Business Horizons (2019) 62, 15—25

Available online at www.sciencedirect.com

ScienceDirect

KELLEY SCHOOL OF BUSINESS
INDIANA UNIVERSITY

www.elsevier.com/locate/bushor

EXECUTIVE DIGEST

Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence

Andreas Kaplan [a,*], Michael Haenlein [b]

[a] ESCP Europe, Heubnerweg 8-10, D-14059 Berlin, Germany
[b] ESCP Europe, 79 Avenue de la République, F-75011 Paris, France

KEYWORDS
Artificial intelligence;
Big data;
Internet of Things;
Expert systems;
Machine learning;
Deep learning

Abstract Artificial intelligence (AI)—defined as a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation—is a topic in nearly every boardroom and at many dinner tables. Yet, despite this prominence, AI is still a surprisingly fuzzy concept and a lot of questions surrounding it are still open. In this article, we analyze how AI is different from related concepts, such as the Internet of Things and big data, and suggest that AI is not one monolithic term but instead needs to be seen in a more nuanced way. This can either be achieved by looking at AI through the lens of evolutionary stages (artificial narrow intelligence, artificial general intelligence, and artificial super intelligence) or by focusing on different types of AI systems (analytical AI, human-inspired AI, and humanized AI). Based on this classification, we show the potential and risk of AI using a series of case studies regarding universities, corporations, and governments. Finally, we present a framework that helps organizations think about the internal and external implications of AI, which we label the Three C Model of Confidence, Change, and Control.

1. Once upon a time, there was a magic mirror . . .

Once upon a time, in a land far, far away, there lived an evil queen who had a magic mirror. This magic mirror knew everything. It knew the faces of all the

* Corresponding author

https://doi.org/10.1016/j.bushor.2018.08.004
0007-6813/

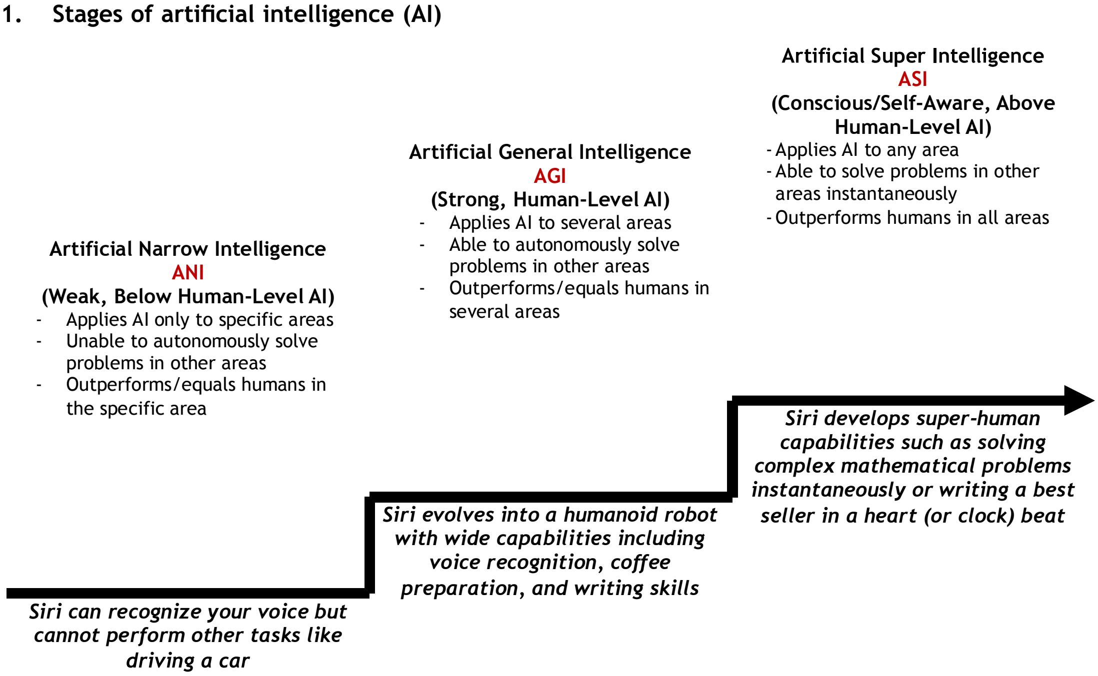
people living in her kingdom and could easily tell her every morning that she was the fairest in the land. Knowing how important beauty was for the evil queen, the magic mirror also tweaked her own image slightly to make her look a little bit more beautiful than she actually was in real life. And even when Snow White became more beautiful than her by having "skin as white as snow, lips as red as blood, and hair as black as ebony" (Grimm, Grimm, & Kliros, 1994), the magic mirror was still of help. It told the evil queen where to find Snow White, with whom she lived, and that she fancied red apples. The queen could use this knowledge to her advantage to influence (well, poison) Snow White—although, as we all know, the story did not exactly end as she had envisioned it.

Who would not want to have such a magic mirror? A mirror that shows not your real image but a slightly improved version of it—similar to the T8 mobile phone developed by the Chinese technology firm Meitu, that uses Magical AI Beautification to make you look better in selfies. A tool that tracks information from all around the kingdom in real time to tell you every morning what is happening—similar to the New York startup Dataminr, which monitors the internet and social media applications to help companies take better PR and stock market decisions. A crystal ball that looks deeply into peoples' souls to tell you which type of fruit (or message) they are best influenced by—similar to the British consulting firm Cambridge Analytica, which used information from Facebook to assess the personality of users and tailor political messages accordingly.

Today, we all have—at least in principle—access to such devices that are marketed under the broad umbrella of artificial intelligence (AI). AI, or more generally the idea that computers can think like humans, has been discussed in literature for more than half a century—since the seminal work of computer scientist Alan Turing. Today, first generation AI applications—those that apply AI only to specific tasks and are generally referred to under the label artificial narrow intelligence (ANI)—are near ubiquitous. They enabled Facebook to recognize faces in images and tag users, they allowed Siri to understand your voice and act accordingly, and they enabled Tesla to develop self-driving cars. In the future, we may see the second generation of AI, artificial general intelligence (AGI), able to reason, plan, and solve problems autonomously for tasks they were never even designed for. And we might possibly see the third generation, artificial super intelligence (ASI), which are truly self-aware and conscious systems that, in a certain way, will make humans redundant. Such systems could apply AI to any area and be capable of scientific creativity, social skills, and general wisdom, which is why some call ASI true artificial intelligence. Figure 1 outlines the three stages of AI.

In this article, we look more deeply into the concept of artificial intelligence. We start by providing a definition of the term and giving a classification of the different types of AI, specifically

Figure 1. Stages of artificial intelligence (AI)



regarding business use. We then discuss how universities, corporations, and governments are already using AI today, how they can use it in the future, and the specific challenges they have to face in the process. Finally, we provide a structured way to think about the organizational implications of AI both internally and externally, which we label as the Three C Model (Confidence, Change, Control). Our discussion finishes with a brief glimpse into an AI-enabled future and the question of if and where humans will have a place in such a world.

2. Interpretations of AI: As white as snow, as red as blood, as black as ebony

Although articles about AI are abundant in popular and business press in recent years, it is surprisingly difficult to define what AI is and what it is not. Or, to put it differently, there are about as many different definitions of AI as there are ways to describe Snow White's beauty, depending on whether one focuses on her white skin, red lips, or black hair. To some extent, this is related to the problem of defining intelligence itself, which is not an easy task. Moreover, the field of AI is moving so fast that what used to be considered as intelligent behavior exhibited by machines 5 years ago is now considered barely noteworthy. We therefore start our analysis by providing a definition of what we mean by AI in this article, followed by a classification of three main types of AI based on this definition.

2.1. Definition

A common way to define artificial intelligence is to do so by referencing human intelligence, which can be seen as the "biopsychological potential to process information . . . to solve problems or create products that are of value in a culture" (Gardner, 1999, pp. 33—34). In 1955, the Dartmouth Research Project defined AI as the problem of "making a machine behave in ways that would be called intelligent if a human were so behaving" (McCarthy, Minsky, Rochester, & Shannon, 1955). In a similar manner, cognitive scientist Marvin Minsky considered AI as "the science of making machines do things that would require intelligence if done by men" (Minsky, 1968, p. v). For the purpose of this article, we follow this general line of thinking but aim to be more specific regarding the way in which AI achieves this goal. Specifically, we define AI as a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation.

Looking at this definition, it is obvious how AI differs from related concepts such as the Internet of Things (IoT) and big data. The IoT (Krotov, 2017; Saarikko, Westergren, & Blomquist, 2017), which describes the idea that devices around us are equipped with sensors and software to collect and exchange data, can be seen as one specific way of obtaining the external data required as an input for AI. The IoT is one input toward big data (Lee, 2017), which describes data sets characterized by huge amounts (volume) of frequently updated data (velocity) in various formats, such as numeric, textual, or images/videos (variety). Big data is, however, broader than the IoT since it also includes data collected through other means, such as (mobile) social media applications (Kaplan, 2012; Kaplan & Haenlein, 2010) or a firm's internal database.

AI uses external information obtained through IoT or other big data sources as an input for identifying underlying rules and patterns by relying on approaches from machine learning, which, broadly speaking, describes methods that help computers learn without being explicitly programmed. These methods can be relatively simple (think of the regression analysis you learned during your MBA) or eye-wateringly complex (such as deep neural networks, which form the basis of deep learning tools like Google's DeepMind). Machine learning is an essential part of AI, but AI is broader than machine learning since it also covers a system's ability to perceive data (e.g., natural language processing or voice/image recognition) or to control, move, and manipulate objects based on learned information be it a robot or another connected device.

2.2. Classification

To classify different types of AI, specifically regarding their business use, we borrow from the management literature and specifically studies investigating the skills shared by successful managers and employees with above-average performance (e.g., Boyatzis, 2008; Hopkins & Bilimoria, 2008; Luthans, Welsh, & Taylor, 1988; McClelland & Boyatzis 1982; Stubbs Koman & Wolff, 2008). This literature generally claimed that outstanding performance is strongly related to the presence of three skills or types of competencies: cognitive intelligence (e.g., competencies related to pattern recognition and systematic thinking), emotional intelligence (e.g., adaptability, self-confidence, emotional self-awareness, achieve-

Figure 2. Types of AI systems

	Expert Systems	Analytical AI	Human-Inspired AI	Humanized AI	Human Beings
Cognitive Intelligence	×	✓	✓	✓	✓
Emotional Intelligence	×	×	✓	✓	✓
Social Intelligence	×	×	×	✓	✓
Artistic Creativity	×	×	×	×	✓
		Supervised Learning, Unsupervised Learning, Reinforcement Learning			

ment orientation), and social intelligence (e.g., empathy, teamwork, inspirational leadership). Figure 2 outlines the types of AI systems.

While the use of cognitive intelligence to classify AI seems straightforward, the applicability of emotional and social intelligence requires some explanation. The mainstream view in psychology is that intelligence is generally innate (i.e., a characteristic that individuals are born with rather than something that can be learned). Still, emotional and social intelligence are related to specific emotional and social skills and it is these skills that individuals can learn and that AI systems can mimic. While machines and AI systems can obviously not experience emotions themselves, they can be trained to recognize them (e.g., through the analysis of facial micro-expressions) and then adapt their reactions accordingly.

Before discussing AI systems, it is important to highlight that *expert systems*—collections of rules programmed by humans in form of if-then statements—are not part of AI since they lack the ability to learn autonomously from external data. In fact, expert systems represent a different approach altogether since they assume that human intelligence can be formalized through rules and hence reconstructed in a top-down approach (also called symbolic or knowledge-based approach). If an expert system were programmed to recognize a human face, then it would check for a list of criteria (e.g., the presence of certain shapes, of a nose, of two eyes) before making a judgment based on embedded rules. Such systems tend to perform poorly during tasks that depend on complex forms of human intelligence, which are implicit and cannot be transferred easily to simple rules. That is not to say that expert systems are not useful. IBM's famous Deep Blue chess-playing algorithm, which beat Garry Kasparov in the late 1990s, was not AI but an expert system. Expert systems like Deep Blue have been key drivers in making AI (or what is sometimes believed to be AI) more prominent among the general public.

Real AI as defined above uses a bottom-up approach (also called connectionist or behavior-based approach) by imitating the brain's structure (e.g., through neural networks) and using vast amounts of data to derive knowledge autonomously. This is similar to how a child would learn to recognize a face—not by applying rules formalized by his/her parents but by seeing hundreds of thousands of faces and, at some point, being able to recognize what is a face and what is a broom. This allows dealing with tasks vastly more complex than what could be handled through expert systems. For example, while chess can be formalized through rules, the Chinese board game Go cannot. Therefore it was never possible to build an expert system able to beat a human Go player. Yet a deep neural network can be trained to play Go simply by observing a very large number of games played by humans.

Based on these three types of competencies, we classify AI systems into three groups (see Figure 2):

1. *Analytical AI* has only characteristics consistent with cognitive intelligence. These AI systems generate a cognitive representation of the world and use learning based on past experience to inform future decisions. Most AI systems used by firms today fall into this group and examples include systems used for fraud detection in financial services, image recognition, or self-driving cars.

2. *Human-Inspired AI* has elements from cognitive as well as emotional intelligence. These systems can, in addition to cognitive elements, understand human emotions and consider them in their decision making. Affectiva, an AI company founded by MIT, uses advanced vision systems to recognize emotions like joy, surprise, and anger at the same level (and frequently better) as humans. Companies can use such systems to recognize emotions during customer interactions or while recruiting new employees. We talk about more examples in the following section.

3. *Humanized AI* shows characteristics of all types of competencies (i.e., cognitive, emotional, and social intelligence). Such systems, which would be able to be self-conscious and self-aware in

their interactions with others, are not available yet. While progress has been made in recognizing and mimicking human activities, building AI systems that actually experience the world in a fundamental way are a project for the (potentially distant) future.

As highlighted in our definition of AI stated above, a defining element of all those systems is the ability to learn from past data. For this, there are three broad types of learning processes: supervised learning, unsupervised learning, and reinforcement learning.

1. *Supervised learning* methods map a given set of inputs to a given set of (labeled) outputs. They are usually the least scary for managers since supervised learning include methods many may be familiar with (at least in principle) from Statistics 101, such as linear regression or classification trees. That being said, more complex methods like neural networks also fall into this group. An example of supervised learning is to use a large database of labeled images to separate between those images showing a Chihuahua and those showing a muffin.

2. In *unsupervised learning,* the inputs are labeled but not the outputs. This means that the algorithm needs to infer the underlying structure from the data itself. Cluster analysis, which aims at grouping elements in similar categories but where neither the structure of those clusters nor their number is known in advance, falls into this group. Since the output is derived by the algorithm itself, it is not possible to assess the accuracy or correctness of the resulting output. Users therefore need to place greater trust and confidence into the AI system and that can make managers uncomfortable. Speech recognition—made familiar with Apple's Siri or Amazon's Alexa—can be conducted using unsupervised learning.

3. In *reinforcement learning,* the system receives an output variable to be maximized and a series of decisions that can be taken to impact the output. Think, for example, of an AI system that aims to learn playing Pac-Man, simply by knowing that Pac-Man can move up, down, left and right and that the objective is to maximize the score obtained in the game. Software giant Microsoft uses reinforcement learning to select headlines on MSN.com by rewarding the system with a higher score when more visitors click on a given link.

Looking at AI this way raises the question of whether there are any skills that remain characteristic for humans and out of reach of AI. This question is difficult to answer given the tremendous progress AI has experienced over the past decade. Still, it seems likely that humans will always have the upper hand where artistic creativity is concerned. Fundamentally, AI is based on pattern recognition or curve fitting (i.e., finding a relationship that explains an existing set of data points), while "creativity is intelligence having fun" as Albert Einstein put it. At this stage, it seems unlikely that AI systems will be able to solve truly creative tasks. That being said, the entertainment company Botnik Studios recently used AI to write a three-page chapter with the title "Harry Potter and the Portrait of What Looked Like a Large Pile of Ash" after training their AI system on all seven of the popular fantasy novels. So the borders are certainly quite fluid in that respect.

3. Illustrations of AI: Appl(e)ications in universities, corporations, and governments

Building on our classification of AI into analytical AI, human-inspired AI, and humanized AI, we look to three industries: universities, corporations, and governments. Specifically, we dive into how AI is already shaping them and what future trends can be expected in years to come (see Table 1). Like in the case of Snow White, we will see the world is rarely as simple as we would like it to be. For every sweet side of the red apple that provides wonderful opportunities, there is also a poisoned side that represents very real risks.

3.1. Universities

Many of the most significant advances in artificial intelligence have their origin in a university context and given the technical nature of AI, this tendency is most likely to go on in the future. The term AI itself was coined at a workshop at Dartmouth College in 1956, organized by the computer scientist John McCarthy who later became a professor at Stanford. DeepMind, a British AI company acquired by Google in 2014, was created by three scientists, two of which met while working at University College London. In 2015, DeepMind developed AlphaGo—the first computer Go program to defeat a human professional Go player. It is therefore natural to start our analysis of the practical applications of AI in an academic context to answer the question of whether universities may have sown the seeds of their own destruction by their research on AI,

Table 1. Illustrations of AI applications within specific sectors

	Analytical AI	Human-Inspired AI	Humanized AI
Universities	Virtual teaching assistants able to answer student questions and tailor reactions to individual data	AI-based career services able to identify emotions to improve interview techniques of students	Robo-teachers animating a student group by acting as moderator and sparring partners
Corporations	Robo-advisors leveraging automation and AI algorithms to manage client portfolios	Stores identifying unhappy shoppers via facial recognition at checkouts to trigger remedial actions	Virtual agents dealing with customer complaints and addressing concerns of unhappy customers
Governments	Automation systems to set the brightness of streetlights based on traffic and pedestrian movements	Virtual army recruiters interviewing and selecting candidates based on emotional cues	AI systems able to psychologically train soldiers before entering a war zone

similar to the spirits cited by Goethe's "The Sorcerer's Apprentice" or the poisoned side of the red apple of the evil queen.

Analytical AI applications are already starting to transform the profession of faculty members. Georgia Tech uses an AI-based virtual teaching assistant called Jill Watson to answer student questions. The performance of the system is so remarkable that many students only realized that Jill Watson is not human after they were told. Other universities, like the Technical University of Berlin and Carnegie Mellon, similarly tested the use of chatbots to streamline teaching and learning. But the AI revolution does not stop at teaching alone. The British RELX Group, owner of Elsevier and LexisNexis, uses AI for automating systematic academic literature reviews or for supporting the review process through checks for plagiarism or misuse of statistics. In a research context, AI is particularly useful for projects that aim to combine ideas across scientific boundaries and that, by consequence, require knowledge of many different literature streams that may be difficult to process by humans.

Human-inspired AI brings all of this to the next level. In an online learning context (Kaplan & Haenlein, 2016), universities could use AI to test whether students pay attention during a virtual class by analyzing facial impressions collected through a webcam. In a traditional setting, systems like RENEE (named for retain, engage, notify, and enablement engine), developed by U.S.-based Campus Management Corporation, can automatically launch interventions based on student profiles, best practices, and other inputs. RENEE might in the future be able to read student emotions like sadness or fear, allowing faculty and staff to identify the most effective coaching strategies or to spot cheating in exams. All these systems will help faculty outsource tedious tasks such as grading and responding to repetitive student questions. This leaves professors, in principle, more time for their core competence of coaching, moderating, and facilitating discussions (Kaplan, 2018). Until, of course, the next generation of humanized AI applications will take care of those tasks as well.

Whether this will ever be the case depends on this fundamental question: Will students prefer to be educated by smart machines or by human professors? The fact that AI systems are cheaper than highly paid faculty members, at least in the long run, makes them preferable from the perspective of university deans who struggle for funding. But are they really the better choice if education becomes less personal? Universities need to make a conscious decision in this context and prepare themselves for the rise of AI. This will also allow them to better prepare their students for a workplace in which AI will become increasingly prominent. In this context, some researchers suggest that universities should introduce a course on artificial intelligence and humanity to answer questions of equity, ethics, privacy, and data ownership, which are of relevance in this context (Keating & Nourbakhsh, 2018, p. 32).

3.2. Corporations

Looking at corporations, AI has already started to impact every single element of a firm's value chain and, in the process, transform industries in a fundamental manner, especially service industries (Huang & Rust, 2018). Analytical AI applications are used in human resource management to help with the screening of CVs and selection of candidates in the form of advanced application tracking systems (ATS). In marketing and sales, AI is used to allow for better targeting and personalized communication. AI systems can identify thousands of psychotypes

(Kosinski, Stillwell, & Graepel, 2013) and create messages that resonate well with their preferences, leading to tens of thousands of variations of the same message used every day. In customer service, AI can be applied in the form of chatbots that can generate automatic responses to inquires sent through social media channels or emails. Modern versions like Google Duplex are even able to conduct phone calls that are difficult to distinguish from conversations with a human counterpart.

Looking at industry effects, the financial services sector has seen the rise of financial technology (fintech) startups which have revolutionized asset management through the creation of robo-advisors and the analysis of financial transaction data (e.g., by spotting early signs of dementia reflected in erratic account movements). In retailing, AI is used for inventory management with the holy grail being Amazon's anticipatory shipping patent that deals with sending items to customers before they even ordered them. In the entertainment sector, AI has been used by newspapers like *The Los Angeles Times* to automatically write articles. In the near future, AI will go beyond written text and create artificial videos in which the moving picture of a person can be overlaid to any text the author desires (Suwajanakorn, Seitz, & Kemelmacher-Shlizerman, 2017). This will give the idea of fake news an entirely new dimension.

Human-inspired AI allows companies like Walmart to identify unhappy and frustrated customers by applying facial recognition techniques to people queuing up at checkouts, thus enabling intervention by either opening new cashiers or proposing snacks and drinks to customers. The same tools can be used to automatically detect fraud and theft orders of magnitude more efficiently than a traditional store detective could. Online firms like Netflix, Spotify, and Pandora already use AI to provide personalized recommendations for music and movies. In the future, an analysis of your past choices combined with facial recognition through your phone's camera (think iPhone X) allows those firms to also detect your current mood and propose matching entertainment content. Alternatively, standalone applications like Replika, your AI friend developed by the San Francisco-based Luka Inc., allows you to build a diary and, in a way, acts like an AI-enabled therapist. This will likely be a major threat to online therapy providers like BetterHelp or Talkspace.

The combination of human-inspired AI and robotics is also where we can get a first glimpse into the world of humanized AI. In 1964, Joseph Weizenbaum from MIT created the first natural language processing computer program called ELIZA. The idea was to generate a program that can pass the Turing test: If a person cannot distinguish whether he/she is talking to a human or a machine, the machine exhibits intelligent behavior (Turing, 1950). Today ELIZA has evolved into Sophia, an AI-inspired robot developed by David Hanson that is so convincing Saudi Arabia granted it citizenship in 2017. Such tools are more than a PR stunt—Sophia is a highly demanded speaker and generated press coverage reaching 10 billion readers in 2017. These robots can serve as buddies for senior citizens who live alone and, broadly speaking, revolutionize the field of elderly care.

3.3. Governments

Sophia's citizenship status naturally leads to the question of how AI should and could impact governments, both directly and indirectly. Like universities and corporations, governments can use AI to make tasks more efficient and it is in this context where the concept of the good vs. bad side of the red apple becomes most obvious. The City of Jacksonville uses analytical AI to manage intelligent streetlights which decide on the brightness of each lamp depending on traffic and pedestrian movements collected by street cams. Another example is the Southern Nevada Health District, which uses AI combined with information from Twitter to decide which restaurants to visit for health inspections. A combination of natural language processing and geotagging helps to spot places where customers report food poisoning and identify those establishments for inspection. In an experiment conducted in Las Vegas, this approach resulted in more demerits and citations, which ultimately could lead to 9,000 fewer cases of food poisoning and over 500 fewer hospitalizations per year.

In the same vein, human-inspired AI is apparently used by the U.S. Army in the recruitment of future soldiers through an advanced SGT Star AI system that is rumored to be able to recognize emotions. SGT Star is an interactive virtual agent that applies AI to respond to questions, review qualifications, and assign selected candidates to actual human recruiters. SGT Star does the workload of more than 50 recruiters with a 94% accuracy rate and boosted engagement time for applicants from 4 minutes to over 10 minutes. Of course, another way to leverage the power of AI in a military context is to rely on AI-enabled robotic soldiers. This is, unfortunately, not a science fiction idea but becoming a reality. In 2013, over 100 researchers, security experts, and company leaders wrote an open letter to the UN asking to ban AI-enabled robots in war. Automatic systems, including drones, missiles, and machine guns, can lead to a level of escalation that older readers may remember from the 1983 movie *War Games*.

A natural question arises when combining AI and governments: Where does improvement end and an Orwellian surveillance state begin? China has proposed a social credit system that combines mass surveillance, big data analytics, and AI to reward the trustworthy and punish the disobedient. In the proposed initiative, punishment for undesirable behavior can include flight bans and restriction related to private schools access, real estate purchases, or even taking a holiday. In Shenzhen, authorities already use facial recognition systems to crackdown on crimes like jaywalking; in Xiamen, users receive mobile phone messages when they are calling citizens with low social credit scores (Xu & Xiao, 2018).

The examples bring up the question of regulation and the need for government intervention in the domain of AI, especially when reaching humanized AI. While some voices argue for immediate and proactive regulation on a national and international level given the quick progress of AI—though it may otherwise be too late—others are concerned that regulation could slow down AI development and limit innovation. The middle ground is to develop common norms instead of trying to regulate technology itself, similar to the consumer and safety testing done for physical products. Such norms could include requirements for the testing and transparency of algorithms, possibly in combination with some form of warranty. This would also allow for regulations to remain stable and eliminate the need for constant updates in response to technological advances. This proposal is complicated by the idea of what AI is and what it can do. AI is itself a moving target and more an issue of interpretation than definition. Should AI be vaguely defined for legal purposes with the risk that everything could count as AI, or defined narrowly, focusing only on certain aspects? Or perhaps no definition is better in the hope that we know it when we see it, following the approach of Supreme Court Justice Potter Stewart when describing his threshold test for obscenity (Jacobellis v. Ohio, 1964).

4. Implications of AI: Are you afraid of poison?

The above examples illustrate that AI will have implications for any kind of organization, both internally and externally. Internally, AI will allow a multitude of tasks to be conducted faster, better, and at lower cost. In the medium term, this will not only affect simple tasks but also more complex ones; even knowledge-heavy industries like consulting, financial services, and law will see major changes. Externally, it will impact the relationship between firms and their customers, other firms, and with society at large.

To help organizations prepare for this future, we look more closely at three common traits that are of relevance both internally and externally: confidence, change, and control—the three Cs of the organizational implications of AI (see Table 2). Like when Snow White decided to trust the evil queen by biting into the red apple, managers will have to be trusted in their ability to manage and consumers will have to put confidence in the company to not misuse their data in any way. In the fairytale, Snow White would admittedly have done better not to put confidence in the queen. In real life, there will have to be certain control mechanisms to protect from damage, internally by controlling the machines and externally through the State controlling the corporations and institutions implementing AI. Finally, change will be ever present, be it change in employees' job descriptions or the rapid change of copying external competitors.

Table 2. The three Cs of organizational implications of AI

	Internal	External
Confidence	Managers need to exude confidence with respect to their employees in a fast-evolving work environment	Consumers need to put confidence in the abilities and recommendations of an organization's AI systems
Change	Employees need to constantly change and adapt their functions and skills through lifelong learning	Competitors need to be monitored and outperformed permanently by use of better hardware or data
Control	Machines need to be controlled to avoid autonomous decisions and implicit biases	States need to control the ecosystem of managers, employees, machines, consumers, and competitors

4.1. Internal

4.1.1. Managers

Managers need to adopt a leadership style that engenders confidence from employees at a time when AI will fundamentally transform the workplace in unprecedented ways. Several leadership skills will be essential, including enabling an open dialogue; proficiency in healthy conflict resolution; and human, ethical, open, and transparent management. Actions taken by such managers start with the smallest of changes. Instead of AI, IBM decided to use the terms cognitive computing and augmented intelligence to signal that systems are designed to make employees more efficient, not to replace them. But they do have a much further reach. Managers in the future need to be experts in assessing skills to identify the best position of each employee in a hybrid system of people and AI. And they need to become creative innovators in order to emphasize the types of intelligence AI will not be able to replace. Managers will need to act as empathetic mentors and data-driven decision makers.

4.1.2. Employees

AI will lead to a constant change in the type of work conducted by employees. While it is unlikely that AI will be able to replace entire jobs completely, there will be more and more tasks that will be outsourced to AI and employees will have to adapt. Combining the rapid speed of AI development with the increasing lifespan of humans (and employees) gives the concepts of lifelong learning and career flexibility a whole new meaning (Pucciarelli & Kaplan, 2016). In such a world, employees will have to constantly develop new skills to complement advances in AI technology. Entrepreneurs, innovators, creators, and generally people who are keen on taking on new challenges and opportunities will be of increasing importance. The necessary training can be financed by firms themselves (e.g., telecom giant AT&T spends $30 million annually to reimburse employees for the cost of training in digital skills) or provided by outside entities such as trade unions, especially for smaller firms where in-house training may not be efficient.

4.1.3. Machines

Machines and AI systems, first and foremost, require control by humans. Even the smartest AI systems can make very stupid mistakes. Look at the systems powering self-driving cars. Tesla's autopilot confused a white truck with a cloud in the sky and Uber's self-driving car did not recognize a pedestrian in Arizona. And these mistakes do not account for the fact that AI systems can be deliberately hacked, similar to the way a computer virus or random ware can take ownership of a PC. Even when leaving all those concerns aside, AI systems are only as smart as the data used to train them since they are, in their essence, nothing more than fancy curve-fitting machines. Using AI to support a court ruling can be highly problematic if past rulings show bias toward certain groups since those biases get formalized and engrained, which makes them even more difficult to spot and fight against.

4.2. External

4.2.1. Consumers

Any AI system implemented by firms is only useful if consumers accept it in one way or another. This specifically means that consumers need to put confidence into the recommendations provided by AI and the use of their personal data. While AI systems are already capable of diagnosing X-ray images as proficiently as, or even better than, most physicians, most consumers would have a difficult time trusting the verdict of a machine. A new stream of AI research called explainable AI focuses on extracting rules ex-post so that humans can at least get a rudimentary understanding of the working of AI systems. A necessary precondition to this confidence, besides better explanation, is that firms do not overpromise on the potential of AI. It is well known from service research that consumers judge the quality of a service based on the gap between their expectations and reality (Parasuraman, Zeithaml, & Berry, 1985). All of us who have tried to speak casually with their Amazon Alexa, Google Home, or Apple Siri will know that the frictionless expectations created by the advertising for those products rarely match reality.

4.2.2. Competitors

In the world of AI, firms will continually be challenged to establish a long-lasting competitive advantage. Since the basic mathematical concepts underlying AI are widely known—and often available to everyone—there are only two ways firms can outperform their competition: through faster hardware or more data. In terms of hardware, chip designers are already working on developing new types of CPUs that embed basic AI tools such as neural nets on the hardware (chip) level instead of programming them into a general purpose system. Looking at data, there will likely be a consolidation toward few large firms that acquire more and more data, which leads to better AI systems and even more data in a self-fueling spiral of growth. In such a world, firms need to constantly change to adapt to evolutions in performance among existing competitors as well as the emergence of new firms.

4.2.3. States

Similar to the idea that AI systems need to be controlled to avoid making stupid mistakes, the whole ecosystem of managers, employees, machines, consumers, and competitors requires close monitoring from the side of the State, as already mentioned. There is a need for rules, legislation, and control to avoid AI getting out of hand. This can include the requirement to spend a certain percentage of revenue in training to prepare employees for upcoming challenges. It also may consist of artificially constraining the competition between machines and humans. In France, a law exists that limits access to the IT self-service systems of public administration bodies after working hours.

A central issue in this context is the topic of privacy and data protection. In the near future, we will face a wide range of dilemmas that require balancing social advances in the name of AI and fundamental privacy rights. The European Union recently made a significant step in legislating this question by introducing the General Data Protection Regulation (GDPR). While such rules clearly protect consumers, they also mean that the EU will unlikely be able to challenge the U.S. or China in AI dominance anytime soon. This puts States in the complex position to decide how much privacy can and should be sacrificed on the altar of economic growth. Different countries are already making different decisions in this respect and those decisions will likely shape AI trends in years and even decades to come.

5. And they lived happily ever after

Years ago, Holloway and Hand (1988, p. 70) published an article in *Business Horizons* on artificial intelligence that started as follows: "Artificial intelligence is no longer an academic term, but a reality. And, in some companies, it seems that the AI system has replaced the human as the business and ethical decision maker." Today, we know that this statement was probably a bit premature. But the revolution Holloway and Hand predicted did happen eventually and it comes with a series of questions that will need to be answered.

One question deals with the third generation of AI—artificial super intelligence (ASI)—and whether this is something to aim for or to avoid. Technically, even a standard microprocessor available for $200 today runs at 10 million times the speed as a human neuron and computers can memorize more pieces of information in 1 second than a human could in a lifetime. So it seems clear that a system with true ASI would easily be able to outperform humans. Yet, what is often forgotten is that humans are used to thinking on a human level while an ASI system would think on an ASI level. Just as humans can never truly understand how chimpanzees think, despite the fact that they share 99% of our DNA, we will not be able to understand how an ASI system thinks. This limits our ability to control such systems, which again makes them appear more dangerous than useful.

Another issue deals with the displacement of the human workforce by machines. Most jobs consist of a series of tasks and not all of them can easily be conducted by AI. While a neural network can easily beat the best players in Go, it has a much harder time assembling an IKEA chair—a fact labeled as the Kamprad test in analogy to the well-known aforementioned Turing test. The vast abilities of AI combined with the increasing availability of data makes it likely that the shift to AI has a more fundamental impact on workforce in general than the Industrial Revolution from 1820—1840. This leads to a series of questions, starting from the idea of a universal basic income to fundamental issues that philosophy and religion will need to deal with, namely how humans can find purpose in life when all their work is conducted by machines.

Given all those challenges and open questions, it is not surprising that the views on AI range from outright alarmist as expressed by Elon Musk to euphoric like the vision of futurist Ray Kurzweil. Recently deceased theoretical physicist Stephen Hawking called AI "either the best, or the worst thing, ever happen to humanity" (Herm, 2016). This brings us back to Snow White who, at the end, had a happy ending with Prince Charming, even after being temporarily poisoned by the apple. We just have to hope that humanity will not end up stuck in a glass coffin made out of the illusion of AI convenience and that one day, even if it's only at the last moment, some prince—or princess!—will come.

References

Boyatzis, R. E. (2008). Competencies in the 21st century. *Journal of Management Development, 27*(1), 5—12.

Gardner, H. (1999). *Intelligence reframed: Multiple intelligences for the 21st century.* New York, NY: Basic Books.

Grimm, J., Grimm, W., & Kliros, T. (1994). *Snow White and other fairy tales.* North Chelmsford, MA: Courier Corporation.

Herm, A. (2016, October 16). Stephen Hawking: AI will be 'either best or worst thing' for humanity. *The Guardian*. Available at https://www.theguardian.com/science/2016/oct/19/stephen-hawking-ai-best-or-worst-thing-for-humanity-cambridge

Holloway, C., & Hand, H. H. (1988). Who's running the store, anyway? Artificial intelligence!!! *Business Horizons*, *31*(2), 70–76.

Hopkins, M. M., & Bilimoria, D. (2008). Social and emotional competencies predicting success for male and female executives. *Journal of Management Development*, *27*(1), 13–35.

Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, *21*(2), 155–172.

Jacobellis v. Ohio, 378 U.S. 184 (1964)

Kaplan, A. M. (2012). If you love something, let it go mobile: Mobile marketing and mobile social media 4 × 4. *Business Horizons*, *55*(2), 129–139.

Kaplan, A. M. (2018). A school is "a building that has 4 walls . . . with tomorrow inside": Toward the reinvention of the business school. *Business Horizons*, *61*(4), 599–608.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of social media. *Business Horizons*, *53*(1), 59–68.

Kaplan, A. M., & Haenlein, M. (2016). Higher education and the digital revolution: About MOOCs, SPOCs, social media, and the Cookie Monster. *Business Horizons*, *59*(4), 441–450.

Keating, J., & Nourbakhsh, I. (2018). Teaching artificial intelligence and humanity. *Communications of the ACM*, *61*(2), 29–32.

Kosinski, M., Stillwell, D., & Graepel, T. (2013). Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences of the United States of America (PNAS)*, *110*(15), 5802–5805.

Krotov, V. (2017). The Internet of Things and new business opportunities. *Business Horizons*, *60*(6), 831–841.

Lee, I. (2017). Big data: Dimensions, evolution, impacts, and challenges. *Business Horizons*, *60*(3), 293–303.

Luthans, F., Welsh, D. H. B., & Taylor, L. A., III. (1988). A descriptive model of managerial effectiveness. *Group and Organization Studies*, *13*(2), 148–162.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (1955). *A proposal for the Dartmouth summer research project on artificial intelligence*. Available at http://www-formal.stanford.edu/jmc/history/dartmouth/dartmouth.html

McClelland, D. C., & Boyatzis, R. E. (1982). Leadership motive pattern and long-term success in management. *Journal of Applied Psychology*, *67*(6), 737–743.

Minsky, M. L. (1968). *Semantic information processing*. Cambridge, MA: MIT Press.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1985). A conceptual model of service quality and its implications for future research. *Journal of Marketing*, *49*(4), 41–50.

Pucciarelli, F., & Kaplan, A. (2016). Competition and strategy in higher education: Managing complexity and uncertainty. *Business Horizons*, *59*(3), 311–320.

Saarikko, T., Westergren, U. H., & Blomquist, T. (2017). The Internet of Things: Are you ready for what's coming? *Business Horizons*, *60*(5), 667–676.

Stubbs Koman, E., & Wolff, S. B. (2008). Emotional intelligence competencies in the team and team leader: A multi-level examination of the impact of emotional intelligence on team performance. *Journal of Management Development*, *27*(1), 55–75.

Suwajanakorn, S., Seitz, S. M., & Kemelmacher-Shlizerman, I. (2017). Synthesizing Obama: Learning lip sync from audio. *ACM Transactions on Graphics*, *36*(4), 95:1–95:13.

Turing, A. (1950). Computing machinery and intelligence. *Mind*, *59*(236), 433–460.

Xu, V. X., & Xiao, B. (2018). China's social credit system seeks to assign citizens scores, engineer social behaviour. *Australia Broadcasting Corporation*. Available at http://www.abc.net.au/news/2018-03-31/chinas-social-credit-system-punishes-untrustworthy-citizens/9596204