected to surge (Sander and Wolfgang, 2014).

3. The current state of the three technologies

The second step in assessing the technical feasibility of technologies posed to take over work activities is to analyze the technologies' current capabilities. In other words, what are the technologies currently able to do? To do this, we follow a framework from Manyika et al. (2017) that identifies five broader areas of capabilities: sensory perception, cognitive capabilities, natural language processing, social and emotional capabilities and physical capabilities, which enable humans to perform 18 activities in the workplace. These categories were developed based on an analysis of 2000 distinct work activities across 800 occupations. The framework is displayed in Figure 3.1.

This section discusses the current state of the technologies for each of these five broader areas of capabilities. The three technologies will be discussed simultaneously because they are closely related and are often used in combination to perform a single activity. It is important to note that many of these capabilities are still only proven in laboratories and are not yet available on the market.

3.1. Sensory perception

The area of sensory perception, or machine perception, covers the sensing and processing of external information from sensors and includes the three subfields of visual, tactile and auditory (Anderson et al., 2017). Sensory perception covers the capabilities of the sensors as well as the underlying software that processes and integrates the information. Sensory perception is essential for a variety of applications, including feedback control systems of automated systems and physical capabilities of robots (Grosz et al., 2016). Over the years, sensors and the underlying machine-learning algorithms have become increasingly sophisticated (Hardesty, 2017), and in some fields machines have even reached a capability level that is at par with the human level, according to McKinsey (Anderson et al., 2017).

Computer vision has developed significantly over the past decade, enabled by advances in sensors, deep learning and the abundance of data due to the internet. In some narrow-classification tasks, computer vision systems can outperform their human counterparts. Meanwhile, developments in sensors and algorithms for 3D object recognition, for example LIDAR (Laser-Imaging Detection and Ranging), allow for more precise distance measuring than ever before. Nonetheless, complex tasks, such as dealing with cluttered vision and fields, still present a challenge for the current technology (Manyika et al., 2013; Frey and Osborne, 2013; Robinson, 2014).

Computer vision is essential for machines to perceive and adapt to their environments and is one of the major enablers of autonomous vehicles. Advances in vision technology also enable progress in other applications, e.g., industrial and software robots.

For example, it enables robots to manage patients at the front desk of a pharmacy and to assemble customized orders in pharmaceutical settings (Qureshi and Sajjad, 2017; Manyika et al., 2013).

"Machine touch" refers to the processing of tactile/haptic information and is indispensable for a robot's ability to grasp and manipulate objects (Izatt et al., 2017; Hardesty, 2017). Though progress is being made to develop sophisticated

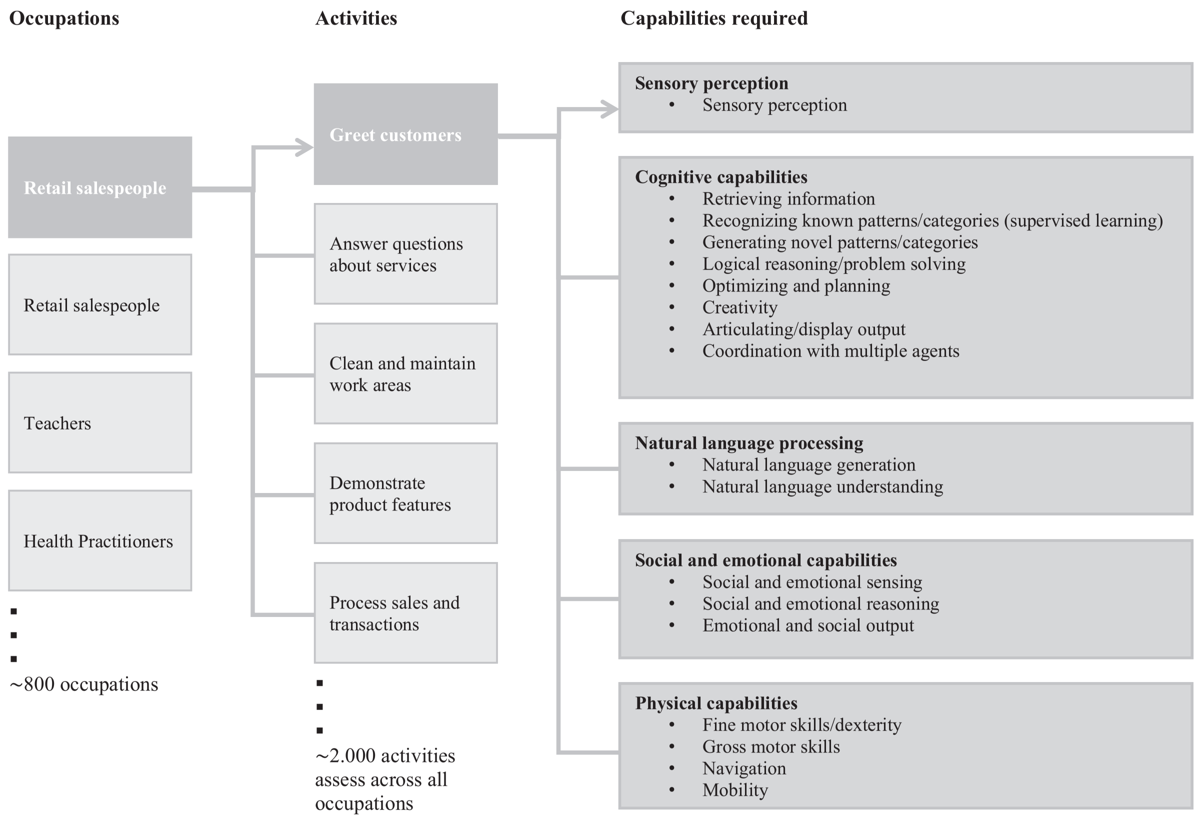

Figure 3.1 Capabilities required in the workplace (Manyika et al., 2017).

haptic sensors that mimic human capabilities, robots still struggle to obtain accurate local information. For example, it is hard to estimate how much force to apply when grabbing an object or to accurately estimate an object's position once it is in the robot's gripper and out of its camera's sight. One recent development is robot skin, a development by Georgia Tech, which gives robots the ability to feel textures (Manyika et al., 2017).

"Machine Hearing" refers to the processing of sound by computers. It is vital for natural language processing and auditory scene analyses, which is the ability to separate and group acoustic data streams (Hahn, 2017). The goal of machine hearing is for machines to be able to distinguish between different sounds, to organize and understand what they hear, and to react in real time (Lyon, 2017, pp. 131–139). For example, a serving robot in a restaurant should be able to distinguish and group the voices of the different customers at a table and accurately take their orders. Today, machine hearing is still in its infancy stage compared to machine vision. For machine-hearing models to be designed, analyzed and understood, math, engineering, physics and signal-processing are essential.

Although some subfields of sensory perception have advanced rapidly, it remains a large challenge to integrate multiple sensor streams into a single system (Hahn, 2017), and it will take several years for the technology to completely surpass the human level (Manyika et al., 2017).

3.2. Cognitive capabilities

This area covers a wide range of capabilities, including making tacit judgments, retrieving information, logical thinking, optimizing and planning, creativity, coordination with multiple agents and recognizing and generating known and novel patterns/categories. Significant developments have been made within the area, but it is also where the most technical challenges lie (Hodson, 2016; Manyika et al., 2017). As of today, there are cognitive systems that beat humans in several activities.

For example, IBM's Watson computer has a 90% success rate in diagnosing lung cancer compared to a human's 50% (Steadman, 2013). Watson also beat the reigning chess champion in 1997 and the champions in gameshow Jeopardy! in 2011 (Knight, 2016). Each individual capability will be discussed briefly.

Optimizing and planning for objective outcomes across various constraints can currently be done by a computer with the same precision as the most skilled humans in this field (Manyika et al., 2017). It includes optimizing operations and logistics in real time, for example, optimizing power plants based on energy prices, weather and other real-time data, or automating machinery to reduce errors and improve efficiency (Henke et al., 2016).

Retrieving information includes being able to search and retrieve information from a wide variety of sources. Based on this information, a computer should also be capable of writing research reports. As of today, technologies are far more skilled at retrieving information than humans (Manyika et al., 2017) because computers are much faster than humans and can go through millions of sources in the blink of an eye. For example, IBM's Watson searched through 20 million cancer research papers and diagnosed a patient with a rare form of leukemia in only ten minutes, while the doctors had missed this for months at the University of Tokyo (Ng, 2016).

Recognizing known patterns/categories is identical to the concept of supervised learning. As explained earlier, supervised learning uses known patterns to categorize and predict for datasets in the future (MathWorks, 2018d). The use and power of supervised learning has increased considerably with the growing availability of large data sets following the internet and advances in sensors. The capability of recognizing patterns is one where computers already outperform humans. For example, a deep-learning based lip-reading system, created by Google's DeepMind and the University of Oxford, trained by watching over 5000 hours of BBC programs, easily outperformed a professional human lip-reader (Frey and Osborne, 2013; Manyika et al., 2017).

Technology has not come as far in generating novel patterns/categories as it has with recognizing them; the field of unsupervised learning, which deals with this problem, is still in an early stage and the capability level of computers is below median human performance (Manyika et al., 2017). One of the difficulties is that the creation of something new requires creative intelligence, which is highly difficult to codify, as will be discussed next. For example, mathematicians perform tasks involving "*developing new principles and new relationships between existing mathematical principles to advance mathematical science*" (Frey and Osborne, 2013, p. 267). This task requires a lot of creativity and is therefore very hard to automate.

Creativity is currently one of the most difficult capabilities to automate. To be creative one must be able to make new combinations of familiar concepts, which requires a rich body of knowledge. The challenge for computers is to make combinations that "make sense" as they lack common knowledge. For this to happen, we must be able to specify our creative values precisely so that they can be codified. Another obstacle is the fact that these creative values vary between cultures and change over time. Despite the challenges, AI has already been used for some creative tasks, like creating music and staging performances (Grosz et al., 2016; Frey and Osborne, 2013).

Logical reasoning and problem-solving can be done on different levels of complexity; from limited knowledge domains with simple combinations of output to many contextual domains with multifaceted, potentially conflicting, inputs. An example of such a task is the ability to recognize the individual parts of an argument and their relationships as well as drawing well-supported conclusions (LSAC, 2018). This capability is also one of the toughest for machines to perform, and performance is still at a low level compared to humans. However, the technologies are improving. Some activities requiring judgment might even be better off being computerized because AI algorithms make unbiased decisions while humans often may not. For example, it has been shown that experienced judges are considerably more generous in their rulings after a lunch break (Manyika et al., 2017; Frey and Osborne, 2013). An algorithm would deliver the same output regardless of the time of day.

Coordination with multiple agents reflects a machine's ability to work together with other machines as well as with humans. This capability, especially human-machine collaboration, is still underdeveloped (Manyika et al., 2017). Early stages of robot collaboration have been proven, but these are largely based on laboratory research (Perry, 2014; Kolling et al., 2016). For example, researchers at Carnegie Mellon University made two different types of robots collaborate by letting a mobile robot bring work to a static robot arm that was controlled by the latter robot (Sklar, 2015).

As pointed out earlier, the general focus has shifted from substitution toward human-machine collaboration. However, the ability of machines to collaborate with humans is currently at a low level (Manyika et al., 2017), limited, for example, by the inability of AI systems to explain their decisions and actions to humans (Turek, 2017) and to understand and produce natural language.

One early example is the humanoid robot Asimo, which has a limited ability to respond to voice commands and human gestures (Boston Dynamics, 2018).

3.3. Natural language processing

Natural language processing comprises both the understanding and generation of natural language. Research within this field has shifted from reacting to clearly specified requests with a limited range of answers to developing refined and sophisticated systems that are able to have actual conversations with people. The generation of natural language is described as "*the ability to deliver spoken messages, with nuanced gestures and human interaction*" (Manyika et al., 2017). Natural language understanding is described as "*the comprehension of language and nuanced linguistic communication in all its rich complexity*" (Manyika et al., 2017). While computers' current level of generation of natural language is comparable to humans, the understanding of natural language remains at a lower level. The development within this area is one of the key factors influencing the pace and extent of automation (Manyika et al., 2017; Henke et al., 2016).

Natural language processing requires lexical, grammatical, semantic and pragmatic knowledge. Despite the fact that computers currently possess some of this knowledge, they are still less capable than humans.

Computers face difficulties in understanding multi-sentence language as well as fragments of language, while incomplete and erroneous language tends to be the norm in society (Bates, Bobrow and Weischedel, 1993). In addition, teaching computer systems and robots to detect sarcasm (Maynard, 2016), both in written and verbal conversations as well as the difference between polite and offensive speech (Steadman, 2013), currently proves to be very difficult.

In order to generate natural language, a machine must know *what to say* and *how to say it*. In order to know *what to say*, the machine must have data and should be able to determine what information from this data to include. The latter process, *how to say it*, requires a machine to know the language rules so that it can make a text (verbal or written) that makes sense. Currently, it is still very difficult for the software to produce grammatically correct and well-formed texts that have natural flows and that fit into an individual's context and needs (Coupel, 2014).

There have been some recent developments within the field, and companies such as Google, Amazon, and Apple use NLP in their products. Every time you ask Alexa, Siri or Google Home what the weather is like at your location or where to find a Japanese restaurant, NLP allows the program to understand your speech and answer in verbal language (Hunckler, 2017).

3.4. Social and emotional capabilities

This area deals with human social intelligence, which includes a machine's capability to sense and reason about social and emotional states as well as the ability to generate emotionally suitable output. These are essential capabilities for daily (human) interaction and for tasks like negotiation, persuasion, and caring. Among the five broader capability areas, social and emotional capabilities is currently the least advanced and will probably not surpass human level for at least two more decades (Manyika et al., 2017; Frey and Osborne, 2013).

Advances in machine learning and sensing have given machines a limited ability to recognize human emotions.

However, the current capabilities of these software programs are still far below human levels and face significant challenges with regards to instantaneous and accurate recognition of emotions. It is even more difficult for machines to comprehend and reason about the social and emotional states of humans.

Existing techniques analyze facial expressions, physiological factors (e.g., heart rate or blood pressure), text and spoken dialogues to detect human emotions. These techniques hold great future potential for several applications like automated call centers (Picard, 2007) and targeted advertisements based on emotional states (Doerrfeld, 2015).

Several emotion recognition software programs are already in use. Affectiva, for example, applies facial expressions analysis to adapt mobile applications to adjust to the emotional state of the user (Turcot, 2015).

To date, even the most advanced algorithms are not capable of communicating in a way that is indistinguishable from humans, and no machine has ever passed the Turing test.[2] The generation of emotionally suitable output is complicated by the existence of "common sense", which is tacit or implicit knowledge possessed by humans and ingrained in human interaction and emotions.

This knowledge is hard to define and articulate and therefore almost impossible to incorporate in algorithms (Hager et al., 2015; Frey and Osborne, 2013; Manyika et al., 2017). Communicating, in the absence of common sense, results in awkwardness or feelings of unnaturalness. There are some robots on the market that have a limited ability to mimic human emotions, like the humanoid Pepper, which can express joy, surprise, anger, doubt and sadness, but the actual creation of emotions is far away (Murphy, 2015).

3.5. Physical capabilities

This area includes fine and gross motor skills, navigation and mobility. It is closely related to the area of sensory perception, which provides the information input for physical activities (Manyika et al., 2013). Machines have already surpassed humans in terms of gross motor skills and the use of robots is widespread in industrial and warehousing settings, for example for picking and placing, welding, packaging and palletizing. Amazon has even completely automated some of its warehouses using robots.

However, on the frontier of fine motor skills and dexterity, technology is lagging behind significantly (Ritter and Haschke, 2015; Manyika et al., 2017). Manual skills are deeply integrated into the human cognitive system. Therefore, grasping and manipulation of smaller and deformable objects are still large sensorimotor challenges for the current technology. Robot dexterity is constrained by the strength of miniaturized actuators as well as visual and tactile sensors, which currently perform far below human levels (Hardesty, 2017; Ritter and Haschke, 2015; Frey and Osborne, 2013). Moreover, robots do not yet have the same degrees-of-freedom as human hands and current control systems are not yet capable of dealing with the multifaceted and unstructured nature of manual tasks. Nevertheless, there are several anthropomorphic robot hands with human-like capabilities on the market. The most advanced of these is the Shadow Dexterous Hand (Ritter and Haschke, 2015), which can perform delicate tasks such as opening a bottle cap and grabbing strawberries without crushing them.

Empowered by advances in machine vision and machine learning, navigation has already surpassed human capabilities. Advanced GPS systems, supported by vast amounts of spatial data, enable the pinpointing of exact locations and navigation toward almost every destination imaginable.

These capabilities are already widely used for example in (partly) autonomous cars and navigation apps, like Google Maps.

Despite advances in computer vision, robot mobility is still at a low level, especially autonomous mobility. Autonomous movement through static environments, e.g., specially designed warehouses, has largely been solved (Grosz et al., 2016; Manyika et al., 2017), but adapting motion to new and dynamic environments remains a substantial challenge (Heess et al., 2017).

Some of the reasons for this are technical challenges, including balance and control (Electronics Teacher, 2017), as well as insufficiently developed algorithms (Heess et al., 2017). Moreover, a lack of research on robot mobility in indoor settings has hampered progress in the area of indoor mobile robots (Grosz et al., 2016).

However, progress is being made on algorithms, as is shown by the DeepMind computer which recently taught itself to move through new, complex environments in a computer simulation (Heess et al., 2017). Real-life examples of advanced mobile robots are Boston Dynamics' Atlas, a humanoid robot which can move to various unknown terrains on two legs (Boston Dynamics, 2018), and Asimo, a humanoid robot capable of running, walking, kicking a ball and reacting to human instructions (Honda, 2018).

3.6. The overall state of current technologies

Though substantial progress is being made in all five capability areas, several capabilities currently remain out of reach for the available technologies. Most notably, technology is underdeveloped for processing and generating natural language and social/emotional output, autonomous mobility, fine motor skills and a range of cognitive capabilities. On the other hand, technology is excelling in fields such as recognizing known patterns, gross motor skills and navigation, and is largely at par with humans in the field of sensory perception. Moreover, further advances are expected in all areas, and machines will likely be at or above human levels for most capabilities within one to two decades (Chui, Manyika and Miremadi, 2015).

However, current technological progress is mainly focused on narrow, individual capabilities.

The integration of several capabilities into well-functioning holistic solutions is another significant challenge that needs to be overcome and will probably take much longer than for the individual capabilities (Frey and Osborne, 2013).

On the other hand, environmental control can mitigate the current limitations of machines. This concept refers to the alteration of the environment or the task to make it simpler and more structured, for example by breaking it down into smaller tasks or by transforming an unstructured environment into a structured one. Environmental control can obviate the need for advanced flexibility, mobility, manual dexterity and cognitive capabilities. For example, Amazon placed bar-code stickers on the floor of its warehouses to assist the robots in their warehouse navigation. They adapted the environment so it would become structured.

However, though environmental control is applied in warehouses and other local environments, countries and cities are still lagging behind in adapting their infrastructures to accommodate the new technologies (Frey and Osborne, 2013; Grosz et al., 2016).

4. The substitution of job tasks

Having discussed the current technological capabilities in the previous section, the ensuing section aims to relate these capabilities to their potential of substituting labor, focusing on the individual tasks that constitute jobs, rather than jobs in their entirety. The reason for this is that jobs include several different types of tasks, which all have a different relation to the current capabilities of technologies. Consequently, some types of tasks can already by automated while others cannot. Hence, it is essential to first understand which individual tasks can be substituted before one analyzes the effect on jobs and labor in general.

The different types of tasks are introduced in the next section, following the task model by Autor, Levy and Murnane (2003), and the substitution potential of each task category will be discussed in relation to the previously mentioned capabilities. In the next section, *The Impact on Labor*, we utilize our findings to make a judgment on the overall effect of automation on a selection of jobs and industries.

4.1. Four types of job tasks

To determine the job substitution potential of computers, Autor, Levy and Murnane (2003) conceptualized work as a series of tasks rather than complete jobs. Specifically, the paper distinguishes routine tasks from non-routine tasks and manual from cognitive tasks. This classification results in a 2 × 2 matrix, which is displayed in Figure 3.2. Routine tasks are defined as tasks that follow explicit rules, which can be exhaustively specified and, hence, translated into code. For non-routine tasks, these rules are not understood sufficiently well, which makes them much harder to codify. As a corollary of this definition, routine tasks are automatically classified as tasks that are easily substituted by technology while non-routine tasks are not.

Manual tasks are physical activities that require motor skills and mobility whereas cognitive task relate to mental processes.

In addition to the matrix in Figure 3.2, there are several other task classifications. For example, Manyika et al. (2017) have developed seven broader activity categories:

1 Predictable physical
2 Processing data
3 Collecting data
4 Unpredictable physical
5 Interfacing with stakeholders
6 Expertise
7 Managing and developing others

These seven categories fit largely within the 2 × 2 matrix of Autor, Levy and Murnane (2003). Predictable and unpredictable physical activities are aligned with the routine manual and non-routine manual task classification of Autor, Levy and Murnane (2003). Data collecting and processing largely fall under

	Cognitive	*Manual*
Routine	Explicit rules Mental processes	Explicit rules Motor skills
Non-routine	Rules difficult to codify Mental processes	Rules difficult to codify Motor skills

Figure 3.2 Four categories of job tasks (Autor, Levy and Murnane, 2003).

routine cognitive tasks, whereas interfacing with stakeholders, applying expertise and managing and developing others can be placed under non-routine cognitive tasks.

Each of the four categories is discussed in more detail in the next section.

4.1.1. Routine manual tasks

The routine manual task category includes physical activities that require systematic repetition of a consistent procedure, i.e., structured physical tasks that take place in predictable environments. The primary capabilities required to perform these types of activities are gross and fine motor skills, sensory perception and, to some extent, mobility.

Examples of activities include assembling, picking and sorting, welding and cooking. These tasks are easily translatable into computer programs and the technology to perform them is at an advanced level, especially for gross motor skills, where machines have been outperforming humans for a long time.

Consequently, this task category has the highest technological potential for substitution by machines (Manyika et al., 2017; Frey and Osborne, 2013; Autor, Levy and Murnane, 2003). Manyika et al. (2017) even predict that in the United States as much as 81% of the tasks in this category can be substituted.

The substitution of routine manual tasks has a long history and goes back to the introduction of the first machines that were capable of functioning automatically. Since then, machines have continuously pushed out humans, and a vast number of manual activities have been automated in the twentieth century (Finnigan, 2016). For example, many processes in the agriculture and car manufacturing industries are currently performed by machines. As a corollary, Autor, Levy and Murnane (2003) found that the percentage of people active in jobs with large proportions of routine manual activities declined between 1960 and 1998.

More recently, advances in sensory perception and manual dexterity have made it possible for robots to be assigned to tasks that require higher precision, e.g., slicing meat, assembling customized orders, manufacturing electronic components (Sander and Wolfgang, 2014; Sirkin, Zinser and Rose, 2015). Robots have also become safer and much more flexible to use, which allows them to quickly switch between different tasks and to safely work next to humans. Furthermore, the advances in mobility and navigation allow robots to move autonomously in static environments like warehouses.

In addition, robots are increasing their presence in the service industry. Simple service tasks, like cleaning, have been performed by robots for over a decade, the most notable example being the robot vacuum cleaner. However, with their increased dexterity and mobility, robots are increasingly able to take on complex routine manual tasks in the service industry. A prime example is the food sector where robots can be deployed to prepare and serve food and beverages (Frey and Osborne, 2013; Manyika et al., 2017).

For instance, the pizza delivery company Zume Pizza has automated its production process almost completely using sophisticated robots (TechCrunch, 2016).

Nonetheless, robot deployment is still in an early stage in this industry and the substitution potential remains limited.

Many routine manual tasks can and most likely will be performed by robots in the future and the share of repetitive, rule-based activities in jobs will decrease. With advances in sensors and increasing robot dexterity, more high-precision tasks will become candidates for substitution, such as manufacturing tasks in the electronics sector. As robots become safer, they will likely take up more positions next to their human coworkers. Further engineering advances are necessary to increase the flexibility of robotic systems by decreasing the reconfiguration time (Robotics Technology Consortium, 2013).

4.1.2. Non-routine manual tasks

Non-routine manual tasks are non-structured physical tasks that take place in unpredictable environments, often involving situational adaptability and in-person interaction. They require capabilities like sensory perception, fine and gross motor skills, social and emotional capabilities, natural language processing, navigation and mobility. The majority of these capabilities have not yet reached human-level performance and the incorporation of flexibility remains a considerable challenge (Autor, 2015; IPsoft, 2018). Consequently, the automation potential of this category is low, only 26% according to Manyika et al. (2017). Examples of tasks include operating a crane, assisting with surgery, janitorial work and making hotel beds.

Recent advances in sensory perception and physical capabilities as well as machine learning have enabled machines to take over an increasing number of manual non-routine tasks. Improvements in sensor technology and manual dexterity allow robots to perform high precision, non-standardized tasks, such as the manipulation of delicate products like fruit and vegetables. By incorporating advanced sensors, computer programs can also take over condition-monitoring tasks, such as checking the state of an aircraft engine or examining the moisture level in a field of crops. When alerted by the program, human operators can perform the required maintenance. Even some maintenance tasks are being substituted.

For example, General Electric has developed robots to climb and maintain wind turbines (Frey and Osborne, 2013).

Another well-known new application of machines for non-routine manual tasks is the autonomous vehicle. Autonomous driving was deemed impossible not so long ago as it requires activities such as parking, switching lanes and adapting to traffic lights, other vehicles and pedestrians (Autor, Levy and Murnane, 2003; Manyika et al., 2017).

However, today, facilitated by machine learning and advanced sensors, Google's autonomous car is driving the streets completely by itself and is even seen by some as safer than human-controlled cars (Frey and Osborne, 2013; Grosz et al., 2016). Autonomous mobility has also entered the warehousing industry (Autor, 2015). Here, enabled by environmental control, many warehouses, such as Amazon's warehouses, have become largely automatic.

Nonetheless, most non-routine manual tasks remain out of reach for machines for now and the near future. Despite the advances in the field of autonomous cars, autonomous mobility in general remains a significant challenge. Likewise, significant progress in perception and dexterity technologies is required before autonomous manipulation is viable in unstructured and delicate settings (Robotics Technology Consortium, 2013). Moreover, tasks that require human interaction demand further advances in language recognition, social and emotional capabilities and user interfaces. One example is walking a patient down a hospital (or nursery) hallway (Grosz et al., 2016). This requires a robot to help a patient get out of bed, which requires that the robot communicate with the person based on their emotional state, possess fine motor skills and sensory perception, to know where to hold/touch the patient and how much force to apply and to navigate through an unstructured environment. The activity is therefore not likely to be automated in a near future.

4.1.3. Routine cognitive tasks

Routine cognitive tasks include all mental (non-physical) tasks that repeat a certain procedure in a predictable environment. To a large extent, this relates to the different aspects of processing structured information, such as data collection, organization and storage (Autor, Levy and Murnane, 2003).

The required capabilities for these tasks are retrieving information, recognizing known patterns, optimizing and planning, logical reasoning/problem solving and natural language processing.

Examples of tasks are data-processing tasks such as calculating and bookkeeping but also routine customer-service activities performed by people such as cashiers, telephone operators and bank tellers. Because of their routine nature, these tasks have a high potential for machine substitution, ranging from 64% for tasks relating to data collection to 69% for tasks relating to data processing in the US, according to Manyika et al. (2017).

The automation of cognitive tasks started with the introduction of the computer (Autor, Levy and Murnane, 2003), which enabled the digitization and automatic processing of information. Subsequently, many processes, including administrative tasks, bookkeeping, invoicing, optimizing resource needs, and numerous others, have already been automated (Acemoglu and Autor, 2011).

Today, technological advances and the current focus on digitalization have brought the automation of routine cognitive tasks to an unprecedented scope and pace. Many companies have embarked on so-called “digital transformations”, which refer to the simplification, standardization, and digitalization of an entire organization (Ketterer, Himmelreich and Schmid, 2016).

At the front-end, this means that large parts of customer interaction interfaces can be automated. Examples range from the automation of customer data collection for mortgage brokers to the employment of full-fledged, AI-based, virtual employees who can take over all aspects of customer interaction (IPsoft, 2018). At the back-end, the restructuring of the organization's IT landscape obviates many processes and activities (Ketterer, Himmelreich and Schmid, 2016).

In addition, for some structured processes that remain in existence, robotic process automation can be employed, which uses software robots to automate well-defined transactions/user actions normally performed by humans (Bughin et al., 2017; Ketterer, Himmelreich and Schmid, 2016). These software robots can be seen as virtual employees who work with existing applications in a similar fashion to humans (Forrester Research Inc., 2014).

The further proliferation of automated data collection and processing activities depends on the pace of digitalization. As companies progress on their digital transformations, more data and processes will be digitized and therefore likely automated. Moreover, further automation of customer service activities will depend on the machines' capability to interact with customers and thus depends on advances in natural language processing and emotional capabilities.

4.1.4. Non-routine cognitive tasks

Non-routine cognitive tasks are mental (non-physical/abstract) tasks that do not follow a structured procedure and/or take place in unpredictable environments (Autor, Levy and Murnane, 2003). These types of tasks require several cognitive capabilities, including creativity, logical reasoning, generating novel patterns and coordination with multiple agents. In addition, natural language processing and social and emotional capabilities are often of high importance (Acemoglu and Autor, 2011). These types of tasks include activities that relate to interfacing with stakeholders, applying expertise and managing and developing others. Examples of activities include legal writing, negotiations, teaching and diagnosing diseases.

Historically, these types of tasks have been the most difficult to automate (Frey and Osborne, 2013; Autor, Levy and Murnane, 2003). However, the availability of big data and recent advances in machine learning (pattern recognition in particular) have enabled machines to enter the realm of unstructured tasks. By applying unsupervised learning, a computer can create its own structure in an unstructured setting. Moreover, developments in the field of user interfaces, like language recognition, enable computers to respond directly to voice and gesture instructions (Manyika et al., 2013).

One of the tasks that can now be automated is fraud detection, a task that requires the ability to detect trends in data as well as to make decisions (Frey and Osborne, 2013). By using machine learning to build models based on historical transactions, social network information, and other external sources, the system can use pattern recognition to detect anomalies, exceptions, and outliers. This means fraudulent behavior can be spotted and fraudulent transactions can be prevented (Wellers, Elliot and Noga, 2017).

The legal domain is another area that machines are entering; nowadays, computers can analyze and order thousands of legal documents swiftly and present their findings graphically to the attorneys and paralegals (Frey and Osborne, 2013).

Yet, most of the involved capabilities remain far under human level for now. Especially tasks that require creativity, problem-solving and complex communication (a confluence of natural language processing and social and emotional capabilities) have a very low substitution potential (Manyika et al., 2017; Autor, Levy and Murnane, 2003).

Even in fields in which machines can outperform people on narrow tasks, like route planning, humans are often still required to set the target, interpret the outcomes and perform common-sense checks. Arguably there, major advances are required before machine learning and artificial intelligence become mature technologies. For instance, there are several examples of failing AI systems, like Microsoft's Tay Chatbot, who had to be shut down only 16 hours after launch because of the highly controversial messages it tweeted. Correspondingly, the three categories identified by Manyika et al. (2017), interfacing with stakeholders, applying expertise, and managing others, all have a substitution potential of below 20%.

Besides other required advances in cognitive, social and emotional capabilities, the availability of a sufficient amount of task-specific information is essential for the automation of cognitive non-routine tasks. In absence of this information, pattern recognition cannot be applied. In addition, as with the other types of tasks, environmental control, or task simplification, can be applied to mitigate engineering bottlenecks. For example, self-checkout stations in supermarkets obviate the need for advanced customer interaction (Frey and Osborne, 2013; Autor, Levy and Murnane, 2003).

4.2. The overall substitution of job tasks

As is evident from the previous discussion, technologies can take over an increasing number of activities. Routine, both manual and cognitive, tasks have been in the automation process for some time, whereas machines have only just acquired the ability to substitute for human labor in some non-routine tasks. The substitution potential for routine tasks is high and will only increase with technological advances. The substitution of non-routine tasks, on the other hand, remains largely limited to narrow applications for which human involvement is still required. A summary of the discussion for each of the job task categories is provided in Figure 3.3. To bring the automation of non-routine tasks to the next level, significant advances in all five capability areas are necessary, with natural language processing capabilities being the most important according to Manyika et al. (2017).

5. The impact on labor

Though several books and papers argue that technology will take over many jobs resulting in mass unemployment (Berg, Buffie and Zanna, 2016; OECD, 2016), as

	Cognitive	*Manual*
Routine	***Primary Required Capabilities*** Retrieving information Recognizing known patterns Optimizing and planning Logical reasoning/problem solving Natural language processing ***Sample Tasks*** Data processing tasks, e.g., calculating and bookkeeping Customer service tasks by e.g., cashiers, telephone operators, bank tellers **Predicted Substitution Rate: 64–69%***	***Primary Required Capabilities*** Gross and fine motor skills Sensory perception Mobility to some extent ***Sample Tasks*** Assembling Picking and sorting Welding Cooking **Predicted Substitution Rate: 81%***
Non-routine	***Primary Required Capabilities*** Creativity Logical reasoning/problem solving Generating novel patterns Coordinating with multiple agents Natural language processing Social and emotional capabilities ***Sample Tasks*** Legal writing Negotiating Teaching Diagnosing diseases **Predicted Substitution Rate: <20%***	***Primary Required Capabilities*** Fine and gross motor skills Sensory perception Social and emotional capabilities Natural language processing Navigation Mobility ***Sample Tasks*** Operating a crane Assisting with surgery Janitorial work Making hotel beds **Predicted Substitution Rate: 26%***

Figure 3.3 Summary of required capabilities, sample tasks and predicted substitution rate (in the USA) for each job task category.

of yet, this scenario seems unlikely to happen (Arntz, Gregory and Zierahn, 2016; Frey and Osborne, 2013; Manyika et al., 2017). Many activities can currently not be substituted by machines, and machines are not capable of performing several types of activities in an integrated way (Manyika et al., 2017; Autor, 2015). Hence, they are generally not capable of substituting labor for entire jobs, which usually include many bundled activities. Rather, to determine the substitution potential of a particular job, it is better to focus on the substitution of the individual activities within that job. A large body of research aligns with this approach and suggests that technology will take over significant parts of every job across all industries and levels of society (Manyika et al., 2017; Arntz, Gregory and Zierahn, 2016; OECD, 2016).

The following section will first analyze the automation potential of individual occupations and broader occupation categories and subsequently the nature of work and the impact of technology on industries.

5.1. The potential of job automation

Estimations of the potential of job automation differ significantly across studies. Frey and Osborne (2013) estimate that as much as 46 percent of all occupations in the United States consist of more than 70% activities that can be automated and are therefore highly automatable. By using the same methodology, but with a task approach rather than an occupation approach, Arntz, Gregory and Zierahn (2016) find that only nine percent of jobs in the US have an automation potential of more than 70%.

While Manyika et al. (2017) does not use 70% as a threshold for high automation potential, one can deduct from their study that around 25% of all jobs are more than 70% automatable in the United States.

Clearly, making an accurate estimation of automation potential is difficult and largely depends on subjective judgment of the capability of technologies and the task structure of occupations. Despite this variance, however, several high-level observations can be made.

Firstly, jobs that can be automated completely are likely to consist entirely of routine manual and routine cognitive tasks that require no human interaction or manual dexterity. Examples of these types of occupations are sewing-machine operators and order clerks.

Secondly, jobs with a high risk of automation also largely consist of routine manual and routine cognitive tasks, but will most likely include some degree of human interaction or unpredictable/high-precision physical activities. Occupation categories that include many highly automatable jobs are, for example, manufacturing and production because of their high degree of manual routine tasks, as well as sales, office and administrative support jobs because of their high dependence on information collecting and processing (World Economic Forum, 2016). Other occupation categories with large elements of routine manual activities are transportation (Frey and Osborne, 2016) and material-moving as well as food and accommodation services. According to Manyika et al. (2017), the latter even has the highest automation potential of all categories.

Lastly, the higher the proportion of non-routine tasks, the lower the automation potential of the job. This effect is enhanced if capabilities such as human interaction (requiring natural language processing and emotional and social capabilities), creativity, logical reasoning/problem solving, high-level dexterity or mobility are required. Jobs that consist entirely, or to a large extent, of these kinds of capabilities are not at all susceptible to automation (Arntz, Gregory and Zierahn, 2016; Manyika et al., 2017).

For example, the job of a choreographer primarily consists of the creative task to develop choreography and of human interaction to deal with stakeholders and train the dancers to bring the choreography to life.

A dentist, on the other hand, requires high-level dexterity and sensory perception as well as emotional and social capabilities to interact with their clients. Hence, both occupations have almost no activities that can be automated.

Still, the majority of occupation categories fall somewhere in between. This includes both routine and non-routine tasks. Therefore, they can be partly automated. For example, cognitive tasks are the core value drivers for investment bankers, yet a large proportion of their job consists of gathering and analyzing information and could thus be automated. The same holds for many legal professions. It is likely that these types of jobs will not disappear, rather, they will harness technology to improve efficiency of humans and the quality of output (Frey and Osborne, 2013).

It is important to note that this is a generalized view. The aforementioned occupation categories also include substantial proportions of jobs with low levels of automation potential, and the substitution potential of a job varies significantly across industries. For example, while supermarket cashiers and specialized software sales agents both fall under the sales occupation category, the substitution potential of the first is high while that of the latter is low because of the required technical expertise and emotional intelligence (World Economic Forum, 2016).

Furthermore, the substitution potential of similar jobs varies across different countries due to alterations in the structure of the jobs, industries and education, and previous investments in technology (Arntz, Gregory and Zierahn, 2016). For example, the automation potential in Sweden might be lower than average because Sweden sits at the forefront of technology investment. Consequently, technology will already have been included in many processes, making it difficult to automate large parts of the remaining activities. In addition, Sweden has a strong focus on high-skilled employees, who typically perform fewer tasks that are automatable. Correspondingly, Arntz, Gregory and Zierahn (2016) estimate that only seven percent of jobs in Sweden are at high risk of being substituted, compared to nine percent for all OECD countries. A discussion of other considerations such as these is provided in the next section.

5.2. The future nature of work

The large-scale substitution of individual tasks will likely change the nature of work and of all jobs (Frey and Osborne, 2013). As machines start to take over routine manual and routine cognitive tasks, human employees will be able to spend more time on complementary tasks where they hold a comparative advantage, such as activities involving creativity and human interaction (Autor, 2015; Finnigan, 2016; Arntz, Gregory and Zierahn, 2016).

Moreover, for many of these tasks, humans will be augmented by machines, and a closer collaboration between technology and humans is expected (International Federation of Robotics, 2017). For example, while a doctor is likely to remain responsible for the final diagnosis of a patient in the next decades, they will be able to base a decision partly on the automated diagnosis advice provided through AI.

As a result, jobs will require more training and a higher understanding of technology. In addition, as the incorporation of technology increases productivity, human employees might spend less of their time on work, resulting in shorter workweeks.

5.3. The effect on the labor market

The automation of activities has caused a well-documented shift in the labor market over the past decades. As part of this shift, scholars observed a polarization of the labor market in both the United States and Europe (Autor and Dorn, 2013; Autor, 2015). This polarization included a sharp decline in the share of middle-skilled jobs accompanied by increases in the share of low-skilled service jobs and high-skilled jobs (Frey and Osborne, 2013; Autor and Dorn, 2013). These middle-skilled jobs could be automated because they consisted primarily of routine manual and routine cognitive tasks, such as collecting and processing data. Tasks that could not be automated included non-routine manual and cognitive tasks. The first are usually found on the low-skill side of the spectrum while the latter are usually found on the high-skill side.

Consequently, the increase in general demand for labor following the productivity growth from automation mostly affected low-skilled jobs, e.g., hairdressers, janitors and high-skilled jobs, e.g., computer scientists, causing an overall polarization effect (Autor, 2015).

However, because of recent and future technological developments, this polarization is expected to taper off. The reason for this is threefold. Firstly, many remaining mid-level jobs require a combination of non-routine tasks and capabilities, including emotional skills, problem-solving, and flexibility, that cannot yet be performed by machines. Secondly, the rise of new technologies has created several new types of middle-skilled jobs, such as healthcare technicians and has stimulated demand for others, such as managers of eating establishments. Lastly, as discussed in this chapter, machines are increasingly able to take over low-skilled service jobs and high-skilled cognitive jobs (Holzer, 2015; Autor, 2015; World Economic Forum, 2016).

There has also been a global debate on the effect of technology on offshoring and reshoring initiatives, especially within the US manufacturing industry. Because the implementation of robotics obviates the need for cheap labor (Robotics Technology Consortium, 2013; International Federation of Robotics, 2017), many argue that it would give rise to a trend of reshoring manufacturing activities to the Western world while the offshoring trend would slow (Van den Bossche et al., 2015). However, more recently, opposing views have arisen, arguing that technology is also enabling the offshoring of many services and simplifying the management of complex global supply chains, leading to an increase in offshoring of manufacturing activities. The latter effects seem to be stronger and the reshoring trend, for example, advocated by the consultancy BCG, seems to have already ended (Boston Consulting Group, 2015). Meanwhile, offshoring is only found to increase (Van den Bossche et al., 2015).

Accurately estimating the overall effect of the previously discussed change drivers on the labor market is nigh on impossible and estimates range from mass unemployment to increases in labor demand. As large parts of jobs can be automated, fewer people will be needed to deliver the same output (Finnigan, 2016).

Consequently, automation could lead to unemployment in the short term (OECD, 2016) before gains in overall productivity raise the demand for labor again. Historically, technological progress has not significantly increased unemployment in the long run, but it remains to be seen whether this time will be the same (Autor, 2015). What is certain is that technology will cause large labor displacements, especially in high-routine occupation categories. Organizations and employees will need to increase their focus on education and training in order to be able to keep up with the increasing pace of change.

5.4. The automation potential of industries

The automation potential of work varies across industries because different industries have different job constellations and similar jobs in different industries might comprise different sets of tasks. In addition, there are also significant differences among countries regarding the job constellation of their industries. For example, an attorney in Sweden might perform very different tasks on a daily basis than an attorney in the United States.

As mentioned before, according to Manyika et al. (2017), the accommodation and food industry has the highest proportion of automatable tasks globally. These findings are supported by a study made in the US on the relation between innovation and employment (Frey and Osborne, 2015). The sector has such a high automation potential because food preparation consists of highly predictable manual tasks. For instance, tasks such as order taking and order serving do not require high levels of emotional intelligence, making them both susceptible to automation. The fast-food chain McDonald's, for example, has automated its ordering and payment processes using digital screens, and many casual-dining operators are implementing tabletop tablet systems in their restaurants.

Other industries with large proportions of automatable tasks identified by both studies are transportation and warehousing, retail trade, wholesale trade and manufacturing. For example, Amazon has already shown that robots can run entire warehouses and the technology for autonomous vehicles is largely ready, creating the opportunity to automate truck transportation.

On the low-end of the automation spectrum are industries such as educational services and the management of companies and enterprises. For many jobs in these sectors, emotional intelligence and complex communications are large and essential parts of daily activities, which substantially decreases automation potential.

The studies also disagree on the automation potential of several industries. For example, for some of the mining, real-estate rental, administrative and support services and construction industries, automation potential is estimated as average by Manyika et al. (2017) and high by Frey and Osborne (2015) while for other industries it is exactly the other way around. For example, the agriculture and information sectors are hardly automatable according to Osborne and Frey while they are averagely automatable according to Manyika et al. (2017).

Manyika et al. (2017) has also performed a study on the Swedish economy. According to the study, three industries have the highest proportions of automatable tasks. These are manufacturing, mining and transportation and warehousing. The industries with the lowest automation potential are educational services, the information sector, and the arts, entertainment and recreational sector.

In terms of the absolute number of employees who could be substituted, the manufacturing sector has by far the largest share. The study estimates that the work of as many as 420,000 people could potentially be automated. Other industries representing large numbers of people are healthcare and social assistance, administrative support and government and retail trade. Overall, Manyika et al. (2017) estimates that 46% of activities could be automated in Sweden, representing a potential redundancy of 2.1 million employees.

6. Other considerations for automation

Though it is technically feasible to substitute human labor with machines in many jobs and job tasks, there are several other factors affecting the pace and extent of automation. Five of these factors are discussed in the following sections: commercial availability, cost of implementation, economic benefits, labor-market dynamics and social, legal and ethical acceptance. We have based these factors on the five factors affecting the pace and extent of automation identified by Manyika et al. (2017). However, we renamed their first factor of technical feasibility as commercial availability in order to remove any confusion with our use of the term technological feasibility in this chapter.

6.1. Commercial availability

Although the previously discussed technologies have been proven in laboratories, the majority of them are yet to be commercialized. Many technologies are still in the early or middle stages of their development; they have not yet reached full maturity and require more scientific research. An example of this is artificial general intelligence (AGI). Despite the vast amount of research in this technology and the demonstration of some applications, much more scientific research is needed and academics estimate it might be 2050 before we can expect widespread adoption of robust AGI platforms (Vorhies, 2016).

Moreover, there is a distinct difference between technological feasibility and commercial adoption. Whereas basic (scientific) research focuses on broad generalizable cases, applied research focusses on developing engineering solutions for specific use cases. Developing viable products out of new technological concepts takes time and effort.

For example, predictive engineering for aircraft engines and predictive health care could be seen as similar scientific problems since both predict the failure of a system. However, both applications would need entirely different software, models and hardware to work and each would take years to be developed (Manyika et al., 2017).

Moreover, the ability to diagnose diseases can already be performed to some extent by computers, but computers diagnosing all types of diseases in the near future is unlikely due to technical difficulty (Bughin et al., 2017).

6.2. Cost of implementation

Besides the availability of commercially ready applications, there must be a solid business case for a company to implement automation and digitalization technologies. Hence, the development and implementation costs of new technologies are an important determinant of their adoption speed and scope. When analyzing these costs, there is a profound difference between the cost size and structure of hardware and software solutions.

6.2.1. Hardware

Hardware includes all physical components involved in a technological solution and often requires sensory perception, fine motor skills, gross motor skills and/or mobility. The capital expenditures for these components are often high and require significant upfront investments. This makes the business case more challenging and raises the need for available capital. Large companies in advanced countries, such as Sweden, are expected to have the fastest adoption rates of these solutions because they face high labor costs and are in the possession of readily available capital. Furthermore, the adoption cycles for industries facing high capital intensity are likely to be longer (Chui, Manyika and Miremadi, 2017).

The primary example of a hardware solution is an industrial robot. The cost of sophisticated robots has been declining over the past decades (Manyika et al., 2013; Frey and Osborne, 2013) and is expected to continue to decline in the future (Sirkin, Zinser and Rose, 2015).

This price drop has been enabled by significant cost decreases of advanced sensors and actuators. In addition, due to increases in production volumes of robots, economies of scale might lead to further cost reductions (Manyika et al., 2013; Grosz et al., 2016).

Despite the price drops, the cost of reliable mechanical devices remains high, and most industrial robots are still relatively expensive, ranging from several tens of thousands to hundreds of thousands of dollars. Moreover, besides the costs of the robot itself, large investments are required for engineering the robot's work cell (Robotics Technology Consortium, 2013). For example, to be able to work safely, an industrial robot often needs advanced safety equipment, and if a robot arm is to work with different tools, a tool-changing system needs to be in place. This kind of equipment is very expensive and can more than double the price of the robot's implementation (Slepov, 2016).

However, with the introduction of simpler general-purpose robots, the automation costs for simple tasks might drop significantly. Besides being cheaper themselves, these robots are more flexible and do not require extensive work cells. Likewise, they are safer for humans to work with, obviating the need for expensive safety equipment. The proliferation of this type of robots could significantly impact the adoption rate of robots. Service robots are, in general, cheaper than their industrial brothers and do not require surrounding equipment (Frey and Osborne, 2013; Manyika et al., 2013).

6.2.2. Software

For software solutions, the capital requirements are much lower, especially for solutions that are cloud-based. These low costs are enabled by increasing performance and decreasing costs of computing power, data storage and cloud computing. Often, the marginal cost of an additional software unit is negligible (Manyika et al., 2013; Autor, 2015).

However, the deployment of software can also incur highly taxing implementation costs, especially if legacy software systems are in place.

These implementation processes comprise activities such as software customization, staff training and new process architecture, and they can be more expensive than the software itself (Forrester Research Inc., 2014). Moreover, the talent required to develop, customize and implement advanced solutions is scarce and therefore extremely expensive.

For example, a study by Paysa, a career-consultancy firm, estimated that, in the United States alone, there were 10,000 open positions for AI talent in 2016, and that companies such as Alphabet and Microsoft are paying millions to acquire talented employees (Ketterer, Himmelreich and Schmid, 2016).

Robotic process automation forms a cheaper and quicker solution than the implementation of expensive new software solutions. This technology can automate workflows and substitute human labor without major investments. However, the overall benefits are limited compared to a complete system redesign (Horton, 2015).

6.3. Economic benefits

Another component in making a solid business case for the adoption of new technologies are the derived economic benefits from implementation. Companies will only be inclined to incorporate new technologies into their organizations if the benefits exceed the costs.

The first and most obvious economic benefit from the implementation of automation technologies is the reduction of labor costs, resulting from the substitution of human labor. As previously discussed, it is unlikely that many jobs will be substituted completely, but it is likely that fewer employees will be necessary to achieve the same output due to increased productivity.

The economic benefits of automation do, however, not only show in forms of saved labor costs but also in the form of new value creation. Examples include benefits such as increased throughput and productivity, improved safety, reduced waste and higher quality, all of which can increase profit in one way or another. These additional benefits can sometimes even exceed the benefits of labor substitution.

For example, implementing autonomous trucks would not only reduce labor costs but would also improve safety, fuel efficiency and productivity as there is no driver that requires stops. In turn, these improvements lead to increased profit. Google DeepMind is another example; the implementation of AI from DeepMind machine learning in Google's data centers has reduced energy consumption by 40%, resulting in increased profit (Grosz et al., 2016; Manyika et al., 2017).

Furthermore, due to the advancements in robotics, robots have become more economically viable options for tasks that were once seen as too expensive or delicate to automate, such as robotic surgery assistance.

As mentioned in the section *Definition of Digitalization*, digitalization is a means to create and capture new value within an organization. For example, it allows companies to open new digital customer channels and to develop new customer insights and products and services, leading to the creation of new value for the customer and the company. Moreover, the automation of routine processes enables employees to spend a larger amount of their time on high-value tasks. For example, within the finance sector, by letting a computer monitor existing processes and learn to recognize different situations (e.g., matching a payment with an order number), finance staff is freed from this activity and can instead focus on more valuable strategic tasks (Wellers, Elliot and Noga, 2017). Consequently, companies and industries that have digitalized to a larger extent, such as media, financial services, and technology, often show higher productivity and wage growth than industries that have digitalized to a lesser extent, such as education, retail and healthcare.

Besides increased profits for companies, society as a whole can gain substantial benefits from the implementation of technologies. Transportation is a prime example. As mentioned before, the automation of truck transportation will lead to higher productivity, higher safety and lower fuel consumption. Higher productivity means that fewer trucks will be necessary, leading to higher fuel reductions and less congested roads. As a result, the public will benefit from lower pollution, fewer traffic jams, fewer accidents and lower spending on road maintenance.

The benefits previously mentioned drive the pace of automation. However, it is important to note that most industries are still in very early stages of the adoption cycle of technologies such as AI, ML and robotics. Because of the small number of existing implementations, it is difficult to estimate what the overall benefits of these technologies will be. Moreover, it often takes years before the indirect economic benefits become visible. This time-lag between investment and benefits is especially large in capital-intensive industries where investments in hardware are required. Consequently, it is difficult for companies and regulators to understand the cost-benefit trade-offs of implementing new technologies (Grosz et al., 2016).

An example is an AI-based system. According to a survey by Bughin et al. (2017), most business leaders do not know what AI can do for them, where to use it, how to integrate it and what the benefits and costs will be.

6.4. Labor market dynamics

Since labor costs form an integral part of the business case for companies, the dynamics of the labor market are an important factor influencing the adoption rate of these technologies. These dynamics include the supply, demand and cost of human labor and are closely related to the demographics of a country and the skill-level of its citizens.

The supply and demand of labor have a large influence on the cost of labor and therefore on the economic benefits derived from the substitution of labor (Frey and Osborne, 2013). A high supply of labor in combination with low demand leads to a decrease in wages. Subsequently, low wages will decrease the economic benefits from labor substitution and thus decrease the incentive for companies to automate. For example, the food industry was identified as one of the industries in the United States with the highest automation potential based on current technologies. However, wages have historically been low in comparison to most other industries due to an oversupply of labor. Consequently, this industry has had little incentive to automate and the current level of automation is low. The opposite holds true when supply of labor is low and demand is high.

The supply of labor is a function of a country's demographics and the skill level of the working population (Manyika et al., 2017). The first influences the number of people on the labor market. In countries with a large working population, there will be an over-supply of labor in many industries and the incentive to automate will be low. On the contrary, for countries with shrinking working populations, such as Sweden and many other Western countries, the incentive to automate is larger (Manyika et al., 2013).

The skill level of the working population determines in which industries there are labor surpluses and deficits. For example, if a significant number of people have followed an education to become an English teacher, the market for English teachers will be saturated and wages will drop. Meanwhile, the market for French teachers could face a deficit of supply, increasing the wages. If activities are substituted by technology, it enables a higher level of human productivity, which would increase the labor supply. These workers can be redeployed if there is demand for activities within their skill range.

However, there often is a mismatch between the skills in demand and the skills that are in oversupply. In such a situation, people are required to reskill themselves through education and training before they can be redeployed. This takes time, money and effort. Consequently, the adoption of labor-substituting technology often leads to short-term unemployment and subsequently a period in which people need to re-educate themselves. However, as the pace of technological change and adoption is increasing, the question is whether the educational and training systems can keep pace. This is particularly difficult for people at the low-end of the skill spectrum.

A labor market polarization emerges when low-skill workers and high-skill workers represent the majority of the working population. In Sweden, technology has changed the labor market over the past 10–20 years as it has in other similar countries. Some argue that the Swedish labor market is undergoing a substitution of labor and that the Swedish regulatory and social security system is not ready for these changes. This will lead to an increased polarization and Sweden will face a difficult time redeploying employees if timely investments in training plans are not made (Breman, 2015).

Lastly, one can never really predict the future of the labor market. One year it can be steady with low unemployment and the next year it can be instable with high unemployment and a large degree of polarization. Unfortunately, the labor market is unlikely to benefit everyone equally when automation technologies are adopted. Some people will be negatively affected by either losing their job or facing wage pressure while others might see wage increases and new job openings. However, government policies, the way organizations choose to work and how individuals seek to learn new skills and jobs can all reduce the disparity in provided benefits across the labor spectrum (Grosz et al., 2016).

6.5. Social, legal and ethical acceptance

In order for the substitution of human labor to truly occur, applications of new technologies must be socially and legally accepted. This factor is one of the most central influencing the pace of automation, perhaps second only to technological feasibility. Social acceptance and legal acceptance are closely connected, and both largely depend on the related concept of ethical acceptance. Therefore, these three concepts will be discussed in combination.

Legal as well as social acceptance of new technologies are processes that take a lengthy amount of time. For example, a patient accepting a robot as a nurse or for a government to implement self-driving buses is not something that will happen overnight. It is therefore inevitable that it will take years for new technology to be completely adopted and adapted into society. Some of the requirements that must be fulfilled are decision makers realizing the potentials and benefits of AI as well as employees and workers adapting to the technologies once they are installed.

One of the major barriers for the automation process is privacy concerns. In order for new technologies and solutions to develop in the best interest of society, a large amount of data is needed. However, due to privacy concerns and regulations, data is difficult to access or anonymize. In addition, people are afraid of giving out their personal information because they do not know who will have access to it, who will use it and for what purpose (Bughin et al., 2017). It also becomes an ethical question when, for example, an employer has access to one's medical records. If someone is ill for some reason, or because they are overweight, an employer may not be interested in hiring this person.

The ethical issue also comes into consideration when technologies are, for example, used for predictive policies. It is a technical challenge to not feed the systems with biased information – e.g., racial, sexist or religious discrimination – to avoid innocent people being unjustifiably monitored and discriminated, when the real world is in fact biased (Grosz et al., 2016). However, when predictive hiring processes are performed with caution, and through careful design, testing and deployment, there is a chance that AI algorithms will make less-biased decisions than humans.

As mentioned, the extent and pace of automation rely on the social acceptance and trust for technology and AI. For example, many of the activities a nurse performs can theoretically be automated, but both coworkers and patients will likely have a difficult time to accept it initially. Arguably a majority of patients expect to be greeted by humans and have human contact when they have their meal delivered to them. In order for the activity to actually be substituted, patients and co-workers have to accept and trust the machines. This can only be accomplished if hospitals exhaustively integrate the automation technologies and make sure that the interaction between intelligent computers and humans feels natural (Manyika et al., 2017; Grosz et al., 2016).

This trust and acceptance is also important for security systems to be able to use the innovative technologies. Today, cities in North America have already deployed AI technologies in border administration and law enforcement and will heavily rely on these techniques in the future. For example, autonomous cars, drones and cameras will be used for surveillance as well as algorithms to detect financial fraud and create predictive policies. However, this is only possible if there is broad social acceptance. Furthermore, regulatory acceptance is also necessary for full-scale adoption. For example, while autonomous vehicles are fully usable they will first be adopted when regulators accept them (Manyika et al., 2017).

Furthermore, questions are raised about accountability when implementing the technologies. Issues such as who is responsible for the actions and conclusions made by robots and AI have never been dealt with before, making them difficult to tackle (Bughin et al., 2017). For example, who is responsible for a traffic accident where an autonomous vehicle is involved and maybe caused it? Is it the owner of the car, the automaker, the city, one of the many software or hardware providers or one of the many programmers who wrote some of the lines of software code?

Once the technologies are adopted, there may be consequences. For example, there is no way to know if AI would optimize the labor market without regard for nuanced social preferences or sell treasured documents about people's skills to private companies or political parties. However, it is unlikely that AI would autonomously *choose* to inflict harm on people, but there nonetheless remains a real risk that it can be *used* by people for a harmful purpose.

To summarize, the social, legal and ethical acceptance are important factors that impact the adoption of automation technologies. It is understandable that social acceptance of new technologies is difficult due to the fear that a lot of people will lose their jobs. However, as discussed earlier in this chapter, it is activities within jobs that will be substituted rather than entire jobs. Regulators must clearly state this fact and that only certain people will have access to personal information, in order for the social acceptance to increase.

7. Conclusion

This chapter aimed at investigating the substitution potential of labor by a selection of technologies. We first discussed the technological feasibility of artificial intelligence, machine learning and robotics to substitute for labor. We found that technology can perform an increasingly wider variety of job activities and that automation is no longer confined to routine tasks. Nevertheless, the automation potential for non-routine tasks remains limited, especially for tasks involving autonomous mobility, creativity, problem-solving and complex communication.

For jobs themselves, we concluded that the majority of jobs will be affected by the automation of individual activities, but that only a few have the potential to be completely substituted. The jobs most at risk are those that consist largely of routine tasks and do not rely on mobility or human interaction. Though few jobs can be substituted completely, automation could still lead to short-term unemployment, often leading to re-training and further education. In addition, we concluded that the nature of jobs will change as mundane tasks will be substituted and people will work more closely together with machines. The industries that have a large potential for activity substitution are food and accommodation services, transportation and warehousing, retail trade, wholesale trade and manufacturing.

In the last section of the chapter, we discussed five major factors that come into play before automation potential turns into actual automation: commercial availability, cost of implementation, economic benefits, labor market dynamics and social and legal acceptance. All five of these factors have a significant influence on the speed and scope of technology adoption. In particular, a lack of applied research, low wages, high costs and legal and ethical boundaries hamper the adoption of technology.

Overall, technology is advancing rapidly and the pace of change is increasing. Consequently, an increasing number of activities will have the potential to be performed by machines rather than by humans. Though the extent and speed of adoption are reduced by several factors, it is inevitable that technology will have a stronger presence in the workplace. It is unlikely that this will cause long-term unemployment, but in the short-term reskilling will be required to enable the reemployment of displaced labor. To cope with the pace of automation, an increased focus on education and training will be required – for individuals, organizations, regions and countries.

Notes

1 This chapter is a reprint of an identical report that was originally released under the same title by the same authors as "Report #5" for The Internet Foundation in Sweden (IIS), as part of the "Innovative Internet" project. The report was originally published by Stockholm School of Economics: Center for Strategy and Competitiveness, Stockholm: Sweden, in 2018 (ISBN: 978–91–86797–32–4). Permission for reprint has been granted by the copyright holder.

2 The Turing test is a computer intelligence test, requiring that a human being should be unable to distinguish the machine from another human being by using the replies to questions posed to both.

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