

**TRILATERAL COMMISSION**  
**TASK FORCE REPORT ON ARTIFICIAL INTELLIGENCE**  
DRAFT FOR DISCUSSION | MARCH 25, 2018

Members of the Task Force Report on Artificial Intelligence (AI) have co-authored a draft report that introduces the possibilities as well as risks associated with AI. The draft report will be presented during the Trilateral Commission's 2018 plenary meeting in Singapore.

Potential applications in education, health care, food and agriculture are analyzed. The report also explores the potential impact on the labour markets, changing demographics as well as related governance issues.

For next steps, the authors aim to develop a perspective that only the Trilateral Commission can enable, thus creating a distinctive and valuable contribution to the field.

In particular, the authors aim to:

- Engage interested Trilateral Commission members on the report;
- Ask Trilateral members to nominate external stakeholders to engage on the report;
- Create a distribution list for the report after the 2018 Singapore plenary meeting;
- Synthesize the report further and publish on the TC website; and
- Guide the agenda setting for upcoming regional meetings.

We welcome your engagement and feedback throughout this process.

Sincerely,

Task Force Members (David Rockefeller Fellows)

- Gabriela Enrique, Founder, Prospera, Guadalajara
- Ryosuke Kobayashi, Founder and Executive Director, HLAB, Tokyo
- Manuel Muñiz, Dean, IE School of International Relations, Madrid
- Claudia Olsson, CEO, Exponential AB, Stockholm
- Matthew Thomas, Product Manager, McKinsey & Company, Toronto
- Alec Wagner, Program Specialist, International Rescue Committee, San Jose
- Yuito Yamada, Partner, McKinsey & Company, Tokyo
- Kenji Kushida, Research Scholar, Stanford University, Palo Alto

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## OPENING PREAMBLE

Today, we are witnessing very rapid advances in the pace of technological change. Artificial Intelligence (AI) is rapidly becoming one of the underlying drivers of the next wave of industrial transformations.

A simple working conception of AI centers around pattern recognition—such as finding underlying relationships in data, images, audio, video—and applied to enable a software system to improve its capabilities, or “learning.” Self-driving cars, for example, are learning about their environment through recognizing patterns of visual data, sometimes combining them with other data, such as maps. The easiest, though simplest way to determine if something deserves to be called AI is to inquire what is the pattern being recognized from what data, and how is the learning occurring and feeding back to the pattern recognition ability.

AI is not new, but the pace of recent progress is. Three factors are driving this acceleration:

- First, machine-learning algorithms have progressed in recent years, especially through the development of deep learning and reinforcement-learning techniques based on neural networks. Software development practices have also progressed, allowing engineers to drive advances in AI faster.
- Second, exponentially increasing computing capacity has become available to train larger and more complex models much faster. New processing units can execute data and algorithm crunching at speeds many times faster than traditional processor chips. This compute capacity has been aggregated in hyper-scalable data centers and is more accessible to users through the cloud.
- Third, massive amounts of data that can be used to train machine learning models are being generated, for example through daily creation of billions of images, online click streams, voice and video, mobile locations, and sensors embedded in the Internet of Things.

Altogether, AI programs and experiments that used to take weeks and days to complete can now be performed in milliseconds. The combination of these breakthroughs has led to demonstrations like DeepMind’s AlphaGo, which defeated the human champion Go, the ancient board game. However, so what if AI can play Go; what does it mean for the real world? In the summer of 2016, Google applied DeepMind to increase the efficiency of its datacenter cooling by 40%, reducing electricity consumption by 15%. This was a significant application of AI with tangible real-world benefits.

Formidable multi-decade long technological challenges must still be overcome, however, before machines can match human performance across the range of cognitive activities and approach “artificial general intelligence” - However, significant progress has been made in situation- specific or “narrow” AI applications -- such as making medical diagnoses from x-

rays, optimizing tractor routes on farms, delivering freight via autonomous self-driving trucks, and writing sports or financial news articles.

Even as automation technologies boost productivity and growth, they will bring with them large-scale transitions for workers, affecting multiple sectors, the mix of occupations, the skills required, and the wages earned. McKinsey Global Institute estimates that between almost zero and one-third of work activities could be displaced by 2030, depending on the pace of automation adoption, with a midpoint of 15 percent, affecting 400 million people.

With AI applications rapidly appearing in industry after industry, governments, executives and individuals will have to explore and develop legal frameworks to govern various issues related to data privacy, ethical decision-making, algorithm biases, income distribution and inequality, and defense & security, to name just a few.

We are only at the beginning of seeing the real impact of AI. As is with many moments of remarkable technological leaps that become the underlying building blocks for vast advances in industry, we are likely to see the impact of AI unfold in several different ways. In the long-run, AI will become so ubiquitous - just like computers, smartphones and the internet are today - that it will become almost invisible to its beneficiaries - workers, consumers and citizens alike.

# ARTIFICIAL INTELLIGENCE: THE ALGORITHMIC REVOLUTION DRIVING THE NEXT INDUSTRIAL TRANSFORMATION

KENJI KUSHIDA

Research Scholar, Asia-Pacific Research Center, Stanford University, Palo Alto  
Project Leader, Stanford Silicon Valley – New Japan Project ([www.stanford-svnj.org](http://www.stanford-svnj.org))  
David Rockefeller Fellow, Trilateral Commission  
[kkushida@stanford.edu](mailto:kkushida@stanford.edu)

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## AI: THE NEW FRONTIER – AND ACCELERATING

Artificial Intelligence (AI) is rapidly becoming one of the underlying drivers of the next wave of industrial transformations. There is every reason to believe that we are on the cusp of a sea change in how human activities and decision-making is transformed by abundant computing power. This research note will provide the basis for understanding the conceptual building blocks and paradigmatic examples of how the development of AI is accelerating, and how its deployment will be transformative.

## WHAT IS AI? IN LAYMAN'S TERMS

The field of AI can be quite broad, and it is not well defined along the edges. Some computer scientists joke that the history of AI is littered with skeletons because areas of research that proved fruitful received their own name (such as machine learning or deep learning), while areas that haven't had much progress have been lumped into the label "AI".) The areas that have experienced radical progress recently, leading to a plethora of new possibilities, are generally centered around "deep learning" using "neural networks" which will be explained more below.

It is also noteworthy some of the confusion around the term "AI" is deliberate. There is commercial pressure to label any analytical service as "AI" since it is likely to sell more than a service that does not -- regardless of what the algorithms are actually doing. Yet, any definition that lacks excludability ceases to have any significance.<sup>1</sup>

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<sup>1</sup> Silicon Valley accelerator Y Combinator even has a blog entry titled, "how to know when products actually use AI."  
<http://blog.ycombinator.com/how-to-know-when-products-actually-use-ai/>

As a general principle, for any phenomenon for which we use a label, we need a definition that includes the ability to exclude things; whenever a word becomes a buzzword, such as "Cloud-based," "Big Data" or "AI", the term itself loses meaning unless one can say which

For our purposes, a simple working conception of AI centers around pattern recognition—such as finding underlying relationships in data, images, audio, video—and applied to enable a software system to improve its capabilities, or “learning.”

*Self-driving cars*, for example, are learning about their environment through recognizing patterns of visual data, sometimes combining them with other data, such as maps. *Natural language processing*, for example, relies on recognizing and learning about language patterns to correlate with meanings, and audio input relies on sound pattern recognition of spoken words. *Motion and manipulation*, which is critical for robotics, often employs a variety of visual and tactile data inputs to enable the system to learn about its environment and how it interacts with it. A nice example of the latter is a little humanoid robot learning to swing on a mini swing-set. A conventionally programmed robot would need extensive programming about when to move its legs at what timing in order to amplify the center of gravity changes that enable it to swing, and then how to adjust as the swinging got bigger. It took a couple days to program such a robot, with numerous adjustments along the way. The same robot that used machine learning had no information about how to operate a swing set and only knew how to swing its legs, and the objective of attaining a pendulum motion. It first randomly swung its legs until it learned which timing would best amplify the swinging, and rapidly improved itself. In a matter of hours, it seemed to “get the hang” of how to swing, and began swinging vigorously – with no human interaction.

The easiest, though simplest way to determine if something deserves to be called AI is to inquire what is the pattern being recognized from what data, and how is the learning occurring and feeding back to the pattern recognition ability.

## SOME VOCABULARY FOR BASIC CONCEPTS

To familiarize The field of AI covers a variety of approaches to solving problems and learning, and it is worth becoming familiar with some of the basic. Many of these approaches and tools were developed decades ago, but have recently undergone breakthrough improvements due to vastly increased computing power available.

*Machine learning* is a broad categorical term, but specific types of approaches include probabilistic tools, for when the information available is incomplete or uncertain, classifiers and statistical learning models, such as placing certain observations in particular categories, and logic approaches for when learning is sequential.

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things are “not AI”. Since all IT services and data analytics are now under marketing pressure to label themselves “AI” or “Big data analysis,” we have to be sure what this excludes. Suppose we have an extremely effective analytical algorithm that actually does not use a great amount of data, and it is a conventional algorithm – it would be highly unattractive if labeled, “small data, non-AI analytics.” Thus, everything is under pressure to be called “AI” and “big data.” However, this obscures the true nature and therefore the extraordinary potential of AI.

*Deep learning* is a methodology employing *neural networks*, patterned after how the human brain works, and is used widely in current pattern recognition. There are multiple layers of relatively simple calculation between the input, which is known, and output, which can be observed and assigned a score.

There are also several types of learning.

*Supervised learning* teaches patterns for which the right answer is known. For an example of supervised learning, Facebook or Google have millions of images of cats, for which people have labeled cats in their photo albums. The AI program is then given an image, and must try to identify whether it is a cat or not. Its success or failure is known, and it can improve. We do not know, however, what it is basing its decision to identify a cat—shape of nose, ears, etc. A traditional algorithm will have to start by specifying parameters for a cat, such as pointy ears, then apply each picture to the rules. The exceptions then become problematic – what if the cat has partially chewed up ears, or is wearing a hat, for example, so that has to be taken into account ahead of time. With AI, however, the algorithm learns by itself what to look for without being told.

*Unsupervised learning* entails simply teaching the AI engine the “rules of the game” and letting it find underlying patterns or categorizations. For example, an unsupervised learning program to play “Go” will know only the rules, and whether it wins the game or not, without using historical data from past games. Its first games will therefore be random, and it will lose badly. After many iterations, however, it will figure out the underlying patterns that are likely to result in losing less badly, then eventually winning more and more decisively.

The term Artificial “Intelligence” is sometimes misleading, since the word “intelligence” can conjure images of computers developing a “consciousness,” or achieving “*Singularity*,” a commonly used word with somewhat unclear meanings, but generally in which computers exceed human capability in all capacities. There are several concepts that must be sorted out to have a reasonable discussion. On the one hand, almost any technology is used by humanity precisely because it outperforms humans at certain tasks. A top fighter jet pilot discovered that once she became an elite of the elite, the planes she flew were so automated that she was not allowed touch the controls—the error margins for takeoff and landing on aircraft carrier were so narrow that only computers could perform these tasks.

On the other hand, it is the specter of a single general purpose program or computer that can outperform humans on *all* different tasks that humans perform that often scares people. In the fighter jet example above, this would be the onboard computer also cooking her breakfast, filing her paperwork, making personnel decisions of those under her command, and managing her parents’ bank transactions. We are still far away from the latter.

Yet, the notion of *consciousness* is very different from attaining skills to perform tasks, which should be treated as a different dimension from performance. Researchers at the forefront of AI generally consider matters of consciousness or singularity to be far off enough

in the future and unclear enough in how such phenomena will unfold, that we are a long way from worrying about these developments.<sup>2</sup> (That being said, many industrial disasters and most disaster movies start out with scientists and engineers vastly underestimating the power and unintended consequences of their creations.)

## WHY IS AI DEVELOPING SO RAPIDLY NOW?

The speed at which recent developments in AI is surprising not only to the general public, but many specialists in the field. They are driven largely by an underlying civilizational transformation in the basic resources available to our civilization—computing resources. *Computing resources—the ability to compute, store, and transmit information—has recently transformed from a scarce to an abundant resource for the first time in human history.*<sup>3</sup>

Throughout human history, computing resources have been scarce, and therefore costly. From stone pyramids through the invention of the atomic bombs, most of humanity's complex calculations and mathematics were done largely by hand.

The extreme nature of exponential growth in processing power after the semiconductor was invented is often underappreciated. As Intel founder Gordon Moore's development objective of doubling the number of transistors on semiconductor chip every 18 months (Moore's Law) held from the mid-1960s onward, computational power available to humanity grow at astonishing rates.

For example, the processing power available to the main computer in the Apollo mission to the moon in 1969—a major milestone in human civilizational attainment—was roughly equivalent to the processor in the Nintendo Family Entertainment system that debuted in 1983, retailing for under \$100 and marketed to children.

The fastest supercomputer in 1985, the Cray II supercomputer, had a roughly equivalent processing power of one sixth that of the iPhone 6, introduced in 2014. Yet, while there were only a handful of Cray II supercomputers in existence in 1985, the number of smartphones shipped in 2017 was over 1.5 billion.<sup>4</sup> Most people in the developed and developing world are carrying around far greater processing power than the world's fastest supercomputer 30 years ago.

A 2016 Intel processor compared to a 1971 Intel processor had 3500 times the processing power, 90,000 times the energy efficient, and 1/60,000 the price. Intel engineers (with a good sense of humor) calculated the equivalent performance increase for a 1971 Volkswagen Beetle. *If the performance of a 1971 Volkswagen Beetle improved at the same rate along the*

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<sup>2</sup> It might be noted that a prominent pioneer of autonomous vehicle driving, Anthony Levandowski, who was head of Google's autonomous driving project before setting up his own company, which was then acquired by Uber, who subsequently left Uber after a lawsuit filed by Google, has set up his own church to worship the "godhead of AI" – but this probably deserves a footnote treatment rather than a serious discussion for now. <https://www.wired.com/story/anthony-levandowski-artificial-intelligence-religion/>

<sup>3</sup> Kushida, K. E., J. Murray and J. Zysman (2015). "Cloud Computing: From Scarcity to Abundance." *Journal of Industry, Competition and Trade* 15(1): 5-19.

<sup>4</sup> <https://www.statista.com/statistics/263437/global-smartphone-sales-to-end-users-since-2007/>



*same dimensions as semiconductors, the 2016 model would have a top speed of 2800 miles per hour, the fuel efficiency would be such that one gallon of fuel would allow it to travel 2 million miles, and the price would be 4 cents.*<sup>5</sup> Of course, the late 2017 model, debuting 18 months later, would double this, traveling at 5600 miles an hour, 4 million miles per gallon, and 2 cents.

This is the driver of computing power abundance.

AI programs and experiments that used to take weeks and days to complete can now be performed in milliseconds. Many of the underlying theories and concepts in AI date from the 1950s and 60s, but it was only recently that enough processing power could be mobilized at low enough costs to solve problems and discover new methods.

## COMPLEMENTARY ENABLING TECHNOLOGIES: CLOUD COMPUTING, SENSORS, SMARTPHONES

Throughout the history of technological change, it is rarely the development of a single breakthrough technology that shapes its diffusion throughout the world. Rather, *it is when complementary technologies are implemented, each through their own market or industry dynamics, that the technologies in question reveal their potential.*<sup>6</sup> Historically, for example, the invention of asphalt, critical to driving automotive vehicles smoothly, was a necessary complementary technological innovation to unlock the potential of the internal combustion engine as implemented in cars. Once it was technically possible to build smooth roads cheaply, it was then it was up to the political decisions to build paved road networks that enabled trucking to displace trains as a low-cost method for moving freight.

For AI, the set of complementary technologies include global scale cloud computing, the advent of low cost sensors, and the vast diffusion of smartphones.

The radical gains in computing power enabled by Moore's law in transistor development became available broadly beyond the exclusive domain of leading edge firms with massive datacenters, due to the advent of global-scale Cloud Computing. Only then could every startup and researcher with even relatively modest financial resources A handful of companies including Amazon, Google, Apple, and Microsoft, are able to offer low cost computing through massive datacenters around the world, constantly updated with the fastest physical resources and software enabling ever-more efficient use of the raw processing power. The Cloud offerings enable users, firms and individuals, low cost access to the frontier of abundant processing power.<sup>7</sup>

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<sup>5</sup> Friedman, T. L. (2016). Thank you for being late: An optimist's guide to thriving in the age of accelerations, Farrar, Straus and Giroux.

<sup>6</sup> Perez, C. (2009). "Technological revolutions and techno-economic paradigms." Cambridge journal of economics: bep051.

<sup>7</sup> Kushida, K. E., J. Murray and J. Zysman (2015). "Cloud Computing: From Scarcity to Abundance." Journal of Industry, Competition and Trade 15(1): 5-19.

Another critical ingredient for the leaps and bounds in AI development have been the availability of massive amounts of data to feed the algorithms. The diffusion of low cost sensors to measure a variety of things have been indispensable to creating the vast data that is most useful for AI.

The diffusion of smartphones has been a driver of diffusing sensors throughout the world. An ordinary smartphone contains numerous sensors, such as accelerometer, proximity sensor, light sensor, barometer, thermometer, gyroscope, magnetometer, pedometer, air humidity sensor, and of course, camera, GPS for location, and microphone for sound. The price of these sensors had dropped dramatically – almost 100 fold for some that are included in smartphones due to advances in nanotechnology and the sheer volume of smartphones shipped.

The sheer quantity of data that can be collected cheaply now enables companies such as Alphabet to use the GPS of Android smartphone users to deliver the real time traffic information on Google Maps, for example.

In various areas of industry, the Internet of Things (IoT) is about how to collect good data and measuring things that have not previously been measurable or observable. With the data fed into AI models for machine learning, pattern recognition and predication can become valuable tools for managing various aspects of industry.

An important perspective moving forward is how to effectively collect the data you want in clever ways by using sensors, and then using AI tools to identify patterns, then feed those outcomes into services, products, or other value-added offerings.

For example, if one airline experience is consistently far better than another's, but they are engaged in price competition, can this difference in service quality be measured objectively through biometric data from passengers willing to wear simple devices in exchange for airline miles? The cost for such an experiment, with AI mobilized to find underlying patterns, is no longer prohibitive.

## THE IMPACT OF AI: HOW WILL IT UNFOLD?

We are only at the beginning of seeing the real impact of AI.

As is with many moments of remarkable technological leaps that become the underlying building blocks for vast advances in industry, we are likely to see the impact of AI unfold in several different ways. Here it is useful to distinguish between frontier companies that are at the forefront of pushing the frontier of AI forward; they bring massive quantities of data unmatched by others, vast financial resources, and the ability to attract top talent to pioneer projects that go beyond considerations of immediate commercialization. Most companies are not at the frontier, and their relationship to AI is to use the tools, services, and platforms offered by frontier companies.

Specialized tool and industry AI companies, use smaller data than frontier companies and often utilize the computing resources or tools provided by frontier companies, but lead the way in applying AI in specialized areas of problem solving, or for particular industries. Examples are below.

Ubiquitous AI will be a phase when AI will be pervasive to the point that it will become the baseline to the point that it will become almost invisible—almost as computers are today. Just as companies now do not brag about using computers in their daily operations, or have Internet connectivity, it will not only make little sense to advertise that they use AI, but it will even be difficult to distinguish which tasks do not rely on AI at some level in the various layers of computing infrastructure and services.

## FRONTIER: A HANDFUL OF COMPANIES WITH VAST DATA AND FINANCIAL RESOURCES

Frontier companies will be pushing the forefront of knowledge on various forms of deep learning, using massive amounts of data and processing power that are unavailable elsewhere. Only these companies, with the most data and financial resources, will be able to hire truly top talent, who will continue to push the frontier forward. Currently, only a small handful of companies are in this position – Alphabet (owner of Google), Amazon, Facebook, and Microsoft.

GAFA – Google, Amazon, Facebook, Apple, are currently the destinations of choice for many graduates of top-notch computer science programs, such as Stanford. The amounts of data available to these companies are an order of magnitude greater than those held elsewhere. An interesting study notes that in hiring, places such as IBM are unable to hire specialists in deep learning because the industrial data available to companies such as IBM are far less than those available elsewhere.<sup>8</sup>

The frontier companies also have not only among the highest market capitalizations in the world, but also the largest cash piles.<sup>9</sup> They are able to hire top talent, and undertake ambitious projects. These projects do not need to have immediate commercial application, but these firms can employ to researchers to push the frontier forward.

The most paradigmatic example of frontier company activity is Deep Mind, the company purchased by Google. Deep Mind created AlphaGo, a program to play the board game of Go, long considered too complex for algorithms to beat humans.<sup>10</sup> In 2015, AlphaGo beat a

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<sup>8</sup> <https://techrunch.com/2017/07/13/jefferies-gives-ibm-watson-a-wall-street-reality-check/>

<sup>9</sup> <http://www.businessinsider.com/chart-us-companies-with-largest-cash-reserves-2017-8>

<sup>10</sup> In 1997, an IBM computer, Deep Blue, had been the world champion chess player Gary Kasparov, but Go is a far more complex game, and computer programs were unable to beat top ranked professionals without handicaps until AlphaGo.

The Economist provides an excellent description of the difficulty of Go. “A 19x19 board offers 361 different places on which Black can put the initial stone. White then has 360 options in response, and so on. The total number of legal board arrangements is in the order of 10<sup>170</sup>, a number so large it defies any physical analogy (there are reckoned to be about 10<sup>80</sup> atoms in the observable universe, for instance).

human professional for the first time, and in 2016, AlphaGo famously beat a top professional, Lee Sedol, in 4 out of 5 matches.

However, so what if AI can play go; what does it mean for the real world? In a news release that surprisingly gained far less attention than it deserved, in the summer of 2016, Google used Deep Mind to optimize the cooling of its datacenters. According to Google's estimates provided to a Stanford researcher, the company consumed 0.01% of the world's electricity in its massive datacenters in 2011.<sup>11</sup> Optimizing cooling is therefore an important task to reduce electricity consumption. Using a program written by Deep Mind, Google found that it was able to increase the efficiency of its datacenter cooling by 40%, reducing electricity consumption by 15%.<sup>12</sup> This was a significant application of AI with tangible real-world benefits.

The critical question for our current society is when Google will make these types of AI tools for practical application available to the general public. For now, it is only available within the company, and we do not know how much processing power was consumed to optimize its datacenter cooling, and how much data was needed, and what types of data it used. However, it is when the cutting edge technology offerings become commonplace commodities that vast new possibilities are opened up. It is quite possible to imagine programs with industrial applicability by Deep Mind, or similar AI offerings, to become externally facing for extremely low costs—perhaps a subscription of perhaps \$10 or \$20 a month.

Amazon, Microsoft, and Google have already begun opening some of their AI engines up to the public, some with tools that enable non-experts in machine learning to use machine learning tools. When an array of powerful tools like this become available to companies more generally, this is when some of the full impacts of AI will be felt.

The vast majority of companies are not frontier companies, but rather users of the tools that frontier companies provide. The question then becomes how prepared and how effectively follower companies can use these tools when they become available.

As tools become available, they will become the new baseline for cutting costs. This type of implementation will be necessary to compete, but there is likely to emerge a robust industry that offers such tools to corporations, making cost cutting alone unlikely to be a competitive differentiator. The question is what value-added activity can be created from the tools.

At the same time that frontier firms are pushing the boundaries of AI, we are seeing an explosion of companies offering specialized tools and industry applications.

## SPECIALIZED TOOLS AND INDUSTRY APPLICATIONS

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<https://www.economist.com/news/science-and-technology/21730391-learning-play-go-only-start-latest-ai-can-work-things-out-without>

<sup>11</sup> <http://www.datacenterknowledge.com/archives/2011/08/01/report-google-uses-about-900000-servers>

<sup>12</sup> <https://deepmind.com/blog/deepmind-ai-reduces-google-data-centre-cooling-bill-40/>

The vast data, talent, and financial resources of the leaders enable another set of firms to offer specialized AI tools and industry applications as they are able to use resources offered by the frontier firms and make use of the advancements that frontier firms enable.

Cloud computing services such as Amazon's AWS, which allows users to pay for the amount of computing power they use without virtually no capacity constraint, and Google's offerings such as databases that can handle extremely large amounts of data, all at low cost, have allowed firms to utilize the world's most powerful datacenters at extremely low costs. This enables companies developing specialized AI tools to flexibly scale up their use of computing power, easily run experiments, and offer their own services built on top of these tools.

As the frontier companies make more and more machine learning and deep learning tools, along with other sources of data available, this accelerates the ability of specialized AI tools and industry application companies to make their own offerings.

Let us run through some examples – some real world and some within the technological realm of possibility that now just requires some enterprising companies to test and implement them.

## INSURANCE: DYNAMIC PRICING AND MEASURING BEHAVIOR DIRECTLY

Automobile insurance is legally required by most countries for people owning cars. Yet, the way that insurance premium rates are calculated are often through proxies. For example, the type of car you drive, your age, amount of driving, whether you use the vehicle to commute to work, your income level, education level, prior history of traffic violations, etc. However, we are now at the cusp of being able to measure peoples' driving directly—through sensors attached to cars, with information sent even by smartphones to networks.

The finer the granularity in capturing data about how people drive, the more sophisticated the models can be created by feeding driving pattern data into AI algorithms to determine the level of riskiness of drivers.

Rather than using current proxies, direct measurement of human behavior, collected at massive scale, can be analyzed using AI.

For auto premiums, one could also add dynamic pricing—those with risky driving despite looking like good drivers in the proxies, could see their premiums rise. By driving well, premiums could decrease. Then, if this incentivized people to drive more safely, there would be fewer accidents, which should benefit insurers as well as society more generally.

The barrier to adopting such models by incumbent insurers is often the legacy IT systems that were not built to cope with the massive amounts of data input and processing that can be done with frontier firms' resources. This opens room for startups or hungry second or third tier firms to aggressively attempt to disrupt the leaders.

## MEDICAL IMAGE DIAGNOSING

In November 2016, Google published a paper in the Journal of the American Medical Association showing how AI could be used to recognize diabetic retinopathy, an eye disease that can lead to blindness if not detected early. Google used image recognition, similar to identifying and labeling people and objects in pictures. Deep Mind was partnering with the National Health Services of Great Britain to identify a variety of diseases and ailments.<sup>13</sup>

In November 2017, Stanford University computer scientists teamed up with Stanford hospital doctors and published a paper document the results of a new deep learning algorithm: the AI algorithm outperformed doctors in detecting pneumonia from patient X-Rays. Pneumonia is notoriously difficult to diagnose. The rapid progression of deep learning results is documented in the Stanford Report news: “Within a week the researchers had an algorithm that diagnosed 10 of the pathologies labeled in the X-rays more accurately than previous state-of-the-art results. In just over a month, their algorithm could beat these standards in all 14 identification tasks. In that short time span, CheXNet also outperformed the four Stanford radiologists in diagnosing pneumonia accurately.” (Stanford Report Nov 15, 2017.)<sup>14</sup>

## “FINTECH” (BEYOND THE HYPE): NEW WAYS OF MEASURING RISK, CUSTOMIZATION

Measuring risk is a core function in finance. Finance was one of the early adopters of computers to perform calculations—especially in insurance.<sup>15</sup> More recently, the financial sectors drove productivity gains, particularly in the US, through massive investments in IT.<sup>16</sup> The financial crisis of 2007-2008 revealed the extent of risk calculations that were conducted by software, as the vast array of complicated risk assessment models discovered that they had actually severely miscalculated how correlated their risks were, and were based on assumptions such as continuously rising real estate prices, which did not hold.

There is a broad range of categories of services that are considered Fintech, including personal lending, microfinancing, equity financing, personal asset management, virtual currencies and exchanges, credit rating, and others. A key theme for many of these areas is new ways of measuring risk, which use data previously unavailable or uncorrelated with individuals, using machine learning to improve credit risk calculations.

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<sup>13</sup> <https://www.wired.com/2016/11/googles-ai-reads-retinas-prevent-blindness-diabetics/>

<sup>14</sup> <https://news.stanford.edu/2017/11/15/algorithm-outperforms-radiologists-diagnosing-pneumonia/>

<sup>15</sup> Cohen, S., J. B. DeLong and J. Zysman (2000). Tools for Thought: What is New and Important about the "E-economy". Berkeley, CA, Berkeley Roundtable on the International Economy, University of California at Berkeley.

<sup>16</sup> Jorgenson, D. W., M. S. Ho and K. J. Stiroh (2005). Information technology and the American growth resurgence. Cambridge, Mass. ; London, MIT.

Using data to analyze peoples' relative risk is nothing new. Almost 30 years ago, word on the street was that American Express used purchases to forecast potential credit risk—specifically, if a married man suddenly bought flowers and jewelry, this suggested an extramarital affair, raising the risk of a divorce, which would often damage him financially.

Now people's behavior can be analyzed in new ways and correlated. The Chinese firm Tencent, which operates WeChat, one of the two Chinese leading platforms for an array of IT services, including payments, is a leader in using human behavior data across domains to assess risk. As explained by a Tencent executive, for a WeChat user to borrow one of the ubiquitous rental bicycles, the system assesses the risk score of each individual. If someone has a propensity to gamble, or likes to drive cars late at night at high speeds, their risky behavior lowers their credit score. If the credit score is too low, they cannot rent the bicycle.

## AUTOMATED DRIVING: THE HOLY GRAIL

There is currently an investment rush into Silicon Valley by existing automobile manufacturers to develop autonomous vehicle driving capabilities. Pattern recognition is the critical task. Google had raised major awareness of the technological possibilities after it hired Sebastian Thrun, who had directed the Stanford Artificial Intelligence Laboratory and won the DARPA's 2005 Grand Challenge with a robotic vehicle. Google's first autonomously driven vehicle was licensed in Nevada in 2012, and it made headlines when it debuted a prototype that had no steering wheel, accelerator, or brake pedals—only an emergency stop button. This experimental vehicle fleet could be seen driving around Mountain View near Google headquarters regularly.

Tesla delivered a paradigm shift when it offered its Autopilot in October 2014. An email from Elon Musk noted that existing customers of its Model S sedan could download the program to their cars overnight, transforming the human activity of driving overnight. The initial version of Autopilot was so effective that it raised concern among regulators when videos made by drivers showing themselves driving with no hands on the steering wheel, or even playing an instrument, eating a meal, and even taking a nap (pretend or real), surfaced on Youtube. A software upgrade required drivers to keep their hands on the steering wheel for the majority of the time that Autopilot would be engaged.

Uber sent shockwaves to the community when it announced suddenly in December 2016 that it would begin deploying a limited number of Uber self-driving cars in San Francisco.

Google noted that it spent over \$1 billion USD on its automated vehicle project between 2009 and 2015, with the division spinning out into its own company, WayMo, in 2016. In 2016, GM purchased Cruise Automation for \$1 billion, and Ford created a joint venture with Argo AI, which was only two months old at the time and founded by a former Google autonomous vehicle engineer. In 2016, Uber purchased a startup Otto, a six month old startup developing systems to enable semi-trucks to drive autonomously, created by Anthony Levandowski, who had left Google's autonomous vehicle project, for almost \$700 million in 2016. In 2017, Intel



purchased an Israeli startup that provided the original vision-based technology to Tesla for its autopilot, for \$15.3 billion USD.<sup>17</sup>

When fully automated driving becomes a reality, its effect on lifestyles and patterns of mobility and settlement will be profound – but it is still unclear in what ways. For example, some people could choose to live far away from their work, using their time to sleep or work, but fully automated driving could also enable vehicles to drive much faster than now. This would actually increase their energy consumption in transportation and potentially accelerate urban sprawl. On the other hand, given that almost of a fifth of American cities devote their space to parking lots, automated driving—especially if car sharing allows their vehicles to run around during work hours to carry short distance transportation customers—could play a role in dramatically increasing the comfortable density of urban areas, enabling more people to live close to their work. This would increase energy efficiency and urban density.

## MATERIAL INFORMATICS: EXAMPLES OF UTILIZING BIG DATA AND ANALYTICS

The number of specialized materials in our world has multiplied radically through advances in materials science and the ceaseless labor of large firms to create new materials for specialized uses. Think of the thousands of specialized materials used in modern cars, compared to the six or seven basic materials that were used in the 1960s.

The creation of new materials for specialized uses is a labor-intensive process within large companies, in which particular properties of the resulting material is desired, but companies need to form hypotheses, then test thousands of times to get results they want.

In the area of alloys, for example, there are about 28 parameters that are significant, and to find the desired output, scientists must effectively grapple with optimizing the values across these 28 parameters. Of the thousands of experiments, only those yielding the desired properties is considered a success, and the others are often put aside and stored in file cabinets, spreadsheets, and pdf files in a decentralized manner that are not utilized later.

Citrine Informatics, a Silicon Valley company, pulls all this information from a variety of formats into a database, and provides information for companies to conduct new experiments.

The service fills in the parameters for values it has data for from the company, and for parameters it does not have data, it uses machine learning algorithms to create estimates. Therefore, when a company specifies the properties it wants, Citrine is able to provide a recommendation based on real data the company has generated previously for some of the parameters, combined with estimates about the other parameters based on its own AI machine learning model.

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<sup>17</sup> <https://spectrum.ieee.org/cars-that-think/transportation/self-driving/google-has-spent-over-11-billion-on-selfdriving-tech>



Then, when large company conducts an experiment based on the recommendation by the software, the AI-estimated values can be replaced by real values. The real values are then fed into the machine learning algorithms to improve its quality for subsequent experiments.

Citrine was founded by a computer science PhD in machine learning, and a Stanford business school graduate who with an advanced degree in materials science.

This pattern of using large datasets gathered from large companies, filling in parameters with values from the data, and using machine learning to estimate other values, with experiments allowing for improvements to the machine learning algorithm, is a promising new area of AI applications in industrial uses.

Startups using the same principles in agriculture for chemical or “organic” fertilizers also reveal the promise to various areas of economic activity.

## AI IN RETAIL: LOGISTICS OPTIMIZATION AND UNDERSTANDING/SHAPING HUMAN BEHAVIOR

Retail is a significant area for both the application and development of AI. Optimizing complex logistics, predicting human behavior based on a variety of behavior and environment data, and discovering underlying patterns in human activity are all strengths of AI, given the collection of vast and valuable data.

IT has long been used in retail to optimize logistics and make predictions—for example, the convenience store chain 7-11 in Japan has used weather reports to build models and automatically adjust order quantities and selection of items such as perishable lunches (as well as umbrellas, of course.)

German retailer Otto famously used an AI deep learning algorithm, originally developed for particle physics experiments at CERN, to customer purchases a week ahead. The reported 90% accuracy of the system’s predictions for purchases within 30 days emboldened to Otto to commit to purchasing 200,000 items per month automatically from third party brands – already as of a year ago, in April 2017.<sup>18</sup>

Moreover, massive, complicated logistics operations are not only opportunities for companies to deploy AI to in order to improve efficiency, but they are also opportunities for frontier firms to gather large amounts of data about that can then be mobilized to develop further AI tools—not just for retail, but in other areas as well.

Amazon’s purchase of Whole Foods, a high-end supermarket, should be seen in this light. Amazon has been a leader in capturing human activity, both in its own warehouses, but also through its wide online retailing operations. Rather than simply aiming to improve the efficiency of the retailer Whole Foods, Amazon’s goals were clearly to also get the

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<sup>18</sup> <https://www.economist.com/news/business/21720675-firm-using-algorithm-designed-cern-laboratory-how-germanys-otto-uses>

opportunity to gather incredible amounts of data from a vast and complex supply chain to apply in its operations elsewhere. Moreover, information about consumer behavior, if correlated among multiple data sources, can yield insights into potential demand as well.

Much of current retail optimization in IT uses information about what is sold to predict consumer behavior. The question is how to generate data about what people did not buy, but would have bought had it been available. Retail models often use data about what was sold to find correlations, but if tools such as low-cost voice recognition can be mobilized in smaller stores to identify what local customers would have bought but could not find, even more fine-grained, locally optimized models based on actual demand could be possible. In this case, AI enters as a tool for voice recognition (since it is unrealistic to expect cashiers to enter information about what customers wanted but could not find manually), and a powerful tool for finding patterns.

## AI AND SECURITY

Security is a broad area in which AI is beginning to play a role, which will likely to become more significant rapidly. There are several types of security and it is worth differentiating between cybersecurity, which is a concern about data—preventing unauthorized access or tampering with data, and making sure the IT systems are operational at all times to allow the data to be available, and data privacy, which is about the rules and regulations surrounding the data of individuals.

The use of AI in physical security in applications such as recognizing people as they appear in various places as video images captured in cameras of all sorts, and their digital footprints as they leave traces in financial and online activities, are part of identifying and tracing people. For example, the American company Shot Spotter uses a variety of sensors and AI in urban areas to triangulate gunshots when they occur, since most gunshots are not reported to the police. A listed company, Shot Spotter operates in over 90 cities around the world, including Cape Town, South Africa among their non-American customer cities.

Companies such as Hikvision, from China, operate video surveillance equipment and analyze data, using it to learn about risks. Unattended bags in crowded venues, for example, and the behavior of people preceding crimes caught on camera provide input to teach the algorithms to look for future risky behavior.

Silicon Valley company Palantir has built itself as a leader in identifying patterns of transactions and various data, ranging from financial data to the movement of people, to conduct surveillance and identify national threats—although the full scope of their activities is classified.

Using AI to identify people who are potential criminals or terrorists before they commit a crime is an area where privacy concerns are weight with security considerations, leaving many of the various implementations to national policy arenas. Data available in some countries or regions are unavailable in others to use for law enforcement. For example,

Tencent uses a variety of online behavior surveillance tools to identify people who are visiting illegal gambling sites, which are often masked as advertisements or other services, and which often move around when detected. Chinese company Cloud Walk Technology is an example of a company that actively tries to identify potential criminals through behavior analysis in security cameras and correlated purchases. The US Federal Bureau of Investigation has long used credit card records and other data inputs to identify potentially risky behavior by identifying people who purchase goods that have a high correlation to terrorist activity, such as bomb-making materials, but the hope is that AI will drastically improve their effectiveness.

An emerging area called RegTech “Regulation Technology,” includes areas such as fraud detection and companies’ compliance with regulations. For example, for large financial institutions, detecting financial fraud and quickly reporting it to government is an extremely costly activity, which entails significant fines if not complied with. A range of startups have appeared which take companies’ financial data, analyze it using machine learning algorithms, and report whether they detect any fraudulent or irregular activity.<sup>19</sup>

## AI IN AGRICULTURE: AGRITECH

Agriculture is an area ripe for the application of AI, coupled with, and enabled by low cost sensors capable of gathering data and learning about various correlations. While agriculture in areas with large landmasses such as the US have been pursuing economies of scale to gain efficiency, most agricultural sectors in the world are unable to do so. Moreover, variations in the nutritional content in soil, nutritional needs of vast varieties of plants, complex logistics and supply chains, and as a sector with relatively low skilled labor, the field of “Agritech” is receiving significant attention.

Data gathering can be done more effectively than ever before, through means such as drones and collecting data using the agricultural machines themselves. The chemical compositions of soil and their incredible variations, and of organic fertilizers, for which the molecules cannot be altered like that of chemical fertilizers, are areas in which platforms such as that of the material informatics service above, can be useful.

Predicting rainfall, cold snaps, or other extreme weather conditions can be critical to crop yields. Accurate weather and climate prediction models become of paramount importance, especially at the very micro-level. This is a computationally intensive challenge, and the use of low cost sensors to get granular data to build models is critical, and can be improved by AI.

Mechanization, and increasing labor productivity is also a challenge for agriculture—another core domain for AI. Understanding the tasks that need to be performed at short notice, such as when high value crops such as fruits become ripe, require bursts of labor. How to best mechanize difficult tasks such as picking raspberries or easily bruised pears which attaining

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<sup>19</sup> For more, see the CB Insights report on Regtech, although they are more narrowly focused on the financial sector. <https://www.cbinsights.com/research/regtech/>

speed and scale are among the challenges that the current state of AI and robotics, along with logistics optimization, are ready to tackle.<sup>20</sup>

## THE AI FRONTIER KEEPS MOVING: LESS DATA NEEDED?

As has been shown so far, advances in AI have been enabled by increased in processing power availability and capabilities to gather massive amounts of data for deep learning.

Recently, frontier research suggests the potential for far small amounts of data required for effective learning. In a paper published in *Nature* in October 2017, Google announced that it had created a new AI program called AlphaGo Zero. The original AlphaGo had employed “supervised learning,” in which it learned to play Go by analyzing data of a large number of previous Go matches to learn tactics and strategies, then engaged in “reinforcement learning” by played against itself to improve its skill. AlphaGo Zero, on the other hand, was engaged in “unsupervised learning” and was only taught the rules, and engaged in “reinforcement learning” by playing itself. While AlphaGo played itself approximately 40 million times over the course of several months, AlphaGo Zero played itself only around 1.5 million times.<sup>21</sup>

When they played each other AlphaGo Zero beat the original AlphaGo by 100 matches to zero. This is the speed at which AI is improving.

However, the new power of unsupervised learning is still only in the realm of games. Yet, past experience suggests it would be premature to consign this type of learning only to the realm of games.

Frontier firms continue to absorb top talent. For example, a leading AI researcher, Fei Fei Lee, was recently hired from Stanford University from Google, and the latter announced that she would be in charge of creating an AI lab in China—despite Google not having core operations there.<sup>22</sup>

## TECHNOLOGY DIFFUSION RELIES ON CONTEXT

For any technology, the pattern in which it diffuses is determined not primarily by attributes of the technology itself, but on the context. The context includes related complementary technologies, industry dynamics, regulations, politics, and other social factors such as relative cost and availability of labor.

In a historical example, the technological innovation of steam power had a globally transformative impact through the railroad, transoceanic shipping, and factories, which reshaped global trade, production systems, the migration of people, and the accompanying

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<sup>20</sup> For a list of interesting agritech startups, see the participants in Nikkei’s Agritech Summit (Ag/Sum). <https://www.agsum.jp/en/exhibitor>

<sup>21</sup> <https://www.nature.com/articles/nature24270>

<sup>22</sup> <https://www.blog.google/topics/google-asia/google-ai-china-center/>

reshaping of global civilization. The complementary technology of advances in steel making (Bessemer steel) rose out of an industrial context, but canals and the advent of shipping lanes, railroads, and global systems of trade all arose from political decisions about how to use resources, and how nations chose to interact with each other.

AI, which necessarily involved the use of data, with much of the data being from people who live in countries with varying sets of rules, will be shaped by national and regional contexts.

Contemporary real world examples of “rules matter” in the deployment of AI are obvious. For autonomous driving for example, Nevada passed a law in 2011 for autonomous cars, requiring a person in the driver and passenger seats during tests. Google’s car was the first autonomous vehicle licensed at the Department of Motor Vehicles in 2012. When Uber suddenly announced its deployment of self-driving vehicles for passengers in 2016, The California Department of Motor Vehicles contended that Uber had not obtained proper licenses, and revoked the car registrations. Uber then move its testing to Arizona, which welcomed them with open arms, in a highly publicized strategy of regulatory arbitrage.

Tencent’s ability to use various personal data to build models of people’s credit risk is allowed by Chinese law, but privacy laws in the EU often forbid personal data from crossing national borders. While there are good arguments for this, the question is whether it creates a disadvantage in developing and deploying systems that can benefit from AI.

For any technology involving human genome alternation, rules and regulations will certainly matter.

Rules and regulations, of course, do not exist in a vacuum, but are the product of political processes, which differ across countries. Powerful industry groups, voters, the media, other political agendas, the bureaucracies are some of the key actors that are empowered very differently across different political regimes around the world. Add to this the array of international institutions ranging from the European Union to the more amorphous and decentralized international industry associations and foundations—such as those that govern the Internet—and we have a highly complicated but extremely relevant set of context actors.

Public investment into infrastructure can also matter. For example, historically, investments into the canal system of the United States’ great lakes, along with the Panama Canal, opened up the waterways that enabled steamships to link trade from previously unconnected areas and fundamentally alter the global economy. Or for the case of the automobile, the United States’ investments into creating nationwide highways in the 1950s under the Eisenhower administration, initially to be able to move military supplies around quickly during the Cold War, was the impetus for transforming long distance transport away from railroads to trucks, automobile, and airplanes. (Many parts of US passenger rail are significantly slower than 60 or even 100 years ago as the technological implementation choice, shaped by policy, moved away from trains.<sup>23</sup>)

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23 [http://www.slate.com/articles/life/transport/2009/05/stop\\_this\\_train.html](http://www.slate.com/articles/life/transport/2009/05/stop_this_train.html)

Similarly, with something like automated driving, the broad consensus among many researchers is that Level 5 in which a vehicle can navigate to any endpoint completely on its own, regardless of driving conditions, is still a ways away (some call it the ever receding 20 year horizon since the 1950s), but Level 4, in which there are bounded limitations, such as good weather, the availability of some form of map, and perhaps markings on the road, are easily within 5 years as a technological possibility. The question which country or region will invest how much into what form of solution—which may profoundly affect the trajectory of development.

Japan, for example, facing a serious labor shortage driven by its rapidly aging and shrinking population, is likely to politically embrace AI solutions to reduce the number of people needed to perform certain tasks—or even to perform jobs for which there are not enough people. The political opposition expected in regions which have labor surpluses may channel the type of AI applications adopted in these areas.

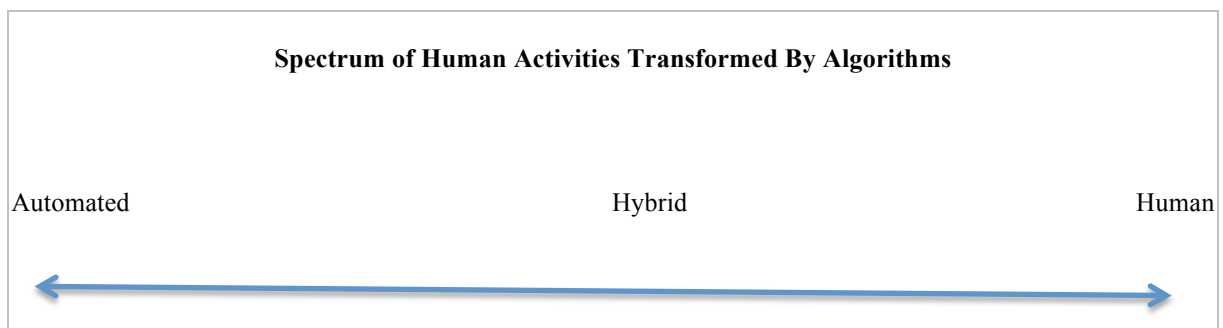
### AI AND A CONCEPTION OF HUMAN TASKS TRANSFORMED: THE “ALGORITHMIC REVOLUTION”

There is a specific way in which IT tools have been transforming human activity, and AI will accelerate this dynamic.

An increasing swath of human activity to be captured by algorithms, which allows it to be split apart, transformed, altered, and recombined.<sup>24</sup> Human activities can be placed along a spectrum of how they are transformed by algorithms.

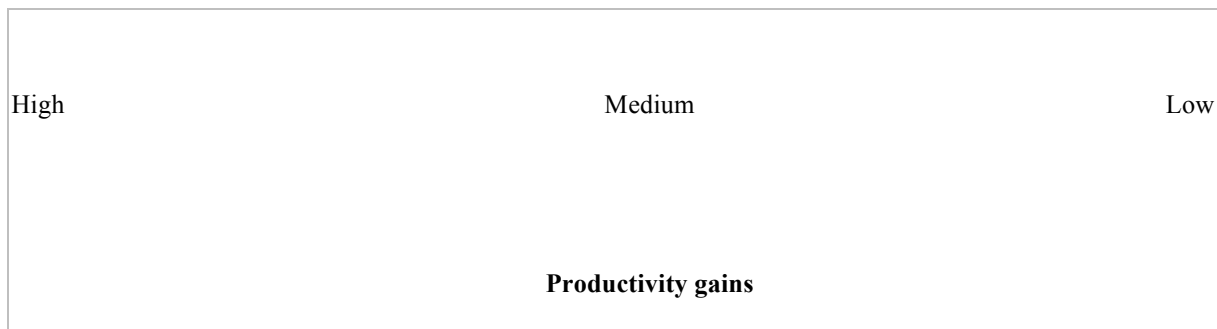
On the one hand is fully automated activities. Data searches, communications, and routine accounting, for example.

On the other end of the spectrum are human activities that cannot (yet) be fully replaced by algorithms, such as haircuts or replacing carpets in homes. In between are hybrid activities, in which human activities are substantially enhanced by algorithms.



24 Zysman, John, Stuart Feldman, Kenji E. Kushida, Jonathan Murray, and Niels Christian Nielsen. "Services with Everything: The ICT-Enabled Digital Transformation of Services." Chapter 4 in *The Third Globalization: Can Wealthy Nations Stay Rich in the Twenty-First Century?* edited by Dan Breznitz and John Zysman. 99-129. New York, NY: Oxford University Press, 2013.

[http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1863550](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1863550)



The range of activities that are moving from human to hybrid and automated activities is growing quickly as the Algorithmic Revolution proceeds with ever-increasingly availability of processing power and storage.

AI radically accelerates the Algorithmic Revolution by allowing human activity to be captured far more easily than ever before. Rather than creating a deep understanding of how human activities are performed, AI can find correlations and capture activities. Jeff Bezos, CEO of Amazon, put this eloquently in his letter to shareholders in 2017.

"Over the past decades computers have broadly automated tasks that programmers could describe with clear rules and algorithms. Modern machine learning techniques now allow us to do the same for tasks where describing the precise rules is much harder." (Jeff Bezos 2017)<sup>25</sup>

It is in this vein that we see activities that could previously only be performed by humans enter into the realm of hybrid, and then automated activities. Uber or Lyft drivers are hybrid in that the skills of learning where to pick up passengers, how to get to their destinations, (and in some countries, how to negotiate for large tips), are automated—although driving from point A to B still takes the same amount of time. By catching times of peak demand, drivers can even increase their productivity by earning more per ride. Eventually, driving will be fully automated.

Even folding clothes, a core human activity that many considered to encapsulate the pinnacle of activities that only humans could perform—William Baumol in his famous paper from the 1960s about how the productivity of service sectors is limited, even used this example<sup>26</sup>--has recently been the target for automation. Startup companies such as Japan's Seven Dreamers, teaming up with Panasonic, is rolling out fully automatic clothes folding machines, the Laundroid, that uses AI to learn and recognize clothes to use mechanical arms to fold them.<sup>27</sup>

## AI VS. IA (INTELLIGENCE AUGMENTATION), AND JOBS

<sup>25</sup> <http://www.businessinsider.com/jeff-bezos-shareholder-letter-on-ai-and-machine-learning-2017-4>

<sup>26</sup> Baumol, W. J. (1967). "Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis." *American Economic Review* 57: 415-426.

<sup>27</sup> <https://laundroid.sevendreamers.com/en/>

A common concern about AI is how fast it will replace jobs, and what types of jobs will be left. A prominent researcher framed the question as not “which jobs will be replaced” but rather, “which jobs would possibly not be replaced” as a better starting point for inquiry.

Arguably the most cited work for specific numbers of jobs lost is a working paper from Oxford scholars Osborne and Frey in 2013, predicting that 47% of US jobs will be lost in 20 years (2033).<sup>28</sup> The specificity of numbers led to an extensive amount of media coverage, and other reports took this as a starting point. The paper itself has grave methodological problems. As some critics note, it was not published in a peer reviewed publication, which in of itself may not be a problem, but may suggest methodological weaknesses. In fact, rather than actually looking at the occupational categories in the US (there are 702) and assessing and evaluating each one’s likelihood of replacement, it instead assesses jobs based on requirements of manual dexterity and social perceptiveness; if below a certain score, they predict it will be automated, and if above, they predict it will remain a human activity. As a researcher from the Information Technology and Innovation Foundation notes, this “methodology produces results that make little sense, as when they predict that technologies such as robots will eliminate the jobs of fashion models, manicurists, carpet installers, barbers, and school bus drivers.”<sup>29</sup>

Another highly cited study is by the McKinsey Global Institute. Many interpret the results as saying that 45% of jobs will be automated, but the actual report predicts that only less than 5% will be fully automated, with the rest coming from shares of employee time. Therefore, certain portions of doctors’ time will be saved by automation, which will amount to the equivalent of a certain number of doctors’ full time work, but it does not predict that this number of doctors will be displaced.<sup>30</sup>

From the early days of AI development, there have been two contrasting approaches to automating human activity. First is the traditional AI, in which people are replaced. Another branch is that of Intelligence Augmentation (IA), in which people remain at the core, with their abilities amplified.<sup>31</sup> This has significant implications for how to think about the future of jobs.

For many tasks, IA will enable unskilled workers to perform the tasks of highly skilled workers. Some highly skilled workers will be completely displaced, but others will simple be able to use their time for more productive activities. For example, if medical imaging diagnostics is more effective using AI tools, then surgeons might focus more on performing surgeries and communicating with families.

The question is how many new opportunities for low-skill workers will be created by IA, and how does that compare with jobs automated by AI? How will tasks performed by individual workers break apart and be recombined?

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28 [https://www.oxfordmartin.ox.ac.uk/downloads/academic/The\\_Future\\_of\\_Employment.pdf](https://www.oxfordmartin.ox.ac.uk/downloads/academic/The_Future_of_Employment.pdf)

29 [https://itif.org/publications/2017/08/07/unfortunately-technology-will-not-eliminate-many-jobs?mc\\_cid=7ec3ca683a&mc\\_eid=03f4769fd2](https://itif.org/publications/2017/08/07/unfortunately-technology-will-not-eliminate-many-jobs?mc_cid=7ec3ca683a&mc_eid=03f4769fd2)

30 *ibid.*

31 Markoff, John. *Machines of loving grace: The quest for common ground between humans and robots.* HarperCollins Publishers, 2016.



Take Komatsu, the Japanese construction equipment company, for example. It currently requires a worker with ten years of experience to perform certain cuts into the ground—using the circular motion of a power shovel to dig a slope at a particular angle, for example. However, with sensors embedded throughout the machine, they are now able to use workers who are almost completely untrained to perform these tasks. The machine will stop them before making an error, and an autopilot will automate some of the more complex maneuvers. Yet, tasks such as assessing the stability of the ground or identifying whether the large shape near the dig site is a rock or plastic bag can be done by an unskilled operator very easily.

Taken as a paradigm, it is fundamentally unknowable at this time how many jobs that are currently high skilled can be performed by low skilled workers, since companies around the world, large and small, are rushing to create such IA systems.

## CONCLUSION AND IMPLICATIONS

The purpose of this overview was to provide some information to raise further questions and spark informed discussions and inquiry. We will end simply with several questions.

For companies: are you preparing for commodity AI tools? Are you prepared for tools such as those used by DeepMind to optimize Google datacenter cooling and apply them to various areas of your organization? Who will identify the tools, and who will make sure they are implemented? Do you have a process for empowering people in your organization that interact with customers or core areas of the business who are not IT experts? The next phase of AI is likely to empower people without specialized knowledge of AI itself to ask valuable questions and design solutions.

For places: what are the technological choices that you are wittingly or unwittingly supporting? For example, there are good reasons for strict privacy laws. The question is how to make these decisions while understanding the potential costs of not being able to attain scale in deploying tools or platforms. What are the policy choices that may shape the trajectories of technological deployment more broadly rather than having to adapt the technology to fit local regulations in a way that makes it more difficult to harness the frontier?

For companies as well as places: are the decisions you are currently making following the logic of computing power abundance, or flying the face of it? Many companies and governments invest vast sums into IT systems that end up being proprietary, with the countries locked into costly long-term contracts. In an era of processing power abundance, every IT-related decision should withstand the question of whether it will withstand the doubling of processing power every 18 months that will enable AI to perform new analyses using new sources of data.

For everybody: What are portions of tasks that are best automated, and how are employment and labor systems able to harness it (not simply automating people, but amplifying people)? Almost every job has portions of tasks that can be automated, and many skills that are

currently high end, high skilled jobs will be able to be performed by lower skilled people amplified by IA tools. As a company, where are you positioned on this? As a country, how do you envision dealing with the transition? As an individual, where do you see yourself positioned on this spectrum. Many of the high end, cutting edge skills of today will be built into the tools of tomorrow? Yet, many tasks currently impossible will become realities. What is your vision moving forward?

Are you falling into the trap of “Weapons of Math Destruction”<sup>32</sup> – blind faith in algorithms. This overview did not have the scope to provide an overview of dangers of using probabilistic tools to determine individual outcomes, or the dangers of having blind faith in algorithms that may be based on assumptions that amplify inherent biases in the data or deployment. While using AI and algorithms to determine the fate of individuals in areas such as criminal justice and employment may have aggregate benefits, it is critical to understand the assumptions behind the models and be aware that it is the responsibility of society to deal with the errors or biases that result from applying the models.

AI and the current frontier of our civilization, will march ahead.

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<sup>32</sup> O’Neil, C. (2016). Weapons of math destruction: how big data increases inequality and threatens democracy. New York, Crown.

## ARTIFICIAL INTELLIGENCE IN HEALTHCARE

CLAUDIA OLSSON

CEO, Exponential AB, Stockholm  
David Rockefeller Fellow, Trilateral Commission  
claudia.olsson@gmail.com

*Briefing note for Trilateral Commission, Singapore, March 25, 2018*

Health systems globally are facing challenges in providing affordable access to high-quality care. The medical systems have largely been built to address short-term catastrophic illnesses, not being prepared to address the rising demand for long-term, chronic disease management. The global health situation is aggravated by the globalization of population aging, unhealthy lifestyles, and the rapid unplanned urbanization. The 2030 Agenda for Sustainable Development recognizes Non Communicable Diseases as a major challenge for sustainable development and the World Health Organization is promoting and monitoring global action against NCDs.

One contributing factor to the historical challenge of approaching health care systems' weaknesses with a coordinated approach is that the infrastructure underpinning the systems often has been designed in silos, geographically or pursuantly medical conditions. Of course the challenges around patient privacy have also increased the challenges of sharing patient data between health care providers. Countries are now in the process of integrating national health records, a process which is often costly given the heritage of historical investments in non-compatible systems and a lack of common health data dictionaries. The integration progress is however, laying the ground for unlocking the potential of rapidly accelerating technologies, where big data and artificial intelligence can make a significant difference. As health care systems generate vast amounts of data, with a prediction of a generation of 40 trillion gigabytes by 2020, this provides a suitable foundation for applying algorithms and software to approximate human cognition in the analysis of the complex medical data and enable evidence-based decisions even beyond the scope of human intelligence.

## CURRENT AND POTENTIAL APPLICATIONS OF AI IN HEALTHCARE

AI is already having a real-world impact in healthcare. Virtual healthcare companies such as Sense.ly and Babylon Health are using AI and telemedicine to automate the triage of primary care patients, giving patients a diagnosis from their smartphone and allowing them to connect with doctors in real time. Digital health assistants in the form of chatbots can be of a great use in many more areas of healthcare, especially if we consider that a big part of the world population has limited access to healthcare, but many own a smartphone. AI healthcare chatbots are already able to answer to simple medical questions, act as home-nurses reminding to people to take their medicine, monitor an individual's health status, schedule

doctor's appointments based on the severity of symptoms and improve the patient experience while eliminating unnecessary doctor's appointments and costs.

Large technology companies are investing substantial amounts in the future of health AI, and are already working with hospitals and medical centres to improve care. Partners HealthCare in Boston has a 10-year collaboration with GE healthcare to integrate deep learning technology throughout their network. IBM's Watson Oncology is being developed at the Cleveland Clinic and Memorial Sloan Kettering Cancer Center. Similarly, Microsoft's Hanover project is analysing medical research to predict the most effective cancer treatments for patients. Google's DeepMind platform is being used to detect health risks via a mobile app as part of a collaboration with the UK National Health Service.

The scale of potential applications for health AI is enormous, especially when considering broader trends in the digitalisation of healthcare information and research. Accenture has analysed the potential impact of AI on healthcare and has estimated that using AI to reduce dosage errors alone could lead to more than \$16 billion in benefits per year by 2026. They estimate that the top three applications for near-term value are robot-assisted surgery (\$40 billion), virtual nursing assistants (\$20 billion) and administrative workflow assistance (\$18 billion).

The applications range from the prosaic to the profound. AI could adjust dosages of painkillers or antibiotics based on previous responses or real-time medical data. It could give out pills, track the number taken, and report back to your physician if there are issues. Robotic surgery is also likely to only grow more capable, taking on more and more surgical tasks and allowing surgeons to focus on the most important and delicate parts of the procedure.

There is significant potential in using AI to assist diagnosis, especially with regards to rarer conditions. It is hard for a single health care provider to keep up with all the ongoing research while AI can help sort through vast amounts of data. It can also look at specific health data and suggest available clinical trials that can benefit the patient.

AI can also help pharmaceutical companies to speed up the drug development process. It's estimated that, on average, to bring one new drug to the market can take 1,000 people, 12-15 years, and up to \$2.6 billion and AI has the potential to reduce the time and money spent for R&D. In 2015, for example, the drug discovery platform Atomwise, launched a virtual search for safe, existing medicines that could be redesigned to treat the Ebola virus. They found two drugs predicted by the company's AI technology, which may significantly reduce Ebola infectivity. This analysis, which typically would have taken months or years, was completed in less than one day.

AI can shepherd the precision health revolution. Through analysis of DNA - the fundamental blocks of life - new combinations of genomics and AI technologies can help patients prevent, triage and predict effective therapies for a tailored approach to healthcare, and one with higher probabilities of success. This can also represent significant public health benefit. For example, the UK is taking the audacious step of sequencing 100,000 whole genomes for the

first time as one cohort in Genomics England's 100,000 Genome Project. The US National Cancer Institute has also recognized the importance of computational infrastructure that is required to collect the petabytes of data required in a precision health endeavor. It has leveraged the combination of genomics in the cloud to store its Cancer Genomics Atlas dataset online in the Cancer Genomics Cloud powered by Seven Bridges Genomics. For the first time, anyone with an internet connection anywhere in the world can have access to petabytes of genomics data with the click of a mouse.

Beyond pure medicine, there is the prospect of using health AI for performance improvement. Orreco and IBM have a partnership to use machine learning to boost athletic performance, and the rise of fitness trackers has demonstrated people's desire to understand their own abilities and improve through technology.

## CHALLENGES AND RISKS WITH AI IN HEALTHCARE

Current AI methodologies such as machine learning and deep learning may have a comparative flaw when it comes to medicine – they are unable to express why they achieved the result they did. They are often a black box, where information goes in and an answer comes out. While this is sufficient for many day-to-day applications, it will not be enough to justify clinical decisions.

AI is of course only as reliable as the data that goes into it. Yet the health data we collect is often messy and biased. Selection for randomised control trials is systematically biased against women, the elderly, and those with comorbid conditions. Pregnant women, pediatrics and new mothers are often excluded entirely. Medical data in general is weighted heavily in favour of white men. This has a number of problematic effects on the healthcare system currently (women are far less likely to receive heart attack treatment because their symptoms do not match the 'typical' [male] symptoms, and are more likely to suffer medication side effects) but the advent of AI would only make this situation worse. An AI that is based on biased data may produce biased results if this challenge isn't accounted for, leading to poorer outcomes for those already neglected by the medical system.

However, one harder challenge that we have to overcome in the near future is the ethics and legal issues that are associated with AI integration into medical data management and clinical decision making. Even though technology is advancing fast and algorithms become more accurate there will always be a potential risk for an error and the question is who will be responsible in case of a misdiagnosis, a false prediction or if AI will analyze incorrectly an X-ray and not recognize a tumor? The industry and the institutions need to establish new rules and regulations in order to protect the individuals, set boundaries on the tasks an AI can perform, and ensure that all the medical data are used securely and responsibly. If we set these ground rules as well as educate and upskill the medical professionals in order to leverage this new technology and cooperate with it, we will be able to revolutionize the healthcare sector.

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This briefing note has been written by Claudia Olsson with contributions from Sam Thorp and Vasiliki Vasilopoulou from Exponential AB as well as Julia Fan Li from Seven Bridges Genomics.

For the briefing note we have drawn upon the following resources:

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# AUTOMATION, AI, AND THE FUTURE OF WORK

## MICHAEL CHUI

Partner, McKinsey Global Institute, San Francisco  
michael\_chui@mckinsey.com

## DIAAN-YI LIN

Senior Partner, McKinsey & Company, Singapore  
diaan-yi\_lin@mckinsey.com

## MATTHEW THOMAS

Product Manager, McKinsey & Company, Toronto  
David Rockefeller Fellow, Trilateral Commission  
matthew\_thomas@mckinsey.com

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This short discussion paper explores how automation and artificial intelligence (AI) technologies are affecting the work that humans do, with far-reaching implications for labour participation, productivity, innovation, education and skill development, and social systems. It is divided into four sections: (1) technological innovation; (2) jobs lost, jobs gained, and jobs changed; (3) the challenge for skills and education; (4) policy implications.

## 1. TECHNOLOGICAL INNOVATION

Today, we are witnessing very rapid advances in the pace of technological change. Physical robots have been around for a long time in manufacturing, but more capable, more flexible, safer, and less expensive robots are now engaging in ever expanding activities. Artificial intelligence (AI) is likewise not new, but the pace of recent progress is. Three factors are driving this acceleration:

- First, machine-learning algorithms have progressed in recent years, especially through the development of deep learning and reinforcement-learning techniques based on neural networks. Software development practices have also progressed, allowing engineers to drive advances in AI faster.
- Second, exponentially increasing computing capacity has become available to train larger and more complex models much faster. New processing units can execute data and algorithm crunching at speeds many times faster than traditional processor chips. This compute capacity has been aggregated in hyper-scalable data centers and is more accessible to users through the cloud.
- Third, massive amounts of data that can be used to train machine learning models are being generated, for example through daily creation of billions of images, online click

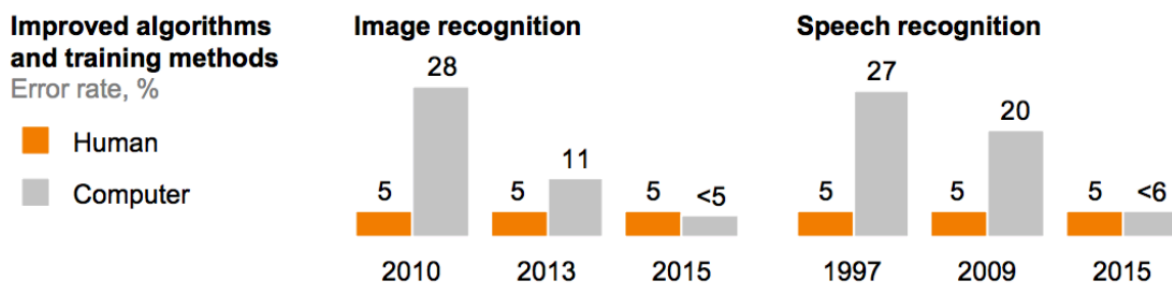


streams, voice and video, mobile locations, and sensors embedded in the Internet of Things.

The combination of these breakthroughs has led to demonstrations like DeepMind’s AlphaGo, which defeated the human champion Go, the ancient board game. Formidable multi-decade long technological challenges must still be overcome, however, before machines can match human performance across the range of cognitive activities and approach “Artificial General Intelligence.”

However, significant progress has been made in specific “narrow” AI applications. Software programmes are able to automate more complex tasks that occur in more uncertain and information-rich environments. Advanced statistical, pattern-recognition, and decision-making methods applied to significantly larger datasets to develop programmes with increasingly higher rates of accuracy and speed compared to human workers (Exhibit 1). The reasons why these programmes use certain inputs and assign certain weights are not clear to humans, a major change from the auditable algorithms of human-written code. For instance, current and emerging AI-powered software programmes are capable of learning and performing knowledge-oriented work and, in some cases, outperform medical experts in making medical diagnoses from X-rays.

EXHIBIT 1



SOURCE: *The zettabyte era: Trends and analysis*, Cisco, updated June 7, 2017; United Nations; MMC Ventures; Nvidia; McKinsey Global Institute analysis

## 2. JOBS LOST, JOBS GAINED, AND JOBS CHANGED

Technological invention has created labour transitions throughout history. In 1900, agriculture employed 41 percent of the US labour force, but increases in agricultural productivity driven by automation reduced its share of employment to under 10 percent by the 1960s and just 2 percent by 2000. More recently, in China, agricultural employment fell as a share of total employment by 32 percentage points in just 25 years, from 60 percent in 1990 to 28 percent in 2015. Yet these sharp declines in one sector, did not result in mass unemployment. Other, service-oriented sectors picked up the majority of new labour supply that might have otherwise gone into agriculture.

Even as automation technologies boost productivity and growth, they will bring with them large-scale transitions for workers, affecting multiple sectors, the mix of occupations, the skills required, and the wages earned. Various economists and research institutes have sought

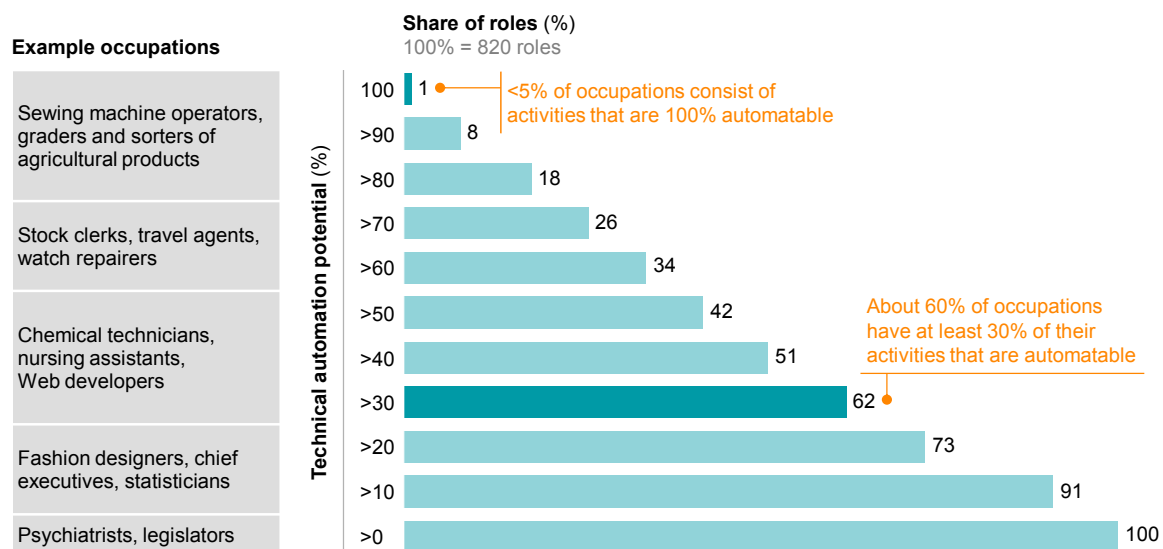
to estimate the potential job displacement that could be caused by automation adoption. The range is wide, from 47 percent of total US occupations that two Oxford University professors estimated to be at “high risk” of automation to a much smaller 9 percent of jobs that economists in an OECD paper see at risk across 21 countries.<sup>33</sup>

The McKinsey Global Institute has sought to estimate the automation potential of the global economy by examining more than 2000 work activities across 800 occupations. It finds that roughly half the current activities carried out by workers globally have the technical potential to be automated. While nearly all occupations will be affected by automation, only about 5 percent consist of activities that are fully automatable using currently demonstrated technologies. However, partial automation is likely to be far more common, with about 30 percent of the activities in 60 percent of all occupations technically automatable. This means that many workers will work alongside rapidly evolving machines. Worker skills will evolve for everyone, from welders to gardeners, mortgage brokers and CEOs (Exhibit 2).

## EXHIBIT 2

### While few occupations are fully automatable, 60 percent of all occupations have at least 30 percent technically automatable activities

Automation potential based on demonstrated technology of occupation titles in the United States (cumulative)<sup>1</sup>



<sup>1</sup> We define automation potential according to the work activities that can be automated by adapting currently demonstrated technology.

SOURCE: Source

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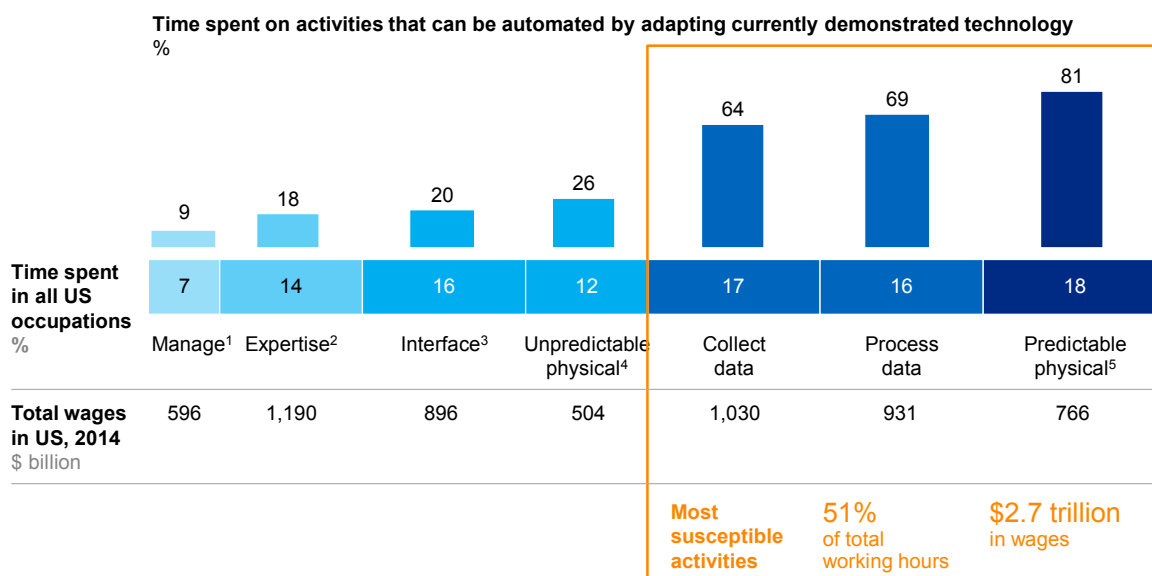
<sup>33</sup> Carl Benedikt Frey and Michael A. Osborne, *The future of employment: How susceptible are jobs to computerisation?* Oxford Martin School, September 17, 2013; Melanie Arntz, Terry Gregory, and Ulrich Zierhahn, *The risk of automation for jobs in OECD countries. A comparative analysis*, OECD Social, Employment and Migration working paper number 189, OECD, May 2016.

Some activities and tasks are more susceptible to automation than others, such as physical activities in highly predictable and structured environments, and data collection and data processing (Exhibit 3).

Technical feasibility is an essential starting point but not the only factor that will affect the pace and extent of adoption in the workplace. Other factors are economic and social, including the cost of deploying the technologies (also taking into account the cost and time to replace existing technologies), the labour-market dynamics (including labour supply quantity, quality, and associated wages), benefits beyond labour substitution, and social factors, for example social acceptance. While computers may be able to fly aeroplanes flawlessly, most passengers will only be reassured if there are also human pilots in the cockpit, for example. Much discussion today focuses on the first factor—technical feasibility—and suggests very high rates of job automation. However, consideration of the other factors suggest that actual adoption will be much slower than technical feasibility alone would suggest.

### EXHIBIT 3

## Three categories of work activities have significantly higher technical automation potential



1 Managing and developing people.  
 2 Applying expertise to decision making, planning, and creative tasks.  
 3 Interfacing with stakeholders.  
 4 Performing physical activities and operating machinery in unpredictable environments.  
 5 Performing physical activities and operating machinery in predictable environments.  
 NOTE: Numbers may not sum due to rounding.

SOURCE: US Bureau of Labor Statistics; McKinsey Global Institute analysis

McKinsey & Company | 3

History shows that technological innovation has been overwhelmingly positive for societal prosperity, including employment, particularly when coupled with public policies—such as education, taxation, and social services—to support those most affected in the short-run. Although technology raises labour productivity growth and may displace workers within a sector, overall employment also grows, particularly when looking over longer periods of time and across the whole economy. Productivity growth and job growth go together over the mid

and long term because output growth speeds up. Prices fall, new goods and services are introduced, and markets expand. When there has been a trade-off between aggregate employment and productivity levels, it has been short-lived. Over the past 50 years in the United States, for example, increased productivity has gone hand-in-hand with increased employment, especially when measured over a five or ten-year period. Even when measured over one-year periods, productivity and employment have both risen 79 percent of the time.

Nonetheless, workplace changes can dislocate millions of workers, and these transitions will likely be significant over the next 10-15 years. McKinsey Global Institute scenarios across 46 countries suggest that between almost zero and one-third of work activities could be displaced by 2030, depending on the pace of automation adoption, with a midpoint of 15 percent, affecting 400 million people.

While the estimates by various researchers of job disruptions vary, many of their core conclusions are similar, including:

- Almost all jobs include activities that are automatable, some more than others;
- Jobs that require secondary school or less education are most susceptible to automation;
- Jobs that require advanced cognitive function and education, such as lawyers, doctors, science, are also susceptible to automation;
- Digital and data skills are increasingly in demand, across all industries, functions and geographies;
- Jobs that have been successfully automated in commercial environments tend not to be carried out by humans again (i.e., they don't 'come back');
- Automation of part of one's job does not always lead to less hours or being let go, instead the extra time can be repurposed to create more value for the organization or customer;
- The rate of job and career switching will increase, requiring humans to be adaptable and learn new skills faster to mitigate against risks of un- and under-employment.

The adoption and impact of automation will vary by sectors, regions, and countries, with advanced economies more affected by automation than developing ones.<sup>34</sup> A number of factors contribute to the geographic differences. They include wage level; higher wages make the business case for automation adoption stronger. However, low-wage countries may be affected if companies adopt automation to boost quality, achieve tighter production control, and move production closer to end consumers in high-wage countries. Some economists anticipate that emerging economies could undergo “premature de-industrialisation.”<sup>35</sup> Other factors influencing geographical differences are demand growth—since countries with

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<sup>34</sup> *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017.

<sup>35</sup> Dani Rodrik, “Premature deindustrialization,” *Journal of Economic Growth*, volume 21, number 1, 2016.

stronger economies are more able to create more jobs—demographics, which affect both labour demand and labour supply, and the specific mix of economic sectors and occupations in each country, which differ.

Other geographic factors may also play a role. A recent study by MIT Media Lab found that small cities face greater impact from automation. This is because the jobs and skills that are more prevalent in smaller cities are the ones that are most susceptible to technological unemployment, while the opposite is true for larger cities. In particular, they found that “bigger cities have a disproportionately large number of jobs for people who do cognitive and analytical tasks, such as software developers and financial analysts – occupations that are less likely to be disrupted by automation. Smaller cities have a disproportionate amount of routine clerical work, such as cashier and food service jobs, which are more susceptible.”<sup>36</sup>

From past experience we also know that technology fundamentally changes some jobs. For example, the invention of the automated teller machine (ATM) meant that banks needed fewer human tellers per branch, but the cost of each branch also decreased resulting in banks in the United States opening more branches and hiring more human tellers. Their role changed from handing out cash or taking deposits to higher value-added activities such as building customer loyalty, offering advice, and providing new services.<sup>37</sup> Following the 2008 financial crisis and with the rise of online banking, the number of tellers began to fall back, however, as the demand was reduced. Something similar happened with information analysts in the Internet era. Their numbers might have been expected to decline: after all, anyone can now conduct Google searches to find data and information. Instead, the Internet stimulated the need for more insightful and low-cost expert analysis, and the number of information analysts has quintupled, from about 400,000 in 1980 to about two million today. Rather than spending their time gathering the data, as they once used to, these analysts now focus on making sense of it.

At the same time, we should not underestimate the number of new occupations that spring up as a result of new technologies, and which cannot be imagined in advance. Recent examples include MRI technicians, professional video game players, and app developers. The PC gave rise to a huge new industry of call center representatives. The same happened in previous eras: the automobile, for example, created new professions ranging from car detailing to the motel business. Recent academic research has calculated that about 0.5 percent of all jobs created annually are in “new” occupations that didn’t previously exist.<sup>38</sup>

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<sup>36</sup> *Small cities face greater impact from automation*, MIT Media Lab, September 2017.

<sup>37</sup> James Bessen, *Learning by doing: The real connection between innovation, wages, and wealth*, Yale University Press, 2015.

<sup>38</sup> Jeffrey Lin, “Technological adaptation, cities, and new work,” *Review of Economics and Statistics*, volume 93, number 2, May 2011.

### 3. THE CHALLENGE FOR SKILLS AND EDUCATION

As we have seen, some occupations are considerably more susceptible to automation than others. Those that are less susceptible tend to involve activities that require expertise, coaching and mentoring, and personal contact with one or numerous stakeholders. Based on this understanding of automation's impact, a number of forecasters have sought to project the types of work that will be most readily available in the future. Among the possibilities that are posited are occupations in the care economy, the circular economy, and the craft economy.<sup>39</sup> In its 2017 report on the future of work, the McKinsey Global Institute identified a number of categories with the highest percentage job growth net of automation to 2030. They include health-care providers; professionals such as engineers, scientists, accountants, and analysts; IT professionals and other technology specialists; managers and executives, whose work cannot easily be replaced by machines; educators, especially in emerging economies with young populations; and “creatives,” a small but growing category of artists, performers, and entertainers who will be in demand as rising incomes create more demand for leisure and recreation.<sup>40</sup>

Whatever the future holds for certain occupations, there will be significant repercussions on skills and education. As humans work increasingly alongside ever more capable machines, in a complementarity that is widely expected, new skills will be required, and people will need to become more flexible in the workplace.<sup>41</sup> Social and emotional skills, creativity, high-level cognitive capabilities and other skills relatively hard to automate will be at a premium (Exhibit 4).

Leaders and supporters of the technology industry have voiced how digital and data skills are the future, and many governments are listening, adapting K12 education curricula and investing heavily in programmes that focus on digital literacy. Data science and analytics—a profession that requires gathering and analyzing large datasets to identify and communicate practical insights that improve organisational outcomes—is one of the most hotly demanded occupations, yet among the shortest in supply, particularly in the Asia-Pacific Region.<sup>42</sup> Others emphasize the importance of humanities-based subjects to complement the scientific, technical, engineering, and mathematical (STEM) ones.<sup>43</sup>

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<sup>39</sup> See for example, *Shift: The Commission on Work, Workers, and Technology*, New America and Bloomberg, May 2017.

<sup>40</sup> *Ibid.* Jobs Lost, Jobs Gained, McKinsey Global Institute, December 2017.

<sup>41</sup> See for example, Erik Brynjolfsson and Andrew McAfee, *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*, W.W. Norton, 2014.

<sup>42</sup> *Data Science and Analytics Skills Shortage*, APEC Human Resource Development Working Group, July 2017.

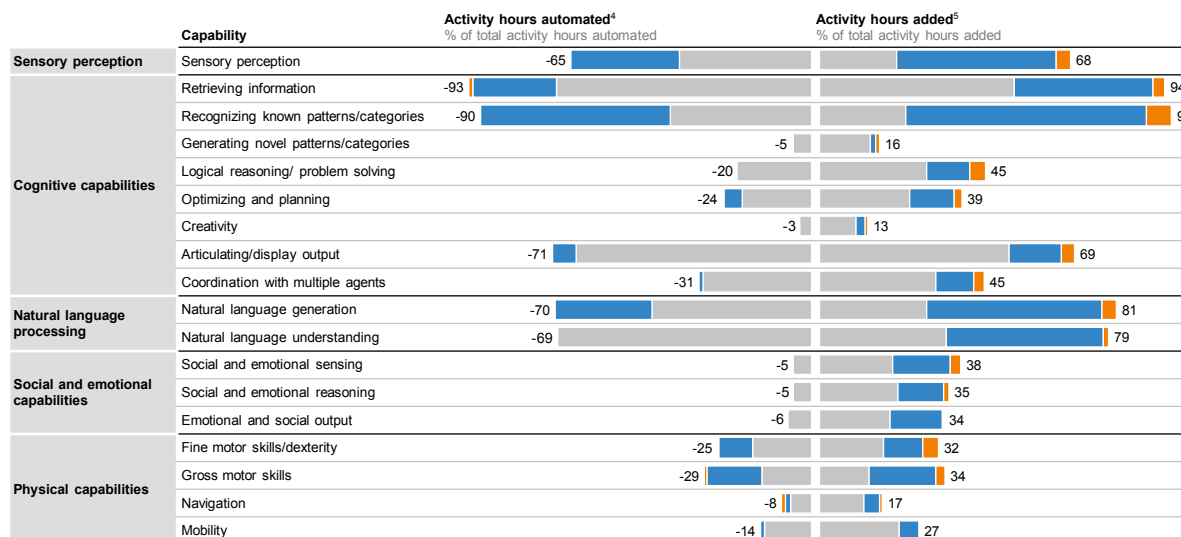
<sup>43</sup> George Anders, *You can do anything: The surprising power of a “useless” liberal arts education*, Little, Brown and Company, 2017.

EXHIBIT 4

Future work activities will require more social emotional, creative, and logical reasoning abilities—and more advanced capabilities across the board

Difference in share of work activity hours which require specified capability, by level of expertise, between new work and displaced work, 2016–30

US example, midpoint automation, step-up scenario



1 Below-median capability required.  
 2 Median human capability required.  
 3 At least 75th percentile capability required.  
 4 80.3 billion activity hours automated (38.6 million jobs).  
 5 66.3 billion activity hours added (31.9 million jobs).  
 NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.

SOURCE: U.S. Bureau of Labor Statistics; McKinsey Global Institute analysis

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The issue of skills and education has quickly become top of mind for corporate executives, policy makers, and philanthropic organizations around the world who focus on automation and its consequences. Fundamentally, the issues are twofold:

- How to reshape school and university curricula for a new age of automation. Some of the occupations that will be in demand in the future are likely to require higher educational attainment. Estimates by the McKinsey Global Institute show that growing occupations in the future in advanced economies are likely to require a college education. Educational requirements will also rise in emerging economies. (Exhibit 5).
- For workers and companies, how to adopt workforce skills to the demands of the new, automated era, with greater interaction between humans and machines. This is already becoming visible in factories, for example. Whereas robots used to be kept in cages, out of range of human co-workers, the latest generation of these machines co-exists on the factory floor and in warehouses without danger. The challenge of "reskilling" midcareer workers is a substantial one, given the very sizable number of people concerned. Some global companies are already starting to address these issues in their own workforce, even as they invest in automation technologies, but most are at an early stage.

Organisations that have active strategies around workforce development will need to answer the following questions:

1. What business are we going to be in, in 5 years and in 10 years?
2. What kinds of activities must we be capable of to win in that business?
3. What kinds of skills do we need more of, and less of, to be in that business?
4. Which functions and activities can be replaced or augmented by AI and robotics?
5. How will we find new talent, re-train existing talent, and let go of talent?
6. What investments should we make to include AI/robotics in our workflow, and when?

Addressing these questions will require an interdisciplinary mix of strategy, marketing, operations, talent/organizational, technology and analytics work. This is another area where AI can help, particularly when it comes to the talent mix questions, leveraging operational, talent and HR data to predict workforce demand, supply and talent pools.

Governments have an important role to play in both areas of education and training through publicly funded education, workforce training programmes, and incentives. This may require a reversal of the decline in publicly funded investments and policies to support the workforce (Exhibit 6).

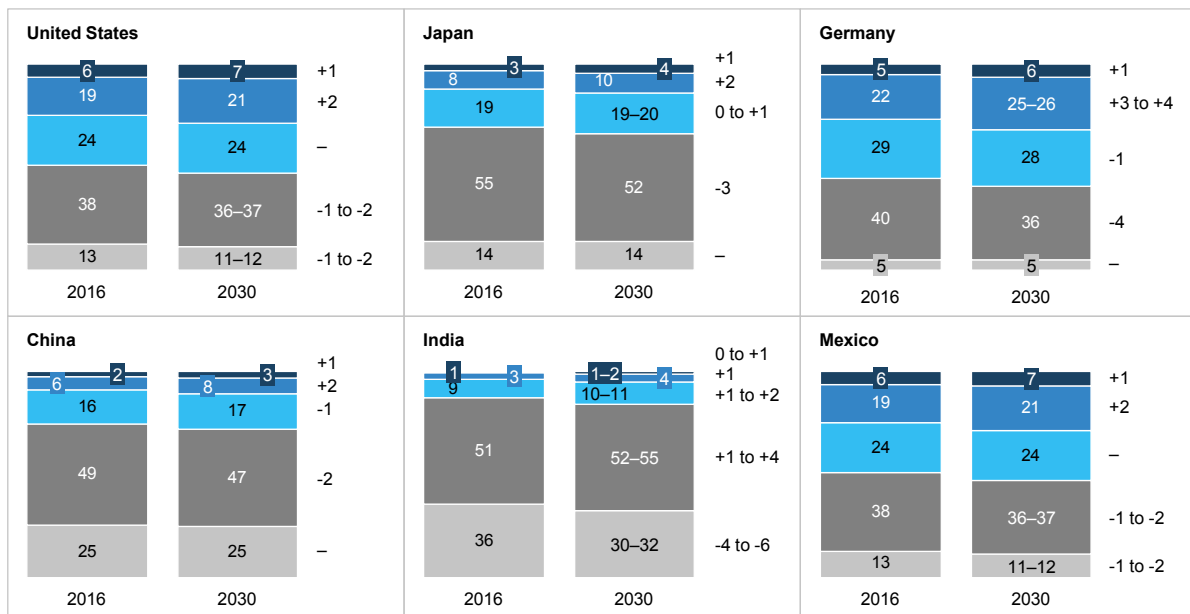
## EXHIBIT 5

### Skill requirements for jobs are increasing globally; an increasing percentage of jobs will require college and advanced degrees

#### Skill requirements, 2016 and 2030, and change

% of sized labor demand; percentage points

Advanced Associate None  
College Secondary



NOTE: All figures are projected using the midpoint automation scenario; only includes the sized labor demand (e.g., the creation of new occupations is not included). Some occupational data projected into 2016 baseline from latest available 2014 data. Numbers may not sum due to rounding.

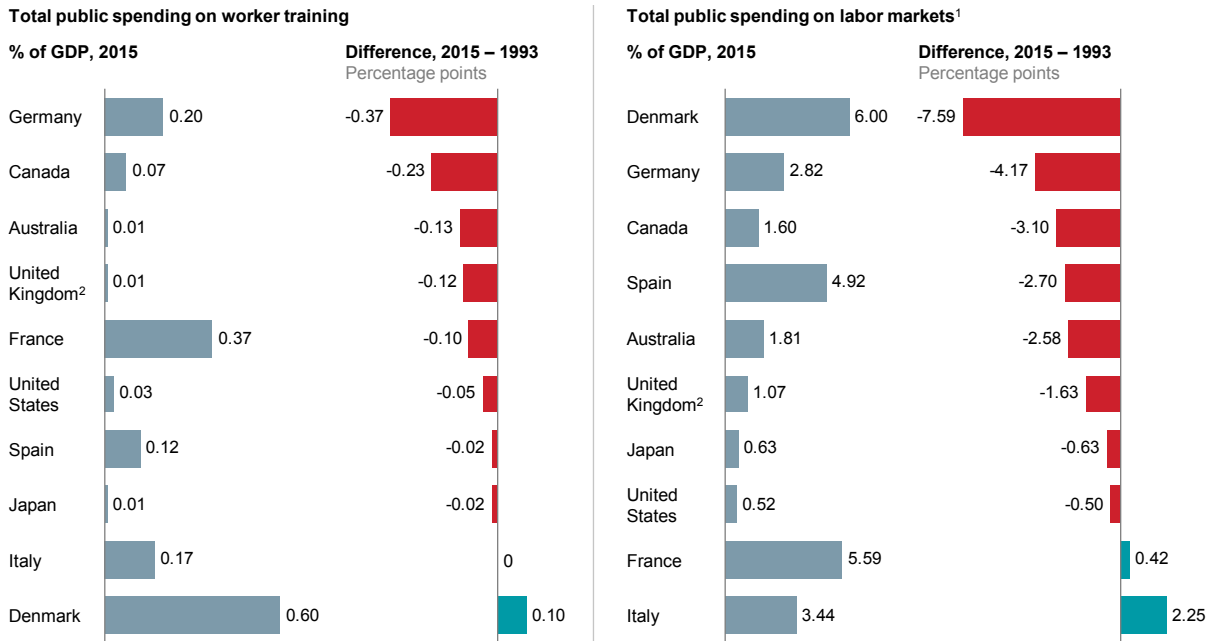
SOURCE: US Bureau of Labor Statistics; McKinsey Global Institute analysis

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## EXHIBIT 6

### Most OECD countries have been spending less on worker training and labor markets over the past 20+ years



<sup>1</sup> Public spending on employment incentives; startup incentives; direct job creation; out-of-work income maintenance and support; early retirement; public employment services and administration; and sheltered and supported employment and rehabilitation (excluding worker training).

<sup>2</sup> 2011 data used for United Kingdom.

NOTE: Countries where 1993 data was not available omitted. Not to scale.

SOURCE: OECD; *Labour market policy expenditure and the structure of unemployment*, Eurostat, 2013; McKinsey Global Institute analysis

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## 4. POLICY IMPLICATIONS

Preparing for the future of work may appear daunting, it is still the best way forward. We should embrace automation technologies for the productivity benefits they bring, even as we deal proactively with the workforce transitions that will accompany adoption. Our societies need that productivity boost, at a time when demographic trends are working against our economies. Beyond the prosperity and employment these technologies can create, there is also an opportunity to extend societal benefits for all. The power of AI has the potential to unleash new “moonshots”, as we use the technology to tackle problems from cancer to climate change.

Among the policy imperatives:

- **Rethinking education, training, and learning:** Policy makers working with education providers could do more to improve basic science, technology, engineering, and math (STEM) skills through the school systems, and put a new emphasis on creativity as well as critical and systems thinking.
- **Public-private partnerships to stimulate infrastructure investment:** The lack of enabling digital infrastructure is holding back the digital benefits for some emerging economies -

and even underserved regions in developed countries. Public-private partnerships could help address market failures.

- Incentivize investment in human capital: A broad range of programmes exist for businesses to make physical capital and R&D investments. Similar incentives are needed to encourage investment in human capital.
- Rethinking income support and safety nets: If automation (full or partial) does result in a significant reduction in employment and/or greater pressure on wages, some ideas such as universal basic income, conditional transfers, and adapted social safety nets may need to be considered and tested.
- Encouraging new forms of entrepreneurship and more rapid new business formation: Digitally enabled opportunities for individuals to earn incomes. In addition, accelerating the rate of new business formation will be critical. This will likely require simplifying regulations, creating tax and other incentives, and encouraging entrepreneurship more generally.

*This briefing note was written by Michael Chui, Diaan-Yi Lin and Matthew Thomas of McKinsey & Company.*

McKinsey Global Institute research reports are available on [www.mckinsey.com/mgi](http://www.mckinsey.com/mgi). For this briefing note, we have drawn on the following reports:

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*Digital America: A tale of the haves and the have-mores, December 2015.*

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# POSITIONING GOVERNMENTS FOR SUCCESS IN THE AI ERA

ALEC WAGNER

Economic Development Program Specialist, International Rescue Committee, San Jose  
David Rockefeller Fellow, Trilateral Commission  
alecjwagner@gmail.com

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Despite the risks associated with labor fluctuation and unethical implementation, the development of AI technologies will result in notable growth of key economic and societal indicators. However, to reap the rewards of AI innovation, greater levels of investment, favorable regulations, and social considerations need to be applied to foster a promising AI environment.

In 2018, we saw increased investment into AI R&D in Japan, Germany, China, South Korea, the U.S., UK, and others in the billions of dollars scale. Each leading government entity had similar financing goals for AI use. Government leaders in the AI space such as Japan, South Korea, China, and several EU countries fixed their targets on developing a smarter society using robotics and autonomous systems. China intends to encourage a \$15 billion level AI market, fostering growth in the mobility, robotics, and IoT subsectors of AI technology; South Korea plans to spend \$840 million on R&D with partners Hyundai, Samsung, LG, SKT, KT, and Naver by 2020; and the US, a longtime proponent of experimental AI technologies, has grown their smart weapons stockpile heavily in 2017. The following case studies showcase the high-level strategic strengths and weaknesses of four governments represented by three of the top ten strongest economies (U.S., China, Germany), two emerging AI industries (South Korea, China), and two established industries (U.S., Germany).

## SOUTH KOREA

Although South Korea is known for its IT industry, AI is a new endeavor. In 2013, South Korea's aggregate AI market size was roughly half of what it is today, and public policy has only recently shifted toward AI innovation.

Two major roadblocks stood in the way of South Korean AI development and investment:

1. Regulations to government use of personal information; and
2. Private companies in South Korea were not collecting enough actionable data for AI to be useful.

Changes to the regulatory framework came in 2014, and significant investment into R&D in the public and private sectors followed in 2016.

In March 2016, South Korea's Park Geun Hye created the country's first AI control tower, entitled to the National Science and Technology Strategy Committee; invested \$698 million spread over five years into R&D personnel and data infrastructure; and invested \$1.72 billion in private and public equity toward the joint public-private sector creation of research labs specifically for AI industry development.

According to an official from South Korea's Ministry of Science, ICT and Future Planning says "[the South Korean government] plans to pour considerable resources into AI," and will be "working on [AI] in diverse ways."

The trend in heavier South Korean investment has resulted in activating smart city and autonomous car technologies by companies like LG Electronics and Hyundai.

An International Data Corporation report projects South Korea's AI market will be worth \$6.5 trillion in 2025; over 50x since 2015 levels.

## GERMANY

Last fall, Chancellor Phillip Hammond announced that Germany would invest over \$450 million in a comprehensive buildout of AI and 5G telecommunications infrastructure in an effort to amplify its existing climate of innovation in the autonomous vehicles and internet of things AI subindustries.

This forward-thinking approach is symbolic of Germany's historically progressive efforts to trailblaze in the AI space. Through a public-private partnership, the German government founded the non-profit German Research Center for AI (DFKI) in 1988, devoted to accelerating the pace of AI R&D.

DFKI has since developed a robust portfolio of AI technologies including Verb mobil, a communications technology completed in the early- and mid-1990s. Verb mobil's aim was to:

1. Give Germany a top international position in language technology, foreseeing globalization in the next millennium; and
2. Promote economic cooperation between Japan and English-speaking countries by focusing its translation capabilities on German, Japanese, and English exclusively.

Inevitably, German AI R&D has advanced dramatically since the start of its DFKI partnership. Substantial capital and intellectual investment into technologies like Res-Com, an Internet of Things (IOT) platform that enables machine-to-machine communications and Smart Factory KL, position Germany as a leader in the highly-decentralized, fourth industrial revolution.

German autonomous vehicle development is promising from a technological standpoint but has been held back by regional regulatory frameworks of the Vienna Convention on Road Traffic and UN ECE. However, Germany has made efforts to adopt legislation conducive to autonomous vehicle R&D and promoting changes to regional policy. A report published in 2016 by international law firm, Norton Rose Fulbright states that the regulatory gaps/uncertainties concerning automated/autonomous driving in the current regulatory framework in Germany have been identified by the German government and are likely to be closed in due time.

## CHINA

With over 700 million smartphone users, internet use by 65% of its population of 1.4 billion, and a young population, China is positioned for unprecedented AI growth.

Foreseeing AI's potential, the Chinese government has invested \$15 billion over the last three years and entered into partnerships with tech-giants Baidu, Tencent, and iFlyTek, a state-owned software enterprise dedicated to the research of intelligent speech and language technologies, development of software and chip products, provision of speech information services, and integration of E-government systems.

The Chinese State Council launched "A New Generation of Artificial Intelligence Development Plan" last July, which laid out a policy roadmap to global AI leadership in 2030. The plan outlined a first-mover approach. Targets included: (1) continued long-term investment in AI R&D, (2) public/private sector collaboration, and (3) an ongoing evaluation of ethical and legal uncertainties.

According to the McKinsey Global Institute, AI could add 0.8 to 1.4 percentage points to GDP growth annually, depending on the speed of adoption. However, China's existing data-protectionist and state-centralized regulatory climate could set the tone for slower growth and invasive AI use irrespective of the new AI development plan.

## US

In late 2016, the Obama Administration released two reports by the National Science and Technology Council outlining the US' comprehensive plans for AI. The *National Artificial Intelligence Research and Development Strategic Plan* posed the following questions:

- What are the important scientific and technological gaps in current AI technologies?
- How can AI technologies be used safely, ethically, and legally?
- What are the right priorities and timeframes for federal investments into AI?

- Are there opportunities for industrial and international R&D collaborations that advance U.S. priorities?
- Among others...

Over the last 25 years, the U.S. has made significant progress in AI R&D because of steady long-term investment and general interest; however, as the report shows, there are serious gaps in the types of AI technology being developed. The report categorizes these as “general” and “narrow” AI. General AI would be considered a technology with transformative, disruptive potential in a variety of industries, whereas narrow AI would only be influential in a single industry or subindustry. The U.S. has disproportionately invested in, researched, and developed narrow AI, which arguably do not have as much potential for long-term impact as general AI.

Furthermore, the enactment of President Donald Trump’s budget increased military spending, while decreasing spending on “intelligent systems” R&D by roughly \$175 million, demonstrating a reduction in willingness to abide by the strategy proposed by President Obama.

Currently the U.S. ranks second behind the UK, and ahead of AI heavyweights, Canada, Korea, Japan, and Germany on Oxford Insight’s *Government AI Readiness Index*. Both the U.S. and the UK share the same difficulty in continuing to uphold a level of investment that competes with the likes of China or Russia, however, because the U.S. shares the Silicon Valley AI R&D bubble with Baidu and other foreign AI government stakeholders, the U.S. faces a challenge of keeping up with innovation and narrowing the gap between the left-leaning west coast and the right-leaning middle America that elected Trump in 2016.

Although, Silicon Valley serves as an example of the decentralized, international, cooperative, yet competitive ecosystem that AI needs to grow internationally.

As you may recognize, the leaders in AI innovation share common challenges, which are:

1. The regulatory frameworks obstructing government access to private information;
2. Access to private sources of data; and
3. Willingness of governments to deploy risk capital for R&D on general AI solutions.

But similarities do also exist in the goals that governments both leading and emerging in the AI industry should consider. They are:

1. Openness to public-private partnerships,
2. Accelerated capital investment into both public and private research,
3. Active public entities devoted exclusively to AI R&D,
4. Goals to develop general AI solutions, and

5. Access to essential population data in large quantities.

Ultimately, AI development presents an extraordinary opportunity to transform governments and societies around the world. It is now up to governments to accelerate their willingness to take advantage of the AI revolution and private companies to work for the long-term benefit of society.

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## HOW ARE AI, BIG DATA AND OTHER LEARNING TECHNOLOGIES IMPACTING EDUCATION LANDSCAPE?

RYOSUKE KOBAYASHI

Founder & Executive Director, HLAB, Tokyo  
David Rockefeller Fellow, Trilateral Commission  
koba@h-lab.co

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This discussion paper is prepared to explore how AI, Big Data and other digital technologies are impacting the field of education.

Given the recent development of AI and job automation, there is a heated debate on what competencies students need to develop to prepare for their professional career. According to “[The Future of Jobs Report](#)” issued by the World Economic Forum in 2016, “65 percent of children entering primary school today will ultimately end up working in completely new job types that don’t exist yet.” Equally important question in education sphere, if not more, is how the digital ecosystem and new learning technologies are impacting the ways of teaching and learning both in and outside of classrooms.

### GROWING INVESTMENT AND BOOM OF EDTECH

The landscape of education is changing at a faster pace than ever before. The innovation is largely driven by technology companies that apply AI, big data, and other technologies to learning environment, coalesced to form an emerging sector called EdTech.

Unlike most other technology sectors, the growth of EdTech sector has been accelerated by funding floating in not only from venture capital but also from public sectors and foundations, such as the Bill and Melinda Gates Foundation. In 2017, investments made to learning technology companies reached over \$9.5 billion, up 30% from 2016, which set the previous record for EdTech funding at \$7.3 billion.<sup>44</sup> As software turns tablets and computers into essential and powerful classroom tools and more educational institutions and teachers adapt new technologies to alter their teaching methods, EdTech innovation is expected to accelerate in the future years.

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<sup>44</sup> Mattaari <http://www.metaari.com/whitepapers.html>

## CURRENT AND POTENTIAL APPLICATION OF AI AND DATA TECHNOLOGIES IN EDUCATION

### 1. MOOCS AND ONLINE LEARNING TECHNOLOGIES

Many of the world's leading universities now embrace Massively Open Online Courses (MOOCs), online education platforms aimed at unlimited participation and open access to their courses via web. While the cost of college tuition has skyrocketed in recent years, those platforms drastically reduced the marginal cost of teaching, enabling students of all background to take courses at a low price or even free of charge.

In 2012, Stanford machine learning expert Andrew Ng founded *Coursera* and Harvard and MIT co-founded *edX*. Those platforms enabled students across the globe access growing number of course contents from global leading universities. Platforms such as *Khan Academy* are rather geared toward K-12 education; while others such as *Udacity* offer vocational trainings for professionals.

The popularity of MOOCs has made a high volume of learner data available for analytic purposes. In addition to conventionally available data such as socioeconomic and demographic background, enrollment information, assessment scores and grades, MOOCs collect behavioral data of classroom activities at the level of details that was never possible in classroom settings. They record every action of users through their inputs: from answer selections and typed solutions, to mouse clicks, video player use, and how long a particular action has taken. Course providers utilize those collected big data to constantly refine curriculum and its delivery methods.

Even for discussion-based classes, academic-oriented conference call technologies enabled teachers to monitor the student's level of concentration and engagement in discussions in real time by tracking the movement of the students' eyes. While learning experiences in online settings are becoming increasingly optimized and similar in quality to those of face-to-face settings, they also provide a strong tool for educators to develop better educational materials and improve on teaching pedagogies.

### 2. ADAPTIVE LEARNING TECHNOLOGIES FOR EFFECTIVE, PERSONALIZED LEARNINGS.

Emerging technologies are driving the future of education toward self-paced, personalized, adaptive learning. Although individualized learning and having a small-size classroom has been believed to benefit students, this has not been a viable solution until recent. With limited time and resources, one teacher cannot possibly look after 30 or more students and provide personalized curriculum for each one of them. A recent research implies that, from an individual's perspective, the vast majority of time in traditional classroom settings is spent on topics that are too easy that one already knows, or too advanced that one cannot follow.

Adaptive learning technologies removed such limitation of traditional classrooms by creating a completely customized learning path for different individuals through data analytics and machine learning technologies. Adaptive learning systems use audience segmentation to

engage learners in different mastery level, and provide contents and problems whose difficulty level match the learner's capabilities. Those tools can understand and highlight key areas where learners are struggling, and focus on those particular areas until they master the topic. The assessment tools provide a feedback effect based on one's performance and constantly update the already tailor-made curriculum and problem sets, thereby accelerating the speed of one's mastery of particular subject.

### 3. AUTOMATING ADMINISTRATIVE TASKS OF EDUCATORS

Most digital learning technologies are meant to support teachers rather than replace them. AI is automating and expediting many of educator's routine academic and administrative tasks, such as grading homework and tests that take up a significant portion of their time. While grading for multiple choice or fill-in-the-blank type questions are already relatively easy tasks of AI, the quality of more complex essay grading is improving as the development of natural language processing technologies matures. Those technologies allow teachers to spend more time on their essential work, such as developing curriculum and spending more time with students.

### 4. ADAPTATION AT SCHOOL --- FUSION OF DIGITAL AND RESIDENTIAL LEARNINGS

How are these new technologies shifting the role of conventional educational institutions? Continuing development of learning technologies do not necessarily mean that they replace the role of current schools or classroom activities, but rather alter them in a way that fits the diverse need of learners.

One trend is the increasing importance of fusion of analog and digital learnings. Counterintuitively, more top-tier schools in recent years have started emphasizing the importance of residential settings as a critical component of their education. For example, Harvard issued a white paper on digital in residential learnings in 2015, in which Provost Garber stated its pursuit of combining recent development in educational technologies with long-standing residential house systems. Harvard College changed its mission statement to "provide diverse living environment" where students live with people who are studying different topics, who come from different walks of life and have evolving identities.

The school has made a number of new attempts on campus since, such as introducing so-called "flipped classroom" methods where students are expected to work on lectures and homework on MOOCs before coming into classroom for discussions; and renovating all 12 undergraduate houses to design spaces in a way that diverse students meet and engage in conversations in dining halls and other communal space in daily life.

Minerva Schools at KGI, founded by San Francisco-based technology startup and now one of the most competitive undergraduate programs in U.S., is another example of how the style of schooling can be diversified with learning technologies. Minerva crafted a curriculum where students participate through online discussions using its own technologies, freeing its students from physical campuses where professors and their family resides. Consequently,

students travel together to seven different cities and stay for a semester each, immersing themselves in local cultures and customs with real-life experience while completing its curriculum in online settings.

The potential impact of AI and other learning technologies in the field of education is quite significant. However, the innovation in education is about fundamentally changing the way students learn, and those technologies need to be effectively adopted by educators and schools in a way that they both benefit learners and educators --- teachers, faculty members, students, parents and community members alike. Because of those people dynamics, the effective adaptation of AI and related technologies in education may take longer than it did for other sectors such as finance.

# PROJECTED CHANGES IN GLOBAL FOOD AND AGRICULTURE DEMAND, AND THE OPPORTUNITIES IN AI/TECHNOLOGY

YUITO YAMADA

Partner, McKinsey & Company, Tokyo  
David Rockefeller Fellow, Trilateral Commission  
yuito\_yamada@mckinsey.com

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## 1. OUTLOOK ON GLOBAL FOODSTUFF SUPPLY AND DEMAND MACRO TRENDS

The world's population is expected to continue increasing, surpassing eight billion people in 2030. This is a gain of at least one billion over 2009 figures. That quantitative growth in and of itself exerts great influence on food supply and demand, but there are also qualitative changes in play. As standards of living increase, per capita calorie intake will also grow, primarily among the affluent. Meat consumption in 2030 will be 70% greater than that of 2009. For the four most-produced crops by volume – corn, wheat, rice, and soybeans – quantitative and qualitative changes are expected to exert such an influence that demand will jump from 40 percent to 50 percent between 2010 and 2030.

Whether the downturn and decrease in productivity will recover is uncertain, due to a global lack of natural resources. 20 percent of the world's arable land has already deteriorated to the point where it is unfit for agriculture, and a shortfall of 27 percent in water resources is likely by 2025.

Factors driving this decline include land deterioration and difficulty in securing farmland, depletion of water resources, and emission of greenhouse gases. These phenomena are attributable in part to intensive agriculture.

For these reasons, new agricultural approaches and ideas are taking the burden imposed on the environment into account. These include new land-use models (e.g. no-till farming, agrosilvopastoral systems), and even models not contingent on the use of arable land.

In response to these megatrends, major players in seeds and agricultural chemicals, such as Monsanto and Syngenta, are working to improve food and agriculture productivity, taking particular note of farm management and other disciplines through the use of data management and software. A major example of this is the Big data/AI Company bought by Monsanto, for USD 930 Mn – this was for Climate Corporation, a large Ag/Big Data solution company.

## 2. SHARP RISES IN FOOD PRICES CAUSED BY THE SUPPLY-DEMAND RELATIONSHIP

The result of expanding food demand and stagnating production globally is a sharp rise in food prices. Even if we only look at data from 1990 onward, we see that food prices hit peaks in 2007-2008 and in 2011, falling into situations that could be called food crises. If we set our 100 index level for food prices at the 2002-2004 levels, we see that these two peaks surpassed 200. As of this writing, though food prices are trending down against the most recent peak, we do expect a recurrence, with additional price hikes over the longer term.

These sharp price increases are translating to an increasing number of people who are unable to secure enough food. In 2007-2008, the number of people without sufficient nutrition worldwide grew to over one billion people. Though the population of those in starvation conditions trended downward until 2000 due to higher productivity and lower foodstuff prices, sharp rises in food prices from 2000 to 2009 precipitated an increase in the number of starving people by 150 million worldwide.

## 3. DEMAND FOR FOOD QUALITY

In addition to the quantitative examination of demand provided above, we also need to explore qualitative demand, and important changes resulting from changes to dietary habits, which are also affecting the agricultural sector worldwide.

Bluntly put, the traditional consumption model of purchasing produce and cooking it at home with the family is vanishing from advanced economies. As a result, the main buyers of agricultural produce have changed from “families” to “eateries, chefs, and processors”

Along with changes in dietary habits, we also need to consider quality and nutritional aspects. Today’s emphasis on agricultural productivity and yield has likely decreased the quality of each individual lot of produce. Analysis of nutritional value for 43 crops reveals that nutritional content has declined almost universally from 1950 to 1999. Iron content in cucumbers, for instance, has fallen by as much as 75 percent, while calcium in tomatoes and vitamin B2 in lettuce have both dropped below half of their original level.

This result is starkly incongruous with the rapid rise in health consciousness among consumers, and suggests a likely uptick in demand for higher quality in agricultural produce.

## 4. OPPORTUNITIES TO HARNESS THE POTENTIAL OF “AGTECH/AI DIGITALIZATION” IMPACT

The huge impact and potential of AgTech/AI, a field that could have as much potential as FinTech. Worldwide, we are seeing increased investment in this field. Research indicates that investment by venture firms into the foodstuff and agricultural field has grown to USD 4.6 billion, or five times the USD 900 million in investments from 2013.

The question of how to utilize solutions derived from AgTech/AI and the data collected thereof is a broad one just for the production location itself. Combining weather, soil, and

other data with past data, farm operation knowledge, and graphical data showing the condition of the farmland can help support decision-making with respect to sowing seeds, distributing agricultural chemicals, and applying fertilizer. The chemical companies including Monsanto, etc. are starting to offer further various solutions to companies these days.

If we look across the entire value chain, we see that there are a great deal of opportunities, not only those at the production site, where AgTech solutions and data can be leveraged.

One example in this area is the AutoTrac system, which automatically drives tractors across optimal routes. This system was developed by Deere, the world's largest agricultural equipment manufacturer. When utilizing the Farmsight IT system, also by Deere, inserting information such as the yield for the producer's fields allows them to build simulations on rates of fertilizer application and seed planting – that is, where to apply how much fertilizer, and whether seeds should be planted. Combining technologies such as AutoTrac and Farmsight can drive an optimal cultivation environment, with tractors automatically driving across a plotted route, applying fertilizer, and planting seeds at the recommended rate.

One other interesting company case study is Zymergen – an AI/fermentation company that utilizes big data/AI to understand how the microbes in the fermentation process can significantly increase productivity. These interesting technologies have started to emerge in the area of agriculture and food too.

With these opportunities taken, we seek a huge opportunity especially in the region – especially in Asia. Due to the rising demand especially on the mid-class consumer front, we predict that agriculture production levels need to rise significantly in the region/Asia, and therefore we hopefully see these discussions go on in the trilateral session's breakout groups on the need for food production improvement, especially leveraging the technologies above.