

SECTION I: WHAT IS ARTIFICIAL INTELLIGENCE?

An accurate and sophisticated picture of AI—one that competes with its popular portrayal—is hampered by the difficulty of pinning down a precise definition of artificial intelligence.

This section describes how researchers and practitioners define “Artificial Intelligence,” and the areas of AI research and application that are currently thriving. It proffers definitions of what AI is and is not, and describes some of the currently “hot” areas of AI Research. This section lays the groundwork for Section II, which elaborates on AI’s impacts and future in eight domains and Section III, which describes issues related to AI design and public policy and makes recommendations for encouraging AI innovation while protecting democratic values.

DEFINING AI

Curiously, the lack of a precise, universally accepted definition of AI probably has helped the field to grow, blossom, and advance at an ever-accelerating pace. Practitioners, researchers, and developers of AI are instead guided by a rough sense of direction and an imperative to “get on with it.” Still, a definition remains important and Nils J. Nilsson has provided a useful one:

“Artificial intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment.”³

From this perspective, characterizing AI depends on the credit one is willing to give synthesized software and hardware for functioning “appropriately” and with “foresight.” A simple electronic calculator performs calculations much faster than the human brain, and almost never makes a mistake.⁴ Is a calculator intelligent? Like Nilsson, the Study Panel takes a broad view that intelligence lies on a multi-dimensional spectrum. According to this view, the difference between an arithmetic calculator and a human brain is not one of kind, but of scale, speed, degree of autonomy, and generality. The same factors can be used to evaluate every other instance of intelligence—speech recognition software, animal brains, cruise-control systems in cars, Go-playing programs, thermostats—and to place them at some appropriate location in the spectrum.

Although our broad interpretation places the calculator within the intelligence spectrum, such simple devices bear little resemblance to today’s AI. The frontier of AI has moved far ahead and functions of the calculator are only one among the millions that today’s smartphones can perform. AI developers now work on improving, generalizing, and scaling up the intelligence currently found on smartphones.

In fact, the field of AI is a continual endeavor to push forward the frontier of machine intelligence. Ironically, AI suffers the perennial fate of losing claim to its acquisitions, which eventually and inevitably get pulled inside the frontier, a repeating pattern known as the “AI effect” or the “odd paradox”—AI brings a new technology into the common fold, people become accustomed to this technology, it stops being considered AI, and newer technology emerges.⁵ The same pattern will continue in the future. AI does not “deliver” a life-changing product as a bolt from the blue. Rather, AI technologies continue to get better in a continual, incremental way.

³ Nils J. Nilsson, *The Quest for Artificial Intelligence: A History of Ideas and Achievements* (Cambridge, UK: Cambridge University Press, 2010).

⁴ Wikimedia Images, accessed August 1, 2016, https://upload.wikimedia.org/wikipedia/commons/b/b6/SHARP_ELSIMATE_EL-W221.jpg.

⁵ Pamela McCorduck, *Machines Who Think: A Personal Inquiry into the History and Prospects of Artificial Intelligence*, 2nd ed. (Natick, MA: A. K. Peters, Ltd., 2004; San Francisco: W. H. Freeman, 1979), Citations are to the Peters edition.

The human measure

Notably, the characterization of intelligence as a spectrum grants no special status to the human brain. But to date human intelligence has no match in the biological and artificial worlds for sheer versatility, with the abilities “to reason, achieve goals, understand and generate language, perceive and respond to sensory inputs, prove mathematical theorems, play challenging games, synthesize and summarize information, create art and music, and even write histories.”⁶

This makes human intelligence a natural choice for benchmarking the progress of AI. It may even be proposed, as a rule of thumb, that any activity computers are able to perform and people once performed should be counted as an instance of intelligence. But matching any human ability is only a sufficient condition, not a necessary one. There are already many systems that exceed human intelligence, at least in speed, such as scheduling the daily arrivals and departures of thousands of flights in an airport.

AI’s long quest—and eventual success—to beat human players at the game of chess offered a high-profile instance for comparing human to machine intelligence. Chess has fascinated people for centuries. When the possibility of building computers became imminent, Alan Turing, who many consider the father of computer science, “mentioned the idea of computers showing intelligence with chess as a paradigm.”⁷ Without access to powerful computers, “Turing played a game in which he simulated the computer, taking about half an hour per move.”

But it was only after a long line of improvements in the sixties and seventies—contributed by groups at Carnegie Mellon, Stanford, MIT, The Institute for Theoretical and Experimental Physics at Moscow, and Northwestern University—that chess-playing programs started gaining proficiency. The final push came through a long-running project at IBM, which culminated with the Deep Blue program beating Garry Kasparov, then the world chess champion, by a score of 3.5–2.5 in 1997. Curiously, no sooner had AI caught up with its elusive target than Deep Blue was portrayed as a collection of “brute force methods” that wasn’t “real intelligence.”⁸ In fact, IBM’s subsequent publication about Deep Blue, which gives extensive details about its search and evaluation procedures, doesn’t mention the word “intelligent” even once!⁹ Was Deep Blue intelligent or not? Once again, the frontier had moved.

An operational definition

AI can also be defined by what AI researchers do. This report views AI primarily as a branch of computer science that studies the properties of intelligence by synthesizing intelligence.¹⁰ Though the advent of AI has depended on the rapid progress of hardware computing resources, the focus here on software reflects a trend in the AI community. More recently, though, progress in building hardware tailored for neural-network-based computing¹¹ has created a

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6 Nilsson, *The Quest for Artificial Intelligence*.

7 Nilsson, *The Quest for Artificial Intelligence*, 89.

8 McCorduck, *Machines Who Think*, 433.

9 Murray Campbell, A. Joseph Hoane Jr., and Feng-hsiung Hsu, “Deep Blue,” *Artificial Intelligence* 134, nos. 1 and 2 (2002): 57–83.

10 Herbert A. Simon, “Artificial Intelligence: An Empirical Science,” *Artificial Intelligence* 77, no. 2 (1995): 95–127.

11 Paul Merolla, John V. Arthur, Rodrigo Alvarez-Icaza, Andrew S. Cassidy, Jun Sawada, Filipp Akopyan, Bryan L. Jackson, Nabil Imam, Chen Guo, Yutaka Nakamura, Bernard Brezzo, Ivan Vo, Steven K. Esser, Rathinakumar Appuswamy, Brian Taba, Arnon Amir, Myron D. Flickner, William P. Risk, Rajit Manohar, and Dharmendra S. Modha, “A Million Spiking-Neuron Integrated Circuit with a Scalable Communication Network and Interface,” accessed August 1, 2016, http://paulmerolla.com/merolla_main_som.pdf.

tighter coupling between hardware and software in advancing AI.

“Intelligence” remains a complex phenomenon whose varied aspects have attracted the attention of several different fields of study, including psychology, economics, neuroscience, biology, engineering, statistics, and linguistics. Naturally, the field of AI has benefited from the progress made by all of these allied fields. For example, the artificial neural network, which has been at the heart of several AI-based solutions^{12 13} was originally inspired by thoughts about the flow of information in biological neurons.¹⁴

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AI RESEARCH TRENDS

Until the turn of the millennium, AI’s appeal lay largely in its promise to deliver, but in the last fifteen years, much of that promise has been redeemed.¹⁵ AI technologies already pervade our lives. As they become a central force in society, the field is shifting from simply building systems that are intelligent to building intelligent systems that are human-aware and trustworthy.

Several factors have fueled the AI revolution. Foremost among them is the maturing of machine learning, supported in part by cloud computing resources and wide-spread, web-based data gathering. Machine learning has been propelled dramatically forward by “deep learning,” a form of adaptive artificial neural networks trained using a method called backpropagation.¹⁶ This leap in the performance of information processing algorithms has been accompanied by significant progress in hardware technology for basic operations such as sensing, perception, and object recognition. New platforms and markets for data-driven products, and the economic incentives to find new products and markets, have also contributed to the advent of AI-driven technology.

All these trends drive the “hot” areas of research described below. This compilation is meant simply to reflect the areas that, by one metric or another, currently receive greater attention than others. They are not necessarily more important or valuable than other ones. Indeed, some of the currently “hot” areas were less popular in past years, and it is likely that other areas will similarly re-emerge in the future.

Large-scale machine learning

Many of the basic problems in machine learning (such as supervised and unsupervised learning) are well-understood. A major focus of current efforts is to scale existing algorithms to work with extremely large data sets. For example, whereas traditional methods could afford to make several passes over the data set, modern ones are designed to make only a single pass; in some cases, only sublinear methods (those that only look at a fraction of the data) can be admitted.

Deep learning

The ability to successfully train convolutional neural networks has most benefited the field of computer vision, with applications such as object recognition, video

12 Gerald Tesauro, “Practical Issues in Temporal Difference Learning,” *Machine Learning*, no. 8 (1992): 257–77.

13 David Silver, Aja Huang, Chris J. Maddison, Arthur Guez, Laurent Sifre, George van den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, Sander Dieleman, Dominik Grewe, John Nham, Nal Kalchbrenner, Ilya Sutskever, Timothy Lillicrap, Madeleine Leach, Koray Kavukcuoglu, Thore Graepel, and Demis Hassabis, “Mastering the game of Go with deep neural networks and tree search,” *Nature* 529 (2016): 484–489.

14 W. McCulloch and W. Pitts, W., “A logical calculus of the ideas immanent in nervous activity,” *Bulletin of Mathematical Biophysics*, 5 (1943): 115–133.

15 Appendix I offers a short history of AI, including a description of some of the traditionally core areas of research, which have shifted over the past six decades.

16 Backpropagation is an abbreviation for “backward propagation of errors,” a common method of training artificial neural networks used in conjunction with an optimization method such as gradient descent. The method calculates the gradient of a loss function with respect to all the weights in the network.

labeling, activity recognition, and several variants thereof. Deep learning is also making significant inroads into other areas of perception, such as audio, speech, and natural language processing.

Reinforcement learning

Whereas traditional machine learning has mostly focused on pattern mining, reinforcement learning shifts the focus to decision making, and is a technology that will help AI to advance more deeply into the realm of learning about and executing actions in the real world. It has existed for several decades as a framework for experience-driven sequential decision-making, but the methods have not found great success in practice, mainly owing to issues of representation and scaling. However, the advent of deep learning has provided reinforcement learning with a “shot in the arm.” The recent success of AlphaGo, a computer program developed by Google Deepmind that beat the human Go champion in a five-game match, was due in large part to reinforcement learning. AlphaGo was trained by initializing an automated agent with a human expert database, but was subsequently refined by playing a large number of games against itself and applying reinforcement learning.

Robotics

Robotic navigation, at least in static environments, is largely solved. Current efforts consider how to train a robot to interact with the world around it in generalizable and predictable ways. A natural requirement that arises in interactive environments is *manipulation*, another topic of current interest. The deep learning revolution is only beginning to influence robotics, in large part because it is far more difficult to acquire the large labeled data sets that have driven other learning-based areas of AI. Reinforcement learning (see above), which obviates the requirement of labeled data, may help bridge this gap but requires systems to be able to safely explore a policy space without committing errors that harm the system itself or others. Advances in reliable machine perception, including computer vision, force, and tactile perception, much of which will be driven by machine learning, will continue to be key enablers to advancing the capabilities of robotics.

Computer vision

Computer vision is currently the most prominent form of machine perception. It has been the sub-area of AI most transformed by the rise of deep learning. Until just a few years ago, support vector machines were the method of choice for most visual classification tasks. But the confluence of large-scale computing, especially on GPUs, the availability of large datasets, especially via the internet, and refinements of neural network algorithms has led to dramatic improvements in performance on benchmark tasks (e.g., classification on ImageNet¹⁷). For the first time, computers are able to perform some (narrowly defined) visual classification tasks better than people. Much current research is focused on automatic image and video captioning.

Natural Language Processing

Often coupled with automatic speech recognition, Natural Language Processing is another very active area of machine perception. It is quickly becoming a commodity for mainstream languages with large data sets. Google announced that 20% of current mobile queries are done by voice,¹⁸ and recent demonstrations have proven the possibility of real-time translation. Research is now shifting towards developing refined and capable systems that are able to interact with people through dialog, not just react to stylized requests.

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17 ImageNet, Stanford Vision Lab, Stanford University, Princeton University, 2016, accessed August 1, 2016, www.image-net.org/.

18 Greg Sterling, “Google says 20% of mobile queries are voice searches,” *Search Engine Land*, May 18, 2016, accessed August 1, 2016, <http://searchengineland.com/google-reveals-20-percent-queries-voice-queries-249917>.

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Collaborative systems

Research on collaborative systems investigates models and algorithms to help develop autonomous systems that can work collaboratively with other systems and with humans. This research relies on developing formal models of collaboration, and studies the capabilities needed for systems to become effective partners. There is growing interest in applications that can utilize the complementary strengths of humans and machines—for humans to help AI systems to overcome their limitations, and for agents to augment human abilities and activities.

Crowdsourcing and human computation

Since human abilities are superior to automated methods for accomplishing many tasks, research on crowdsourcing and human computation investigates methods to augment computer systems by utilizing human intelligence to solve problems that computers alone cannot solve well. Introduced only about fifteen years ago, this research now has an established presence in AI. The best-known example of crowdsourcing is Wikipedia, a knowledge repository that is maintained and updated by netizens and that far exceeds traditionally-compiled information sources, such as encyclopedias and dictionaries, in scale and depth. Crowdsourcing focuses on devising innovative ways to harness human intelligence. Citizen science platforms energize volunteers to solve scientific problems, while paid crowdsourcing platforms such as Amazon Mechanical Turk provide automated access to human intelligence on demand. Work in this area has facilitated advances in other subfields of AI, including computer vision and NLP, by enabling large amounts of labeled training data and/or human interaction data to be collected in a short amount of time. Current research efforts explore ideal divisions of tasks between humans and machines based on their differing capabilities and costs.

Algorithmic game theory and computational social choice

New attention is being drawn to the economic and social computing dimensions of AI, including incentive structures. Distributed AI and multi-agent systems have been studied since the early 1980s, gained prominence starting in the late 1990s, and were accelerated by the internet. A natural requirement is that systems handle potentially misaligned incentives, including self-interested human participants or firms, as well as automated AI-based agents representing them. Topics receiving attention include computational mechanism design (an economic theory of incentive design, seeking incentive-compatible systems where inputs are truthfully reported), computational social choice (a theory for how to aggregate rank orders on alternatives), incentive aligned information elicitation (prediction markets, scoring rules, peer prediction) and algorithmic game theory (the equilibria of markets, network games, and parlor games such as Poker—a game where significant advances have been made in recent years through abstraction techniques and no-regret learning).

Internet of Things (IoT)

A growing body of research is devoted to the idea that a wide array of devices can be interconnected to collect and share their sensory information. Such devices can include appliances, vehicles, buildings, cameras, and other things. While it's a matter of technology and wireless networking to connect the devices, AI can process and use the resulting huge amounts of data for intelligent and useful purposes. Currently, these devices use a bewildering array of incompatible communication protocols. AI could help tame this Tower of Babel.

Neuromorphic Computing

Traditional computers implement the von Neumann model of computing, which separates the modules for input/output, instruction-processing, and memory. With the success of deep neural networks on a wide array of tasks, manufacturers are

actively pursuing alternative models of computing—especially those that are inspired by what is known about biological neural networks—with the aim of improving the hardware efficiency and robustness of computing systems. At the moment, such “neuromorphic” computers have not yet clearly demonstrated big wins, and are just beginning to become commercially viable. But it is possible that they will become commonplace (even if only as additions to their von Neumann cousins) in the near future. Deep neural networks have already created a splash in the application landscape. A larger wave may hit when these networks can be trained and executed on dedicated neuromorphic hardware, as opposed to simulated on standard von Neumann architectures, as they are today.

Overall trends and the future of AI research

The resounding success of the data-driven paradigm has displaced the traditional paradigms of AI. Procedures such as theorem proving and logic-based knowledge representation and reasoning are receiving reduced attention, in part because of the ongoing challenge of connecting with real-world groundings. Planning, which was a mainstay of AI research in the seventies and eighties, has also received less attention of late due in part to its strong reliance on modeling assumptions that are hard to satisfy in realistic applications. Model-based approaches—such as physics-based approaches to vision and traditional control and mapping in robotics—have by and large given way to data-driven approaches that close the loop with sensing the results of actions in the task at hand. Bayesian reasoning and graphical models, which were very popular even quite recently, also appear to be going out of favor, having been drowned by the deluge of data and the remarkable success of deep learning.

Over the next fifteen years, the Study Panel expects an increasing focus on developing systems that are human-aware, meaning that they specifically model, and are specifically designed for, the characteristics of the people with whom they are meant to interact. There is a lot of interest in trying to find new, creative ways to develop interactive and scalable ways to teach robots. Also, IoT-type systems—devices and the cloud—are becoming increasingly popular, as is thinking about social and economic dimensions of AI. In the coming years, new perception/object recognition capabilities and robotic platforms that are human-safe will grow, as will data-driven products and their markets.

The Study Panel also expects a reemergence of some of the traditional forms of AI as practitioners come to realize the inevitable limitations of purely end-to-end deep learning approaches. We encourage young researchers not to reinvent the wheel, but rather to maintain an awareness of the significant progress in many areas of AI during the first fifty years of the field, and in related fields such as control theory, cognitive science, and psychology.

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SECTION II: AI BY DOMAIN

Though different instances of AI research and practice share common technologies, such as machine learning, they also vary considerably in different sectors of the economy and society. We call these sectors “domains,” and in this section describe the different states of AI research and implementation, as well as impacts and distinct challenges, in eight of them: transportation; home/service robotics; healthcare; education; low-resource communities; public safety and security; employment and workplace; and entertainment. Based on these analyses, we also predict trends in a typical North American city over the next fifteen years. Contrary to AI’s typical depiction in popular culture, we seek to offer a balanced overview of the ways in which AI is already beginning to transform everyday life, and how those transformations are likely to grow by the year 2030.

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TRANSPORTATION

Transportation is likely to be one of the first domains in which the general public will be asked to trust the reliability and safety of an AI system for a critical task. Autonomous transportation will soon be commonplace and, as most people’s first experience with physically embodied AI systems, will strongly influence the public’s perception of AI. Once the physical hardware is made sufficiently safe and robust, its introduction to daily life may happen so suddenly as to surprise the public, which will require time to adjust. As cars will become better drivers than people, city-dwellers will own fewer cars, live further from work, and spend time differently, leading to an entirely new urban organization. Further, in the typical North American city in 2030, changes won’t be limited to cars and trucks, but are likely to include flying vehicles and personal robots, and will raise social, ethical and policy issues.

A few key technologies have already catalyzed the widespread adoption of AI in transportation. Compared to 2000, the scale and diversity of data about personal and population-level transportation available today—enabled by the adoption of smartphones and decreased costs and improved accuracies for variety of sensors—is astounding. Without the availability of this data and connectivity, applications such as real-time sensing and prediction of traffic, route calculations, peer-to-peer ridesharing and self-driving cars would not be possible.

Smarter cars

GPS was introduced to personal vehicles in 2001 with in-car navigation devices and has since become a fundamental part of the transportation infrastructure.¹⁹ GPS assists drivers while providing large-scale information to technology companies and cities about transportation patterns. Widespread adoption of smartphones with GPS technology further increased connectivity and the amount of location data shared by individuals.

Current vehicles are also equipped with a wide range of sensing capabilities. An average automobile in the US is predicted to have seventy sensors including gyroscopes, accelerometers, ambient light sensors, and moisture sensors.²⁰ Sensors are not new to vehicles. Automobiles built before 2000 had sensors for the internal state of the vehicle such as its speed, acceleration, and wheel position.²¹

¹⁹ Mark Sullivan, “A brief history of GPS,” *PCWorld*, August 9, 2012, accessed August 1, 2016, <http://www.pcworld.com/article/2000276/a-brief-history-of-gps.html>.

²⁰ William J. Fleming, “New Automotive Sensors - A Review,” *IEEE Sensors Journal* 8, no 11, (2008): 1900-1921.

²¹ Jean Jacques Meneu, ed., “Automotive Sensors: Now and in the Future,” *Arrow*, September 24, 2015, accessed August 1, 2016, <https://www.arrow.com/en/research-and-events/articles/automotive-sensors-now-and-in-the-future>.

They already had a number of functionalities that combined real-time sensing with perception and decision-making such as Anti-lock Braking Systems (ABS), airbag control, Traction Control Systems (TCS), and Electronic Stability Control (ESC).²² Automated capabilities have been introduced into commercial cars gradually since 2003 as summarized in the following table.

Context	Automated Functionality	Release Date
Parking	Intelligent Parking Assist System	Since 2003 ²³
Parking	Summon	Since 2016 ²⁴
Arterial & Highway	Lane departure system	Since 2004 in North America ²⁵
Arterial & Highway	Adaptive cruise control	Since 2005 in North America ²⁶
Highway	Blind spot monitoring	2007 ²⁷
Highway	Lane changing	2015 ²⁸

These functionalities assist drivers or completely take over well-defined activities for increased safety and comfort. Current cars can park themselves, perform adaptive cruise control on highways, steer themselves during stop-and-go traffic, and alert drivers about objects in blind spots during lane changes. Vision and radar technology were leveraged to develop pre-collision systems that let cars autonomously brake when risk of a collision is detected. Deep learning also has been applied to improve automobiles' capacity to detect objects in the environment and recognize sound.²⁹

Self-driving vehicles

Since the 1930s, science fiction writers dreamed of a future with self-driving cars, and building them has been a challenge for the AI community since the 1960s. By the 2000s, the dream of autonomous vehicles became a reality in the sea and sky, and even on Mars, but self-driving cars existed only as research prototypes in labs. Driving in a city was considered to be a problem too complex for automation due to factors like pedestrians, heavy traffic, and the many unexpected events that can happen outside of the car's control. Although the technological components required to

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22 Carl Liersch, "Vehicle Technology Timeline: From Automated to Driverless," Robert Bosch (Australia) Pty. Ltd., 2014, accessed August 1, 2016, http://dpti.sa.gov.au/__data/assets/pdf_file/0009/246807/Carl_Liersch_Presentation.pdf.

23 "Intelligent Parking Assist System," *Wikipedia*, last modified July 26, 2016, accessed August 1, 2016, https://en.wikipedia.org/wiki/Intelligent_Parking_Assist_System.

24 The Tesla Motors Team, "Summon Your Tesla from Your Phone," Tesla, January 10, 2016, accessed August 1, 2016, <https://www.teslamotors.com/blog/summon-your-tesla-your-phone>.

25 "Lane departure warning system," *Wikipedia*, last modified July 24, 2016, accessed August 1, 2016, https://en.wikipedia.org/wiki/Lane_departure_warning_system.

26 "Autonomous cruise control system," *Wikipedia*, last modified July 30, 2016, accessed August 1, 2016, https://en.wikipedia.org/wiki/Autonomous_cruise_control_system.

27 "Blind spot monitor," *Wikipedia*, last modified April 20, 2016, accessed August 1, 2016, https://en.wikipedia.org/wiki/Blind_spot_monitor.

28 Dana Hull, "Tesla Starts Rolling Out Autopilot Features," *Bloomberg Technology*, October 14, 2015, accessed August 1, 2016, <http://www.bloomberg.com/news/articles/2015-10-14/tesla-software-upgrade-adds-automated-lane-changing-to-model-s>.

29 Aaron Tilley, "New Qualcomm Chip Brings Deep Learning To Cars," *Forbes*, January 5, 2016, accessed August 1, 2016, <http://www.forbes.com/sites/aarontilley/2016/01/05/along-with-nvidia-new-qualcomm-chip-brings-deep-learning-to-cars/#4cb4e9235357>.

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make such autonomous driving possible were available in 2000—and indeed some autonomous car prototypes existed^{30 31 32}—few predicted that mainstream companies would be developing and deploying autonomous cars by 2015. During the first Defense Advanced Research Projects Agency (DARPA) “grand challenge” on autonomous driving in 2004, research teams failed to complete the challenge in a limited desert setting.

But in eight short years, from 2004-2012, speedy and surprising progress occurred in both academia and industry. Advances in sensing technology and machine learning for perception tasks has sped progress and, as a result, Google’s autonomous vehicles and Tesla’s semi-autonomous cars are driving on city streets today. Google’s self-driving cars, which have logged more than 1,500,000 miles (300,000 miles without an accident),³³ are completely autonomous—no human input needed. Tesla has widely released self-driving capability to existing cars with a software update.³⁴ Their cars are semi-autonomous, with human drivers expected to stay engaged and take over if they detect a potential problem. It is not yet clear whether this semi-autonomous approach is sustainable, since as people become more confident in the cars’ capabilities, they are likely to pay less attention to the road, and become less reliable when they are most needed. The first traffic fatality involving an autonomous car, which occurred in June of 2016, brought this question into sharper focus.³⁵

In the near future, sensing algorithms will achieve super-human performance for capabilities required for driving. Automated perception, including vision, is already near or at human-level performance for well-defined tasks such as recognition and tracking. Advances in perception will be followed by algorithmic improvements in higher level reasoning capabilities such as planning. A recent report predicts self-driving cars to be widely adopted by 2020.³⁶ And the adoption of self-driving capabilities won’t be limited to personal transportation. We will see self-driving and remotely controlled delivery vehicles, flying vehicles, and trucks. Peer-to-peer transportation services such as ridesharing are also likely to utilize self-driving vehicles. Beyond self-driving cars, advances in robotics will facilitate the creation and adoption of other types of autonomous vehicles, including robots and drones.

It is not yet clear how much better self-driving cars need to become to encourage broad acceptance. The collaboration required in semi-self-driving cars and its implications for the cognitive load of human drivers is not well understood. But if future self-driving cars are adopted with the predicted speed, and they exceed human-level performance in driving, other significant societal changes will follow. Self-driving cars will eliminate one of the biggest causes of accidental death and injury in United States, and lengthen people’s life expectancy. On average, a

30 “Navlab,” *Wikipedia*, last updated June 4, 2016, accessed August 1, 2016, <https://en.wikipedia.org/wiki/Navlab>.

31 “Navlab: The Carnegie Mellon University Navigation Laboratory,” Carnegie Mellon University, accessed August 1, 2016, <http://www.cs.cmu.edu/afs/cs/project/alv/www/>.

32 “Eureka Prometheus Project,” *Wikipedia*, last modified February 12, 2016, accessed August 1, 2016, https://en.wikipedia.org/wiki/Eureka_Prometheus_Project.

33 “Google Self-Driving Car Project,” Google, accessed August 1, 2016, <https://www.google.com/selfdrivingcar/>. 33 Molly McHugh, “Tesla’s Cars Now Drive Themselves, Kinda,” *Wired*, October 14, 2015, accessed August 1, 2016, <http://www.wired.com/2015/10/tesla-self-driving-over-air-update-live/>.

34 Molly McHugh, “Tesla’s Cars Now Drive Themselves, Kinda,” *Wired*, October 14, 2015, accessed August 1, 2016, <http://www.wired.com/2015/10/tesla-self-driving-over-air-update-live/>.

35 Anjali Singhvi and Karl Russell, “Inside the Self-Driving Tesla Fatal Accident,” *The New York Times*, Last updated July 12, 2016, accessed August 1, 2016, <http://www.nytimes.com/interactive/2016/07/01/business/inside-tesla-accident.html>.

36 John Greenough, “10 million self-driving cars will be on the road by 2020,” *Business Insider*, June 15, 2016, accessed August 1, 2016, <http://www.businessinsider.com/report-10-million-self-driving-cars-will-be-on-the-road-by-2020-2015-5-6>.

commuter in US spends twenty-five minutes driving each way.³⁷ With self-driving car technology, people will have more time to work or entertain themselves during their commutes. And the increased comfort and decreased cognitive load with self-driving cars and shared transportation may affect where people choose to live. The reduced need for parking may affect the way cities and public spaces are designed. Self-driving cars may also serve to increase the freedom and mobility of different subgroups of the population, including youth, elderly and disabled.

Self-driving cars and peer-to-peer transportation services may eliminate the need to own a vehicle. The effect on total car use is hard to predict. Trips of empty vehicles and people's increased willingness to travel may lead to more total miles driven. Alternatively, shared autonomous vehicles—people using cars as a service rather than owning their own—may reduce total miles, especially if combined with well-constructed incentives, such as tolls or discounts, to spread out travel demand, share trips, and reduce congestion. The availability of shared transportation may displace the need for public transportation—or public transportation may change form towards personal rapid transit, already available in four cities,³⁸ which uses small capacity vehicles to transport people on demand and point-to-point between many stations.³⁹

As autonomous vehicles become more widespread, questions will arise over their security, including how to ensure that technologies are safe and properly tested under different road conditions prior to their release. Autonomous vehicles and the connected transportation infrastructure will create a new venue for hackers to exploit vulnerabilities to attack. Ethical questions are also involved in programming cars to act in situations in which human injury or death is inevitable, especially when there are split-second choices to be made about whom to put at risk. The legal systems in most states in the US do not have rules covering self-driving cars. As of 2016, four states in the US (Nevada, Florida, California, and Michigan), Ontario in Canada, the United Kingdom, France, and Switzerland have passed rules for the testing of self-driving cars on public roads. Even these laws do not address issues about responsibility and assignment of blame for an accident for self-driving and semi-self-driving cars.⁴⁰

Transportation planning

By 2005, cities had started investing in the transportation infrastructure to develop sensing capabilities for vehicle and pedestrian traffic.⁴¹ The sensors currently used include inductive loops, video cameras, remote traffic microwave sensors, radars, and GPS.⁴² For example, in 2013 New York started using a combination of microwave sensors, a network of cameras, and pass readers to detect vehicle traffic in the city.⁴³

37 Brian McKenzie and Melanie Rapino, "Commuting in the United States: 2009," *American Community Survey Reports*, United States Census Bureau, September 2011, accessed August 1, 2016, <https://www.census.gov/prod/2011pubs/acs-15.pdf>.

38 Morgantown, West Virginia; Masdar City, UAE; London, England; and Suncheon, South Korea.

39 "Personal rapid transit," *Wikipedia*, Last modified July 18, 2016, accessed August 1, 2016, https://en.wikipedia.org/wiki/Personal_rapid_transit.

40 Patrick Lin, "The Ethics of Autonomous Cars," *The Atlantic*, October 8, 2013, accessed August 1, 2016, <http://www.theatlantic.com/technology/archive/2013/10/the-ethics-of-autonomous-cars/280360/>.

41 Steve Lohr, "Bringing Efficiency to the Infrastructure," *The New York Times*, April 29, 2009, accessed August 1, 2016, <http://www.nytimes.com/2009/04/30/business/energy-environment/30smart.html>.

42 "Intelligent transportation system," *Wikipedia*, last modified July 28, 2016, accessed August 1, 2016, https://en.wikipedia.org/wiki/Intelligent_transportation_system.

43 Access Science Editors, "Active traffic management: adaptive traffic signal control," *Access Science*, 2014, accessed August 1, 2016, <http://www.accessscience.com/content/active-traffic-management-adaptive-traffic-signal-control/BR0106141>.

Shared transportation

**may displace the need for
public transportation—
or public transportation
may change form towards
personal rapid transit
that uses small capacity
vehicles to transport
people on demand.**

Ethical questions arise when programming cars to act in situations in which human injury or death is inevitable, especially when there are split-second choices to be made about whom to put at risk.

Cities use AI methods to optimize services in several ways, such as bus and subway schedules, and tracking traffic conditions to dynamically adjust speed limits or apply smart pricing on highways, bridges, and HOV lanes.⁴⁴⁴⁵⁴⁶ Using sensors and cameras in the road network, they can also optimize traffic light timing for improving traffic flow and to help with automated enforcement.⁴⁷⁴⁸ These dynamic strategies are aimed at better utilizing the limited resources in the transportation network, and are made possible by the availability of data and the widespread connectivity of individuals.

Before the 2000s, transportation planners were forced to rely on static pricing strategies tied to particular days or times of day, to manage demand. As dynamic pricing strategies are adopted, this raises new issues concerning the fair distribution of public goods, since market conditions in high-demand situations may make services unavailable to segments of the public.

The availability of large-scale data has also made transportation an ideal domain for machine learning applications. Since 2006, applications such as Mapquest, Google Maps, and Bing Maps have been widely used by the public for routing trips, using public transportation, receiving real-time information and predictions about traffic conditions,⁴⁹⁵⁰ and finding services around a location.⁵¹⁵² Optimal search algorithms have been applied to the routing of vehicles and pedestrians to a given destination (i.e.,⁵³⁵⁴).

Despite these advances, the widespread application of sensing and optimization techniques to city infrastructure has been slower than the application of these techniques to individual vehicles or people. Although individual cities have implemented sensing and optimization applications, as yet there is no standardization of the sensing infrastructure and AI techniques used. Infrastructure costs, differing priorities among cities, and the high coordination costs among the parties involved have slowed adoption, as have public concerns over privacy related to sensing. Still,

44 Kitae Jang, Koohong Chung, and Hwasoo Yeo, "A Dynamic Pricing Strategy for High Occupancy Toll Lanes," *Transportation Research Part A: Policy and Practice* 67 (2014): 69–80.

45 "Seattle Variable Tolling Study," City of Seattle Department of Transportation, May 2009, accessed August 1, 2016, <http://www.seattle.gov/transportation/docs/FINAL%20Tolling%20Study%20report%20revised%206.25.10.pdf>.

46 James F. Peltz, "Dynamic Pricing Is Catching On in the Public and Private Sectors," *Government Technology*, March 21, 2016, accessed August 1, 2016, <http://www.govtech.com/budget-finance/Dynamic-Pricing-Is-Catching-On-in-the-Public-and-Private-Sectors.html>.

47 Arthur G Sims and Kenneth W. Dobinson. "The Sydney Coordinated Adaptive Traffic (SCAT) System Philosophy and Benefits." *IEEE Transactions on Vehicular Technology* 29, no. 2 (1980): 130–137.

48 "New York City Launches Nation's Most Sophisticated Active Traffic Management System Powered by TransCore's TransSuite Traffic Management Software and RFID Technology," *Business Wire*, September 27, 2009, accessed August 1, 2016, <http://www.businesswire.com/news/home/20110927005530/en/York-City-Launches-Nation%20%80%99s-Sophisticated-Active-Traffic>.

49 Eric Horvitz, Johnson Apacible, Raman Sarin, and Lin Liao, "Prediction, Expectation, and Surprise: Methods, Designs, and Study of a Deployed Traffic Forecasting Service," *Proceedings of the Twenty-First Conference on Uncertainty and Artificial Intelligence* (2005) (Arlington, Virginia: AUAI Press, July 2005), 275–283.

50 Timothy Hunter, Ryan Herring, Pieter Abbeel, and Alexandre Bayen, "Path and Travel Time Inference from GPS Probe Vehicle Data," *MPS Analyzing Networks and Learning with Graphs* 12, no. 1 (2009).

51 John Krumm and Eric Horvitz, "Predestination: Inferring Destinations from Partial Trajectories," *UbiComp 2006: Ubiquitous Computing, Proceedings of the 8th International Conference*, September 2006, (Springer Berlin, Heidelberg, 2006), 243–260.

52 Jill Duffy, "Get Organized: Using Location-Based Reminders," *PC Magazine*, June 30, 2014, accessed August 1, 2016, <http://www.pcmag.com/article2/0,2817,2460207,00.asp>.

53 Robert J. Szczerba, Peggy Galkowski, I. S. Glickstein, and Noah Ternullo. "Robust Algorithm for Real-time Route Planning," *IEEE Transactions on Aerospace and Electronic Systems* 36, no. 3 (2000): 869–878.

54 Matt Duckham and Lars Kulik, "Simplest" Paths: Automated Route Selection for Navigation," *Spatial Information Theory. Foundations of Geographic Information Science, Proceedings of the International Conference, COSIT 2003*, September 2003 (Springer-Verlag Berlin Heidelberg, 2003), 169–185.

AI is likely to have an increasing impact on city infrastructure. Accurate predictive models of individuals' movements, their preferences, and their goals are likely to emerge with the greater availability of data. The ethical issues regarding such an emergence are discussed in Section III of this report.

The United States Department of Transportation released a call for proposals in 2016 asking medium-size cities to imagine smart city infrastructure for transportation.⁵⁵ This initiative plans to award forty million dollars to a city to demonstrate how technology and data can be used to reimagine the movement of people as well as goods.

One vision is a network of connected vehicles that can reach a high level of safety in driving with car-to-car communication.⁵⁶ If this vision becomes reality, we expect advances in multi-agent coordination, collaboration, and planning will have a significant impact on future cars and play a role in making the transportation system more reliable and efficient. Robots are also likely to take part in transportation by carrying individuals and packages (c.f., Segway robot). For transportation of goods, interest in drones has increased, and Amazon is currently testing a delivery system using them,⁵⁷ although questions remain about the appropriate safety rules and regulations.

The increased sensing capabilities, adoption of drones, and the connected transportation infrastructure will also raise concerns about the privacy of individuals and the safety of private data. In coming years, these and related transportation issues will need to be addressed either by preemptive action on the part of industry or within the legal framework. As noted in the Section III policy discussion, how well this is done will affect the pace and scope of AI-related advances in the transportation sector.

On-demand transportation

On-demand transportation services such as Uber and Lyft have emerged as another pivotal application of sensing, connectivity, and AI,⁵⁸ with algorithms for matching drivers to passengers by location and suitability (reputation modeling).⁵⁹⁶⁰

Through dynamic pricing, these services ration access by willingness-to-pay, with dynamic pricing also encouraging an increase in the supply of drivers, and have become a popular method for transportation in cities. With their rapid advance have come multiple policy and legal issues, such as competition with existing taxi services and concerns about lack of regulation and safety. On-demand transportation services seem likely to be a major force towards self-driving cars.

Carpooling and ridesharing have long been seen as a promising approach to decrease traffic congestion and better utilize personal transportation resources. Services such as Zimride and Nuride bring together people sharing similar routes for a joint trip. But this approach to carpooling has failed to gain traction on a large scale.

Our Study Panel doesn't expect drones that can fly, swim, and drive, or flying quadcoptors to become a common means of transportation by 2030 (although prototypes exist today).

55 "U.S. Department of Transportation Launches Smart City Challenge to Create a City of the Future," Transportation.gov, U.S. Department of Transportation, December 7, 2015, accessed August 1, 2016, <https://www.transportation.gov/briefing-room/us-department-transportation-launches-smart-city-challenge-create-city-future>.

56 Will Knight, "Car-to-Car Communication: A simple wireless technology promises to make driving much safer," *MIT Technology Review*, accessed August 1, 2016, <https://www.technologyreview.com/s/534981/car-to-car-communication/>.

57 "Amazon Prime Air," Amazon, accessed August 1, 2016, <http://www.amazon.com/b?node=8037720011>.

58 Jared Meyer, "Uber and Lyft are changing the way Americans move about their country," *National Review*, June 7, 2016, accessed August 1, 2016, <http://www.nationalreview.com/article/436263/uber-lyft-ride-sharing-services-sharing-economy-are-future>.

59 Alexander Howard, "How Digital Platforms Like LinkedIn, Uber And TaskRabbit Are Changing The On-Demand Economy," *The Huffington Post*, July 14, 2015, accessed August 1, 2016, http://www.huffingtonpost.com/entry/online-talent-platforms_us_55a03545e4b0b8145f72ccf6.

60 "Announcing UberPool," Uber Newsroom, August 5, 2014, accessed August 1, 2016, <https://newsroom.uber.com/announcing-uberpool/>.

Over the next fifteen years, coincident advances in mechanical and AI technologies promise to increase the safe and reliable use and utility of home robots in a typical North American city.

Interacting with people

For decades, people have imagined wildly different, futuristic-looking transportation vehicles. Although future cars will be smarter and drones will be available widely, it is unlikely that by 2030 we will have widely adopted transportation vehicles that look and function differently than the ones we have today. Our Study Panel doesn't expect drones that can fly, swim, and drive, or flying quadcopters to become a common means of transportation in this time horizon (although prototypes exist today).

We do expect humans to become partners to self-driving cars and drones in their training, execution, and evaluation. This partnering will happen both when humans are co-located with machines and also virtually. We predict advances in algorithms to facilitate machine learning from human input. We also expect models and algorithms for modeling of human attention, and to support communication and coordination between humans and machine. This is an integral part of the development of future vehicles.

HOME/SERVICE ROBOTS

Robots have entered people's homes in the past fifteen years. Disappointingly slow growth in the diversity of applications has occurred simultaneously with increasingly sophisticated AI deployed on existing applications. AI advances are often inspired by mechanical innovations, which in turn prompt new AI techniques to be introduced.

Over the next fifteen years, coincident advances in mechanical and AI technologies promise to increase the safe and reliable use and utility of home robots in a typical North American city. Special purpose robots will deliver packages, clean offices, and enhance security, but technical constraints and the high costs of reliable mechanical devices will continue to limit commercial opportunities to narrowly defined applications for the foreseeable future. As with self-driving cars and other new transportation machines, the difficulty of creating reliable, market-ready hardware is not to be underestimated.

Vacuum cleaners

In 2001, after many years of development, the Electrolux Trilobite, a vacuum cleaning robot, became the first commercial home robot. It had a simple control system to do obstacle avoidance, and some navigation. A year later, iRobot introduced Roomba, which was a tenth the price of the Trilobite and, with only 512 bytes of RAM, ran a behavior based controller. The most intelligent thing it did was to avoid falling down stairs. Since then, sixteen million Roombas have been deployed all over the world and several other competing brands now exist.

As the processing power and RAM capacity of low cost embedded processors improved from its dismal state in the year 2000, the AI capabilities of these robots also improved dramatically. Simple navigation, self-charging, and actions for dealing with full dust bins were added, followed by ability to deal with electrical cords and rug tassels, enabled by a combination of mechanical improvements and sensor based perception. More recently, the addition of full VSLAM (Visual Simultaneous Location and Mapping)—an AI technology that had been around for twenty years—has enabled the robots to build a complete 3D world model of a house as they clean, and become more efficient in their cleaning coverage.

Early expectations that many new applications would be found for home robots have not materialized. Robot vacuum cleaners are restricted to localized flat areas, while real homes have lots of single steps, and often staircases; there has been very little research on robot mobility inside real homes. Hardware platforms remain challenging to build, and there are few applications that people want enough to buy. Perceptual algorithms

for functions such as image labeling, and 3D object recognition, while common at AI conferences, are still only a few years into development as products.

Home robots 2030

Despite the slow growth to date of robots in the home, there are signs that this will change in the next fifteen years. Corporations such as Amazon Robotics and Uber are developing large economies of scale using various aggregation technologies. Also:

System in Module (SiM), with a lot of System on Chip (SoC) subsystems, are now being pushed out the door by phone-chip makers (Qualcomm's SnapDragon, Samsung's Artik, etc.). These are better than supercomputers of less than ten years ago with eight or more sixty-four-bit cores, and specialized silicon for cryptography, camera drivers, additional DSPs, and hard silicon for certain perceptual algorithms. This means that low cost devices will be able to support much more onboard AI than we have been able to consider over the last fifteen years.

Cloud ("someone else's computer") is going to enable more rapid release of new software on home robots, and more sharing of data sets gathered in many different homes, which will in turn feed cloud-based machine learning, and then power improvements to already deployed robots.

The great advances in speech understanding and image labeling enabled by deep learning will enhance robots' interactions with people in their homes.

Low cost 3D sensors, driven by gaming platforms, have fueled work on 3D perception algorithms by thousands of researchers worldwide, which will speed the development and adoption of home and service robots.

In the past three years, low cost and safe robot arms have been introduced to hundreds of research labs around the world, sparking a new class of research on manipulation that will eventually be applicable in the home, perhaps around 2025. More than half a dozen startups around the world are developing AI-based robots for the home, for now concentrating mainly on social interaction. New ethics and privacy issues may surface as a result.

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HEALTHCARE

For AI technologies, healthcare has long been viewed as a promising domain. AI-based applications could improve health outcomes and quality of life for millions of people in the coming years—but only if they gain the trust of doctors, nurses, and patients, and if policy, regulatory, and commercial obstacles are removed. Prime applications include clinical decision support, patient monitoring and coaching, automated devices to assist in surgery or patient care, and management of healthcare systems. Recent successes, such as mining social media to infer possible health risks, machine learning to predict patients at risk, and robotics to support surgery, have expanded a sense of possibility for AI in healthcare. Improvements in methods for interacting with medical professionals and patients will be a critical challenge.

As in other domains, data is a key enabler. There has been an immense forward leap in collecting useful data from personal monitoring devices and mobile apps, from electronic health records (EHR) in clinical settings and, to a lesser extent, from robots designed to assist with medical procedures and hospital operations. But using this data to enable more finely-grained diagnostics and treatments for both individual patients and patient populations has proved difficult. Research and deployment have been slowed by outdated regulations and incentive structures. Poor human-computer interaction methods and the inherent difficulties and risks of implementing technologies in such a large and complex system have slowed realization of AI's

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promise in healthcare.⁶¹ The reduction or removal of these obstacles, combined with innovations still on the horizon, have the potential to significantly improve health outcomes and quality of life for millions of people in the coming years.

The clinical setting

For decades, the vision of an AI-powered clinician's assistant has been a near cliché. Although there have been successful pilots of AI-related technology in healthcare,⁶² the current healthcare delivery system unfortunately remains structurally ill-suited to absorb and deploy rapid advances. Incentives provided by the Affordable Care Act have accelerated the penetration of electronic health records (EHRs) into clinical practice, but implementation has been poor, eroding clinicians' confidence in their usefulness. A small group of companies control the EHR market, and user interfaces are widely considered substandard, including annoying pop-ups that physicians routinely dismiss. The promise of new analytics using data from EHRs, including AI, remains largely unrealized due to these and other regulatory and structural barriers.

Looking ahead to the next fifteen years, AI advances, if coupled with sufficient data and well-targeted systems, promise to change the cognitive tasks assigned to human clinicians. Physicians now routinely solicit verbal descriptions of symptoms from presenting patients and, in their heads, correlate patterns against the clinical presentation of known diseases. With automated assistance, the physician could instead supervise this process, applying her or his experience and intuition to guide the input process and to evaluate the output of the machine intelligence. The literal "hands-on" experience of the physician will remain critical. A significant challenge is to optimally integrate the human dimensions of care with automated reasoning processes.

To achieve future advances, clinicians must be involved and engaged at the outset to ensure that systems are well-engineered and trusted. Already, a new generation of more tech savvy physicians routinely utilize specialized apps on mobile devices. At the same time, workloads on primary care clinicians have increased to the point that they are grateful for help from any quarter. Thus, the opportunity to exploit new learning methods, to create structured patterns of inference by mining the scientific literature automatically, and to create true cognitive assistants by supporting free-form dialogue, has never been greater. Provided these advances are not stymied by regulatory, legal, and social barriers, immense improvements to the value of healthcare are within our grasp.

Healthcare analytics

At the population level, AI's ability to mine outcomes from millions of patient clinical records promises to enable finer-grained, more personalized diagnosis and treatment. Automated discovery of genotype-phenotype connections will also become possible as full, once-in-a-lifetime genome sequencing becomes routine for each patient.

A related (and perhaps earlier) capability will be to find "patients like mine" as a way to inform treatment decisions based on analysis of a similar cohort. Traditional and non-traditional healthcare data, augmented by social platforms, may lead to the emergence of self-defined subpopulations, each managed by a surrounding ecosystem of healthcare providers augmented with automated recommendation and monitoring systems. These developments have the potential to radically transform healthcare

61 LeighAnne Olsen, Dara Aisner, and J. Michael McGinnis, eds., "Institute of Medicine (US) Roundtable on Evidence-Based Medicine," *The Learning Healthcare System: Workshop Summary*. (Washington (DC): National Academies Press (US); 2007), accessed August 1, 2016, <http://www.ncbi.nlm.nih.gov/books/NBK53500/>.

62 Katherine E. Henry, David N. Hager, Peter J. Pronovost, and Suchi Saria, "A Targeted Real-time Early Warning Score (TREWScore) for Septic Shock," *Science Translational Medicine* 7, (299), 299ra122.

delivery as medical procedures and lifetime clinical records for hundreds of millions of individuals become available. Similarly, the automated capture of personal environmental data from wearable devices will expand personalized medicine. These activities are becoming more commercially viable as vendors discover ways to engage large populations (e.g. ShareCare)⁶³ and then to create population-scale data that can be mined to produce individualized analytics and recommendations.

Unfortunately, the FDA has been slow to approve innovative diagnostic software, and there are many remaining barriers to rapid innovation. HIPAA (Health Insurance Portability and Accountability Act) requirements for protecting patient privacy create legal barriers to the flow of patient data to applications that could utilize AI technologies. Unanticipated negative effects of approved drugs could show up routinely, sooner, and more rigorously than they do today, but mobile apps that analyze drug interactions may be blocked from pulling the necessary information from patient records. More generally, AI research and innovation in healthcare are hampered by the lack of widely accepted methods and standards for privacy protection. The FDA has been slow to approve innovative software, in part due to an unclear understanding of the cost/benefit tradeoffs of these systems. If regulators (principally the FDA) recognize that effective post-marketing reporting is a dependable hedge against some safety risks, faster initial approval of new treatments and interventions may become possible.

Automated image interpretation has also been a promising subject of study for decades. Progress on interpreting large archives of weakly-labeled images, such as large photo archives scraped from the web, has been explosive. At first blush, it is surprising that there has not been a similar revolution in interpretation of medical images. Most medical imaging modalities (CT, MR, ultrasound) are inherently digital, the images are all archived, and there are large, established companies with internal R&D (e.g. Siemens, Philips, GE) devoted to imaging.

But several barriers have limited progress to date. Most hospital image archives have only gone digital over the past decade. More importantly, the problem in medicine is not to recognize what is in the image (is this a liver or a kidney?), but rather to make a fine-grained judgement about it (does the slightly darker smudge in the liver suggest a potentially cancerous tumor?). Strict regulations govern these high-stakes judgements. Even with state-of-the-art technologies, a radiologist will still likely have to look at the images, so the value proposition is not yet compelling. Also, healthcare regulations preclude easy federation of data across institutions. Thus, only very large organizations of integrated care, such as Kaiser Permanente, are able to attack these problems.

Still, automated/augmented image interpretation has started to gain momentum. The next fifteen years will probably not bring fully automated radiology, but initial forays into image “triage” or second level checking will likely improve the speed and cost-effectiveness of medical imaging. When coupled with electronic patient record systems, large-scale machine learning techniques could be applied to medical image data. For example, multiple major healthcare systems have archives of millions of patient scans, each of which has an associated radiological report, and most have an associated patient record. Already, papers are appearing in the literature showing that deep neural networks can be trained to produce basic radiological findings, with high reliability, by training from this data.⁶⁴

A small group of companies control the EHR market, and user interfaces are widely considered substandard, including annoying pop-ups that physicians routinely dismiss.

63 Sharecare, accessed August 1, 2016, <https://www.sharecare.com>.

64 Hoo-Chang Shin, Holger R. Roth, Mingchen Gao, Le Lu, Ziyue Xu, Isabella Nogues, Jianhua Yao, Daniel Mollura, and Ronald M. Summers, “Deep Convolutional Neural Networks for Computer-aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning,” *IEEE Transactions on Medical Imaging* 35, no. 5 (2016): 1285–1298.

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Healthcare robotics

Fifteen years ago, healthcare robotics was largely science fiction. One company called Robodoc,⁶⁵ a spin-out from IBM, developed robotic systems for orthopedic surgeries, such as hip and knee replacements. The technology worked, but the company struggled commercially, and was ultimately shut down and acquired for its technology.⁶⁶ More recently, though, the research and practical use of surgical robotics has exploded.

In 2000 Intuitive Surgical⁶⁷ introduced the da Vinci system, a novel technology initially marketed to support minimally invasive heart bypass surgery, and then gained substantial market traction for treatment of prostate cancer and merged with its only major competition, Computer Motion, in 2003. The da Vinci, now in its fourth generation, provides 3D visualization (as opposed to 2D monocular laparoscopy) and wristed instruments in an ergonomic platform. It is considered the standard of care in multiple laparoscopic procedures, and used in nearly three quarters of a million procedures a year,⁶⁸ providing not only a physical platform, but also a new data platform for studying the process of surgery.

The da Vinci anticipates a day when much greater insight into how medical professionals carry out the process of providing interventional medical care will be possible. The presence of the da Vinci in day-to-day operation has also opened the doors to new types of innovation—from new instrumentation to image fusion to novel biomarkers—creating its own innovation ecosystem. The success of the platform has inspired potential competitors in robotic surgery, most notably the Alphabet spin-off Verb, in collaboration with J&J/Ethicon.⁶⁹ There are likely to be many more, each exploring a unique niche or space and building out an ecosystem of sensing, data analytics, augmentation, and automation.

Intelligent automation in hospital operations has been less successful. The story is not unlike surgical robotics. Twenty years ago, one company, HelpMate, created a robot for hospital deliveries,⁷⁰ such as meals and medical records, but ultimately went bankrupt. More recently, Aethon⁷¹ introduced TUG Robots for basic deliveries, but few hospitals have invested in this technology to date. However, robotics in other service industries such as hotels and warehouses, including Amazon Robotics (formerly Kiva), are demonstrating that these technologies are practical and cost effective in at least some large-scale settings, and may ultimately spur additional innovation in health care.

Looking ahead, many tasks that appear in healthcare will be amenable to augmentation, but will not be fully automated. For example, robots may be able to deliver goods to the right room in a hospital, but then require a person to pick them up and place them in their final location. Walking a patient down the corridor may

65 ROBODOC, accessed August 1, 2016, <http://www.robodoc.com/professionals.html>.

66 THINK Surgical, accessed August 1, 2016, <http://thinksurgical.com/history>.

67 Intuitive Surgical, accessed August 1, 2016, <http://www.intuitivesurgical.com>.

68 Trefis Team, “Intuitive Surgical Maintains Its Growth Momentum With Strong Growth In Procedure Volumes,” *Forbes*, January 22, 2016, accessed August 1, 2016, <http://www.forbes.com/sites/greatspeculations/2016/01/22/intuitive-surgical-maintains-its-growth-momentum-with-strong-growth-in-procedure-volumes/#22ae6b0939a1>.

69 Evan Ackerman, “Google and Johnson & Johnson Conjugate to Create Verb Surgical, Promise Fancy Medical Robots,” *IEEE Spectrum*, December 17, 2015, accessed August 1, 2016, <http://spectrum.ieee.org/automaton/robotics/medical-robots/google-verily-johnson-johnson-verb-surgical-medical-robots>.

70 John M. Evans and Bala Krishnamurthy, “HelpMate®, the trackless robotic courier: A perspective on the development of a commercial autonomous mobile robot,” *Lecture Notes in Control and Information Sciences* 236, June 18, 2005 (Springer-Verlag London Limited, 1998), 182–210, accessed August 1, 2016, <http://link.springer.com/chapter/10.1007%2FBFb0030806>.

71 Aethon, accessed August 1, 2016, <http://www.aethon.com>.

be relatively simple once a patient is standing in a walker (though will certainly not be trivial for patients recovering from surgery and/or elderly patients, especially in corridors crowded with equipment and other people). Driving a needle to place a suture is relatively straightforward once the needle is correctly placed.⁷² This implies that many future systems will involve intimate interaction between people and machines and require technologies that facilitate collaboration between them.

The growth of automation will enable new insights into healthcare processes. Historically, robotics has not been a strongly data-driven or data-oriented science. This is changing as (semi)automation infiltrates healthcare. As the new surgical, delivery, and patient care platforms come online, the beginnings of quantification and predictive analytics are being built on top of data coming from these platforms.⁷³ This data will be used to assess quality of performance, identify deficiencies, errors, or potential optimizations, and will be used as feedback to improve performance. In short, these platforms will facilitate making the connection between what is done, and the outcome achieved, making true “closed-loop” medicine a real possibility.

Mobile health

To date, evidence-driven analytics on healthcare have relied on traditional healthcare data—mainly the electronic medical records discussed above. In the clinical setting, there are hopeful trends towards bringing new data to bear. For example, Tele-Language enables a human clinician to conduct language therapy sessions with multiple patients simultaneously with the aid of an AI agent trained by the clinician. And Lifograph, which extracts behavioral patterns and creates alerts from data passively collected from a patient’s smartphone, has been adopted by psychiatrists in Israel to detect early signs of distressful behavior in patients.

Looking ahead, driven by the mobile computing revolution, the astonishing growth of “biometrics in the wild”—and the explosion of platforms and applications that use them—is a hopeful and unanticipated trend. Thousands of mobile apps now offer information, introduce behavior modification, or identify groups of “people like me.” This, combined with the emerging trend of more specialized motion tracking devices, such as Fitbit, and the emerging (inter)connectedness between the home environment and health-monitoring devices, has created a vibrant new sector of innovation.

By combining social and healthcare data, some healthcare apps can perform data mining, learning, and prediction from captured data, though their predictions are relatively rudimentary. The convergence of data and functionality across applications will likely spur new and even obvious products, such as an exercise app that not only proposes a schedule for exercise but also suggests the best time to do it, and provides coaching to stick to that schedule.

Specialized motion tracking devices... and the emerging (inter)connectedness between the home environment and health-monitoring devices have created a vibrant new sector of innovation.

⁷² Azad Shademan, Ryan S. Decker, Justin D. Opfermann, Simon Leonard, Axel Krieger, and Peter CW Kim, “Supervised Autonomous Robotic Soft Tissue Surgery,” *Science Translational Medicine* 8, no. 337 (2016): 337ra64–337ra64.

⁷³ Carolyn Chen, Lee White, Timothy Kowalewski, Rajesh Aggarwal, Chris Lintott, Bryan Comstock, Katie Kuksenok, Cecilia Aragon, Daniel Holst, and Thomas Lendvay, “Crowd-Sourced Assessment of Technical Skills: a novel method to evaluate surgical performance.” *Journal of Surgical Research* 187, no. 1 (2014): 65–71.

Better hearing aids and visual assistive devices will mitigate the effects of hearing and vision loss, improving safety and social connection.

Personalized rehabilitation and in-home therapy will reduce the need for hospital stays.

Elder care

Over the next fifteen years the number of elderly in the United States will grow by over 50%.⁷⁴ The National Bureau of Labor Statistics projects that home health aides will grow 38% over the next ten years. Despite the broad opportunities in this domain—basic social support, interaction and communication devices, home health monitoring, a variety of simple in-home physical aids such as walkers, and light meal preparation—little has happened over the past fifteen years. But the coming generational shift will accompany a change in technology acceptance among the elderly. Currently, someone who is seventy was born in 1946 and may have first experienced some form of personalized IT in middle age or later, while a fifty-year-old today is far more technology-friendly and savvy. As a result, there will be a growing interest and market for already available and maturing technologies to support physical, emotional, social, and mental health. Here are a few likely examples by category:

Life quality and independence

- Automated transportation will support continued independence and expanded social horizons.
- Sharing of information will help families remain engaged with one another at a distance, and predictive analytics may be used to “nudge” family groups toward positive behaviors, such as reminders to “call home.”
- Smart devices in the home will help with daily living activities when needed, such as cooking and, if robot manipulation capabilities improve sufficiently, dressing and toileting.

Health and wellness

- Mobile applications that monitor movement and activities, coupled with social platforms, will be able to make recommendations to maintain mental and physical health.
- In-home health monitoring and health information access will be able to detect changes in mood or behavior and alert caregivers.
- Personalized health management will help mitigate the complexities associated with multiple co-morbid conditions and/or treatment interactions.

Treatments and devices

- Better hearing aids and visual assistive devices will mitigate the effects of hearing and vision loss, improving safety and social connection.
- Personalized rehabilitation and in-home therapy will reduce the need for hospital or care facility stays.
- Physical assistive devices (intelligent walkers, wheel chairs, and exoskeletons) will extend the range of activities of an infirm individual.

The Study Panel expects an explosion of low-cost sensing technologies that can provide substantial capabilities to the elderly in their homes. In principle, social agents with a physical presence and simple physical capabilities (e.g. a mobile robot with basic communication capabilities) could provide a platform for new innovations. However, doing so will require integration across multiple areas of AI—Natural Language Processing, reasoning, learning, perception, and robotics—to create a system that is useful and usable by the elderly.

These innovations will also introduce questions regarding privacy within various circles, including friends, family, and care-givers, and create new challenges to accommodate an evermore active and engaged population far past retirement.

⁷⁴ Jennifer M. Ortman, Victoria A. Velkoff, and Howard Hogan, “An Aging Nation: The Older Population in the United States: Population Estimates and Projections,” *Current Population Reports*, U.S. Census Bureau (May 2014), accessed August 1, 2016, <https://www.census.gov/prod/2014pubs/p25-1140.pdf>.

EDUCATION

The past fifteen years have seen considerable AI advances in education. Applications are in wide use by educators and learners today, with some variation between K-12 and university settings. Though quality education will always require active engagement by human teachers, AI promises to enhance education at all levels, especially by providing personalization at scale. Similar to healthcare, resolving how to best integrate human interaction and face-to-face learning with promising AI technologies remains a key challenge.

Robots have long been popular educational devices, starting with the early Lego Mindstorms kits developed with the MIT Media Lab in the 1980s. Intelligent Tutoring Systems (ITS) for science, math, language, and other disciplines match students with interactive machine tutors. Natural Language Processing, especially when combined with machine learning and crowdsourcing, has boosted online learning and enabled teachers to multiply the size of their classrooms while simultaneously addressing individual students' learning needs and styles. The data sets from large online learning systems have fueled rapid growth in learning analytics.

Still, schools and universities have been slow in adopting AI technologies primarily due to lack of funds and lack of solid evidence that they help students achieve learning objectives. Over the next fifteen years in a typical North American city, the use of intelligent tutors and other AI technologies to assist teachers in the classroom and in the home is likely to expand significantly, as will learning based on virtual reality applications. But computer-based learning systems are not likely to fully replace human teaching in schools.

Teaching robots

Today, more sophisticated and versatile kits for use in K-12 schools are available from a number of companies that create robots with new sensing technologies programmable in a variety of languages. Ozobot is a robot that teaches children to code and reason deductively while configuring it to dance or play based on color-coded patterns.⁷⁵ Cubelets help teach children logical thinking through assembling robot blocks to think, act, or sense, depending upon the function of the different blocks.⁷⁶ Wonder Workshop's Dash and Dot span a range of programming capabilities. Children eight years old and older can create simple actions using a visual programming language, Blockly, or build iOS and Android applications using C or Java.⁷⁷ PLEO rb is a robot pet that helps children learn biology by teaching the robot to react to different aspects of the environment.⁷⁸ However, while fun and engaging for some, in order for such kits to become widespread, there will need to be compelling evidence that they improve students' academic performance.

Intelligent Tutoring Systems (ITS) and online learning

ITS have been developed from research laboratory projects such as Why-2 Atlas, which supported human-machine dialogue to solve physics problems early in the era.⁷⁹ The rapid migration of ITS from laboratory experimental stages to real use is

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75 Ozobot, accessed August 1, 2016, <http://ozobot.com/>.

76 "Cubelets," Modular Robotics, accessed August 1, 2016, <http://www.modrobotics.com/cubelets>.

77 "Meet Dash," Wonder Workshop, accessed August 1, 2016, <https://www.makewonder.com/dash>.

78 "Pleo rb," Innvo Labs, accessed August 1, 2016, http://www.pleoworld.com/pleo_rb/eng/lifeform.php.

79 Kurt VanLehn, Pamela W. Jordan, Carolyn P. Rosé, Dumisizwe Bhembe, Michael Böttner, Andy Gaydos, Maxim Makatchev, Umarani Pappuswamy, Michael Ringenberg, Antonio Roque, Stephanie Siler, and Ramesh Srivastava, "The Architecture of Why2-Atlas: A Coach for Qualitative

It can be argued that AI is the secret sauce that has enabled instructors, particularly in higher education, to multiply the size of their classrooms by a few orders of magnitude—class sizes of a few tens of thousands are not uncommon.

surprising and welcome. Downloadable software and online systems such as Carnegie Speech or Duolingo provide foreign language training using Automatic Speech Recognition (ASR) and NLP techniques to recognize language errors and help users correct them.⁸⁰ Tutoring systems such as the Carnegie Cognitive Tutor⁸¹ have been used in US high schools to help students learn mathematics. Other ITS have been developed for training in geography, circuits, medical diagnosis, computer literacy and programming, genetics, and chemistry. Cognitive tutors use software to mimic the role of a good human tutor by, for example, providing hints when a student gets stuck on a math problem. Based on the hint requested and the answer provided, the tutor offers context specific feedback.

Applications are growing in higher education. An ITS called SHERLOCK⁸² is beginning to be used to teach Air Force technicians to diagnose electrical systems problems in aircraft. And the University of Southern California's Information Sciences Institute has developed more advanced avatar-based training modules to train military personnel being sent to international posts in appropriate behavior when dealing with people from different cultural backgrounds. New algorithms for personalized tutoring, such as Bayesian Knowledge Tracing, enable individualized mastery learning and problem sequencing.⁸³

Most surprising has been the explosion of the Massive Open Online Courses (MOOCs) and other models of online education at all levels—including the use of tools like Wikipedia and Khan Academy as well as sophisticated learning management systems that build in synchronous as well as asynchronous education and adaptive learning tools. Since the late 1990s, companies such as the Educational Testing Service and Pearson have been developing automatic NLP assessment tools to co-grade essays in standardized testing.⁸⁴ Many of the MOOCs which have become so popular, including those created by EdX, Coursera, and Udacity, are making use of NLP, machine learning, and crowdsourcing techniques for grading short-answer and essay questions as well as programming assignments.⁸⁵ Online education systems that support graduate-level professional education and lifelong learning are also expanding rapidly. These systems have great promise because the need for face-to-face interaction is less important for working professionals and career changers. While not the leaders in AI-supported systems and applications, they will become early adopters as the technologies are tested and validated.

It can be argued that AI is the secret sauce that has enabled instructors, particularly in higher education, to multiply the size of their classrooms by a few orders of magnitude—class sizes of a few tens of thousands are not uncommon. In order to continually test large classes of students, automated generation of the questions is

Physics Essay Writing,” *Intelligent Tutoring Systems: Proceedings of the 6th International Conference*, (Springer Berlin Heidelberg, 2002), 158–167.

80 VanLehn et al, “The Architecture of Why2-Atlas.”

81 “Resources and Support,” Carnegie Learning, accessed August 1, 2016, <https://www.carnegielearning.com/resources-support/>.

82 Alan Lesgold, Suzanne Lajoie, Marilyn Bunzo, and Gary Eggan, “SHERLOCK: A Coached Practice Environment for an Electronics Troubleshooting Job,” in J. H. Larkin and R. W. Chabay, eds., *Computer-Assisted Instruction and Intelligent Tutoring Systems: Shared Goals and Complementary Approaches* (Hillsdale, New Jersey: Lawrence Erlbaum Associates, 1988).

83 Michael V. Yudelson, Kenneth R. Koedinger, and Geoffrey J. Gordon, (2013). “Individualized Bayesian Knowledge Tracing Models,” *Artificial Intelligence in Education*, (Springer Berlin Heidelberg, 2013), 171–180.

84 Jill Burstein, Karen Kukich, Susanne Wolff, Chi Lu, Martin Chodorow, Lisa Braden-Harder, and Mary Dee Harris, “Automated Scoring Using a Hybrid Feature Identification Technique” in *Proceedings of the Annual Meeting of the Association of Computational Linguistics*, Montreal, Canada, August 1998, accessed August 1, 2016, https://www.ets.org/Media/Research/pdf/erater_acl98.pdf.

85 EdX, <https://www.edx.org/>, Coursera, <https://www.coursera.org/>, Udacity, <https://www.udacity.com/>, all accessed August 1, 2016.

also possible, such as those designed to assess vocabulary,⁸⁶ wh (who/what/when/where/why) questions,⁸⁷ and multiple choice questions,⁸⁸ using electronic resources such as WordNet, Wikipedia, and online ontologies. With the explosion of online courses, these techniques are sure to be eagerly adopted for use in online education. Although the long term impact of these systems will have on the educational system remains unclear, the AI community has learned a great deal in a very short time.

Learning analytics

Data sets being collected from massive scale online learning systems, ranging from MOOCs to Khan Academy, as well as smaller scale online programs, have fueled the rapid growth of the field of learning analytics. Online courses are not only good for widespread delivery, but are natural vehicles for data collection and experimental instrumentation that will contribute to scientific findings and improving the quality of learning at scale. Organizations such as the Society for Learning Analytics Research (SOLAR), and the rise of conferences including the Learning Analytics and Knowledge Conference⁸⁹ and the Learning at Scale Conference (L@S)⁹⁰ reflect this trend. This community applies deep learning, natural language processing, and other AI techniques to analysis of student engagement, behavior, and outcomes.

Current projects seek to model common student misconceptions, predict which students are at risk of failure, and provide real-time student feedback that is tightly integrated with learning outcomes. Recent work has also been devoted to understanding the cognitive processes involved in comprehension, writing, knowledge acquisition, and memory, and to applying that understanding to educational practice by developing and testing educational technologies.

Challenges and opportunities

One might have expected more and more sophisticated use of AI technologies in schools, colleges, and universities by now. Much of its absence can be explained by the lack of financial resources of these institutions as well as the lack of data establishing the technologies' effectiveness. These problems are being addressed, albeit slowly, by private foundations and by numerous programs to train primarily secondary school teachers in summer programs. As in other areas of AI, excessive hype and promises about the capabilities of MOOCs have meant that expectations frequently exceed the reality. The experiences of certain institutions, such as San Jose State University's experiment with Udacity,⁹¹ have led to more sober assessment of the potential of the new educational technologies.

86 Jonathan C. Brown, Gwen A. Frishkoff, and Maxine Eskenazi, "Automatic Question Generation for Vocabulary Assessment," *Proceedings of Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing (HLT/EMNLP)*, Vancouver, October 2005, (Association for Computational Linguistics, 2005), 819–826.

87 Michael Heilman, "Automatic Factual Question Generation from Text," PhD thesis CMU-LTI-11-004, (Carnegie Mellon University, 2011), accessed August 1, 2016, <http://www.cs.cmu.edu/~ark/mheilman/questions/papers/heilman-question-generation-dissertation.pdf>.

88 Tahani Alsubait, Bijan Parsia, and Uli Sattler, "Generating Multiple Choice Questions from Ontologies: How Far Can We Go?," in eds. P. Lambrix, E. Hyvönen, E. Blomqvist, V. Presutti, G. Qi, U. Sattler, Y. Ding, and C. Ghidini, *Knowledge Engineering and Knowledge Management: EKAW 2014 Satellite Events, VISUAL, EKM1, and ARCOE-Logic* Linköping, Sweden, November 24–28, 2014 Revised Selected Papers, (Switzerland: Springer International Publishing, 2015), 66–79.

89 The 6th International Learning Analytics & Knowledge Conference, accessed August 1, 2016, <http://lak16.solaresearch.org/>.

90 Third Annual ACM Conference on Learning at Scale, <http://learningatscale.acm.org/las2016/>.

91 Ry Rivard, "Udacity Project on 'Pause,'" *Inside Higher Ed*, July 18, 2013, accessed August 1, 2016, <https://www.insidehighered.com/news/2013/07/18/citing-disappointing-student-outcomes-san-jose-state-pauses-work-udacity>.

The current absence of sophisticated use of AI technologies in schools, colleges, and universities may be explained by the lack of financial resources as well as the lack of data establishing the technologies' effectiveness.

While formal education will not disappear, the Study Panel believes that MOOCs and other forms of online education will become part of learning at all levels, from K-12 through university, in a blended classroom experience.

In the next fifteen years, it is likely that human teachers will be assisted by AI technologies with better human interaction, both in the classroom and in the home. The Study Panel expects that more general and more sophisticated virtual reality scenarios in which students can immerse themselves in subjects from all disciplines will be developed. Some steps in this direction are being taken now by increasing collaborations between AI researchers and researchers in the humanities and social sciences, exemplified by Stanford's Galileo Correspondence Project⁹² and Columbia's Making and Knowing Project.⁹³ These interdisciplinary efforts create interactive experiences with historical documents and the use of Virtual Reality (VR) to explore interactive archeological sites.⁹⁴ VR techniques are already being used in the natural sciences such as biology, anatomy, geology and astronomy to allow students to interact with environments and objects that are difficult to engage with in the real world. The recreation of past worlds and fictional worlds will become just as popular for studies of arts and other sciences.

AI techniques will increasingly blur the line between formal, classroom education and self-paced, individual learning. Adaptive learning systems, for example, are going to become a core part of the teaching process in higher education because of the pressures to contain cost while serving a larger number of students and moving students through school more quickly. While formal education will not disappear, the Study Panel believes that MOOCs and other forms of online education will become part of learning at all levels, from K-12 through university, in a blended classroom experience. This development will facilitate more customizable approaches to learning, in which students can learn at their own pace using educational techniques that work best for them. Online education systems will learn as the students learn, supporting rapid advances in our understanding of the learning process. Learning analytics, in turn, will accelerate the development of tools for personalized education.

The current transition from hard copy books to digital and audio media and texts is likely to become prevalent in education as well. Digital reading devices will also become much 'smarter', providing students with easy access to additional information about subject matter as they study. Machine Translation (MT) technology will also make it easier to translate educational material into different languages with a fair degree of accuracy, just as it currently translates technical manuals. Textbook translation services that currently depend only upon human translators will increasingly incorporate automatic methods to improve the speed and affordability of their services for school systems.

Online learning systems will also expand the opportunity for adults and working professionals to enhance their knowledge and skills (or to retool and learn a new field) in a world where these fields are evolving rapidly. This will include the expansion of fully online professional degrees as well as professional certifications based on online coursework.

Broader societal consequences

In countries where education is difficult for the broad population to obtain, online resources may have a positive effect if the population has the tools to access them. The development of online educational resources should make it easier for foundations that support international educational programs to provide quality

⁹² Stanford University: Galileo Correspondence Project, accessed August 1, 2016, <http://galileo.stanford.edu>.

⁹³ The Making and Knowing Project: Reconstructing the 16th Century Workshop of BNF MS. FR. 640 at Columbia University, accessed August 1, 2016, <http://www.makingandknowing.org>.

⁹⁴ Paul James, "3D Mapped HTC Vive Demo Brings Archaeology to Life," *Road to VR*, August 31, 2015, accessed August 1, 2016, <http://www.roadtovr.com/3d-mapped-htc-vive-demo-brings-archaeology-to-life/>.

education by providing tools and relatively simple amounts of training in their use. For example, large numbers of educational apps, many of them free, are being developed for the iPad. On the negative side, there is already a major trend among students to restrict their social contacts to electronic ones and to spend large amounts of time without social contact, interacting with online programs. If education also occurs more and more online, what effect will the lack of regular, face-to-face contact with peers have on students' social development? Certain technologies have even been shown to create neurological side effects.⁹⁵ On the other hand, autistic children have benefited from interactions with AI systems already.⁹⁶

LOW-RESOURCE COMMUNITIES

Many opportunities exist for AI to improve conditions for people in low-resource communities in a typical North American city—and, indeed, in some cases it already has. Understanding these direct AI contributions may also inform potential contributions in the poorest parts of the developing world. There has not been a significant focus on these populations in AI gatherings, and, traditionally, AI funders have underinvested in research lacking commercial application. With targeted incentives and funding priorities, AI technologies could help address the needs of low-resource communities. Budding efforts are promising. Counteracting fears that AI may contribute to joblessness and other societal problems, AI may provide mitigations and solutions, particularly if implemented in ways that build trust in them by the affected communities.

Machine learning, data mining approaches

Under the banner of “data science for social good,” AI has been used to create predictive models to help government agencies more effectively use their limited budgets to address problems such as lead poisoning,⁹⁷ a major public health concern that has been in the news due to ongoing events in Flint, Michigan. Children may be tested for elevated lead levels, but that unfortunately means the problem is only detected after they have already been poisoned. Many efforts are underway to use predictive models to assist government agencies in prioritizing children at risk, including those who may not yet have been exposed.⁹⁸ Similarly, the Illinois Department of Human Services (IDHS) uses predictive models to identify pregnant women at risk for adverse birth outcomes in order to maximize the impact of prenatal care. The City of Cincinnati uses them to proactively identify and deploy inspectors to properties at risk of code violations.

Scheduling, planning

Task assignment scheduling and planning techniques have been applied by many different groups to distribute food before it spoils from those who may have excess, such as restaurants, to food banks, community centers and individuals.⁹⁹

⁹⁵ Scientist have studied, for example, the way reliance on GPS may lead to changes in the hippocampus. Kim Tingley, “The Secrets of the Wave Pilots,” *The New York Times*, March 17, 2016, accessed August 1, 2016, <http://www.nytimes.com/2016/03/20/magazine/the-secrets-of-the-wave-pilots.html>.

⁹⁶ Judith Newman, “To Siri, With Love: How One Boy With Autism Became BFF With Apple’s Siri,” *The New York Times*, October 17, 2014, accessed August 1, 2016, <http://www.nytimes.com/2014/10/19/fashion/how-apples-siri-became-one-autistic-boys-bff.html>.

⁹⁷ Eric Potash, Joe Brew, Alexander Loewi, Subhabrata Majumdar, Andrew Reece, Joe Walsh, Eric Rozier, Emile Jorgensen, Raed Mansour, and Rayid Ghani, “Predictive Modeling for Public Health: Preventing Childhood Lead Poisoning,” *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (New York: Association for Computing Machinery, 2015), 2039–2047.

⁹⁸ Data Science for Social Good, University of Chicago, accessed August 1, 2016, <http://dssg.uchicago.edu/>.

⁹⁹ Senay Solak, Christina Scherrer, and Ahmed Ghoniem, “The Stop-and-Drop Problem in Nonprofit Food Distribution Networks,” *Annals of Operations Research* 221, no. 1 (October 2014):

With targeted incentives and funding priorities, AI technologies could help address the needs of low-resource communities. Budding efforts are promising.

One of the more successful uses of AI analytics is in detecting white collar crime, such as credit card fraud. Cybersecurity (including spam) is a widely shared concern, and machine learning is making an impact.

Reasoning with social networks and influence maximization

Social networks can be harnessed to create earlier, less-costly interventions involving large populations. For example, AI might be able to assist in spreading health-related information. In Los Angeles, there are more than 5,000 homeless youth (ages thirteen-twenty-four). Individual interventions are difficult and expensive, and the youths' mistrust of authority dictates that key messages are best spread through peer leaders. AI programs might be able to leverage homeless youth social networks to strategically select peer leaders to spread health-related information, such as how to avoid spread of HIV. The dynamic, uncertain nature of these networks does pose challenges for AI research.¹⁰⁰ Care must also be taken to prevent AI systems from reproducing discriminatory behavior, such as machine learning that identifies people through illegal racial indicators, or through highly-correlated surrogate factors, such as zip codes. But if deployed with great care, greater reliance on AI may well result in a reduction in discrimination overall, since AI programs are inherently more easily audited than humans.

PUBLIC SAFETY AND SECURITY

Cities already have begun to deploy AI technologies for public safety and security. By 2030, the typical North American city will rely heavily upon them. These include cameras for surveillance that can detect anomalies pointing to a possible crime, drones, and predictive policing applications. As with most issues, there are benefits and risks. Gaining public trust is crucial. While there are legitimate concerns that policing that incorporates AI may become overbearing or pervasive in some contexts, the opposite is also possible. AI may enable policing to become more targeted and used only when needed. And assuming careful deployment, AI may also help remove some of the bias inherent in human decision-making.

One of the more successful uses of AI analytics is in detecting white collar crime, such as credit card fraud.¹⁰¹ Cybersecurity (including spam) is a widely shared concern, and machine learning is making an impact. AI tools may also prove useful in helping police manage crime scenes or search and rescue events by helping commanders prioritize tasks and allocate resources, though these tools are not yet ready for automating such activities. Improvements in machine learning in general, and transfer learning in particular—for speeding up learning in new scenarios based on similarities with past scenarios—may facilitate such systems.

The cameras deployed almost everywhere in the world today tend to be more useful for helping solve crimes than preventing them.^{102 103} This is due to the low quality of event identification from videos and the lack of manpower to look at massive video streams. As AI for this domain improves, it will better assist crime prevention and prosecution through greater accuracy of event classification and efficient automatic processing of video to detect anomalies—including, potentially,

407–426.

100 Jordan Pearson, “Artificial Intelligence Could Help Reduce HIV Among Homeless Youths,” Teamcore, University of Southern California, February 4, 2015, accessed August 1, 2016, http://teamcore.usc.edu/news/motherboard_news_ai_could_help_reduce_HIV.pdf.

101 “RSA Adaptive Authentication,” RSA, accessed August 1, 2016, <https://www.rsa.com/en-us/products-services/fraud-prevention/adaptive-authentication>.

102 Takeshi Arikuma and Yasunori Mochizuki, “Intelligent multimedia surveillance system for safer cities” *APSIPA Transactions on Signal and Information Processing* 5 (2016): 1–8.

103 “Big Op-Ed: Shifting Opinions On Surveillance Cameras,” *Talk of the Nation*, NPR, April 22, 2013, accessed August 1, 2016, <http://www.npr.org/2013/04/22/178436355/big-op-ed-shifting-opinions-on-surveillance-cameras>.

evidence of police malpractice. These improvements could lead to even more widespread surveillance. Some cities have already added drones for surveillance purposes, and police use of drones to maintain security of ports, airports, coastal areas, waterways, industrial facilities is likely to increase, raising concerns about privacy, safety, and other issues.

The New York Police Department's CompStat was the first tool pointing toward predictive policing,¹⁰⁴ and many police departments now use it.¹⁰⁵ Machine learning significantly enhances the ability to predict where and when crimes are more likely to happen and who may commit them. As dramatized in the movie *Minority Report*, predictive policing tools raise the specter of innocent people being unjustifiably targeted. But well-deployed AI prediction tools have the potential to actually remove or reduce human bias, rather than reinforcing it, and research and resources should be directed toward ensuring this effect.

AI techniques can be used to develop intelligent simulations for training law-enforcement personnel to collaborate. While international criminal organizations and terrorists from different countries are colluding, police forces from different countries still face difficulty in joining forces to fight them. Training international groups of law enforcement personnel to work as teams is very challenging. The European Union, through the Horizon 2020 program, currently supports such attempts in projects such as LawTrain.¹⁰⁶ The next step will be to move from simulation to actual investigations by providing tools that support such collaborations.

Tools do exist for scanning Twitter and other feeds to look for certain types of events and how they may impact security. For example, AI can help in social network analysis to prevent those at risk from being radicalized by ISIS or other violent groups. Law enforcement agencies are increasingly interested in trying to detect plans for disruptive events from social media, and also to monitor activity at large gatherings of people to analyze security. There is significant work on crowd simulations to determine how crowds can be controlled. At the same time, legitimate concerns have been raised about the potential for law enforcement agencies to overreach and use such tools to violate people's privacy.

The US Transportation Security Administration (TSA), Coast Guard, and the many other security agencies that currently rely on AI will likely increase their reliance to enable significant efficiency and efficacy improvements.¹⁰⁷ AI techniques—vision, speech analysis, and gait analysis—can aid interviewers, interrogators, and security guards in detecting possible deception and criminal behavior. For example, the TSA currently has an ambitious project to redo airport security nationwide.¹⁰⁸ Called DARMS, the system is designed to improve efficiency and efficacy of airport security by relying on personal information to tailor security based on a person's risk categorization and the flights being taken. The future vision for this project is a tunnel that checks people's security while they walk through it. Once again, developers of this technology should be careful to avoid building in bias (e.g. about a person's risk level category) through use of datasets that reflect prior bias.¹⁰⁹

As dramatized in the movie *Minority Report*, predictive policing tools raise the specter of innocent people being unjustifiably targeted. But well-deployed AI prediction tools have the potential to actually remove or reduce human bias.

¹⁰⁴ Walter L. Perry, Brian McInnis, Carter C. Price, Susan Smith, and John S. Hollywood, "The Role of Crime Forecasting in Law Enforcement Operations," *Rand Corporation Report 233* (2013).

¹⁰⁵ "CompStat," *Wikipedia*, last modified July 28, 2016, accessed August 1, 2016, <https://en.wikipedia.org/wiki/CompStat>.

¹⁰⁶ LAW-TRAIN, accessed August 1, 2016, <http://www.law-train.eu/>.

¹⁰⁷ Milind Tambe, *Security and Game Theory: Algorithms, Deployed Systems, Lessons Learned* (New York: Cambridge University Press, 2011).

¹⁰⁸ Peter Neffenger, "TSA's 2017 Budget—A Commitment to Security (Part I)," Department of Homeland Security, March 1, 2016, accessed August 1, 2016, <https://www.tsa.gov/news/testimony/2016/03/01/hearing-fy17-budget-request-transportation-security-administration>.

¹⁰⁹ Crawford, "AI's White Guy Problem."

EMPLOYMENT AND WORKPLACE

While AI technologies are likely to have a profound future impact on employment and workplace trends in a typical North American city, it is difficult to accurately assess current impacts, positive or negative. In the past fifteen years, employment has shifted due to a major recession and increasing globalization, particularly with China's introduction to the world economy, as well as enormous changes in non-AI digital technology. Since the 1990s, the US has experienced continued growth in productivity and GDP, but median income has stagnated and the employment to population ratio has fallen.

AI will likely replace tasks rather than jobs in the near term, and will also create new kinds of jobs. But the new jobs that will emerge are harder to imagine in advance than the existing jobs that will likely be lost.

There are clear examples of industries in which digital technologies have had profound impacts, good and bad, and other sectors in which automation will likely make major changes in the near future. Many of these changes have been driven strongly by "routine" digital technologies, including enterprise resource planning, networking, information processing, and search. Understanding these changes should provide insights into how AI will affect future labor demand, including the shift in skill demands. To date, digital technologies have been affecting workers more in the skilled middle, such as travel agents, rather than the very lowest-skilled or highest skilled work.¹¹⁰ On the other hand, the spectrum of tasks that digital systems can do is evolving as AI systems improve, which is likely to gradually increase the scope of what is considered routine. AI is also creeping into high end of the spectrum, including professional services not historically performed by machines.

To be successful, AI innovations will need to overcome understandable human fears of being marginalized. AI will likely replace tasks rather than jobs in the near term, and will also create new kinds of jobs. But the new jobs that will emerge are harder to imagine in advance than the existing jobs that will likely be lost. Changes in employment usually happen gradually, often without a sharp transition, a trend likely to continue as AI slowly moves into the workplace. A spectrum of effects will emerge, ranging from small amounts of replacement or augmentation to complete replacement. For example, although most of a lawyer's job is not yet automated,¹¹¹ AI applied to legal information extraction and topic modeling has automated parts of first-year lawyers' jobs.¹¹² In the not too distant future, a diverse array of job-holders, from radiologists to truck drivers to gardeners, may be affected.

AI may also influence the size and location of the workforce. Many organizations and institutions are large because they perform functions that can be scaled only by adding human labor, either "horizontally" across geographical areas or "vertically" in management hierarchies. As AI takes over many functions, scalability no longer implies large organizations. Many have noted the small number of employees of some high profile internet companies, but not of others. There may be a natural scale of human enterprise, perhaps where the CEO can know everyone in the company. Through the creation of efficiently outsourced labor markets enabled by AI, enterprises may tend towards that natural size.

AI will also create jobs, especially in some sectors, by making certain tasks more important, and create new categories of employment by making new modes of interaction possible. Sophisticated information systems can be used to create new

¹¹⁰ Jeremy Ashkenas and Alicia Parlapiano, "How the Recession Reshaped the Economy, in 255 Charts," *The New York Times*, June 6, 2014, accessed August 1, 2016, <http://www.nytimes.com/interactive/2014/06/05/upshot/how-the-recession-reshaped-the-economy-in-255-charts.html>.

¹¹¹ R Dana Remus and Frank S. Levy, "Can Robots Be Lawyers? Computers, Lawyers, and the Practice of Law," *Social Science Research Network*, last modified February 12, 2016, accessed August 1, 2016, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2701092.

¹¹² John Markoff, "Armies of Expensive Lawyers, Replaced by Cheaper Software," *The New York Times*, March 4, 2011, accessed August 1, 2016, <http://www.nytimes.com/2011/03/05/science/05legal.html>.

markets, which often have the effect of lowering barriers to entry and increasing participation—from app stores to AirBnB to taskrabbit. A vibrant research community within AI studies further ways of creating new markets and making existing ones operate more efficiently.

While work has intrinsic value, most people work to be able to purchase goods and services they value. Because AI systems perform work that previously required human labor, they have the effect of lowering the cost of many goods and services, effectively making everyone richer. But as exemplified in current political debates, job loss is more salient to people—especially those directly affected—than diffuse economic gains, and AI unfortunately is often framed as a threat to jobs rather than a boon to living standards.

There is even fear in some quarters that advances in AI will be so rapid as to replace all human jobs—including those that are largely cognitive or involve judgment—within a single generation. This sudden scenario is highly unlikely, but AI will gradually invade almost all employment sectors, requiring a shift away from human labor that computers are able to take over.

The economic effects of AI on cognitive human jobs will be analogous to the effects of automation and robotics on humans in manufacturing jobs. Many middle-aged workers have lost well-paying factory jobs and the socio-economic status in family and society that traditionally went with such jobs. An even larger fraction of the total workforce may, in the long run, lose well-paying “cognitive” jobs. As labor becomes a less important factor in production as compared to owning intellectual capital, a majority of citizens may find the value of their labor insufficient to pay for a socially acceptable standard of living. These changes will require a political, rather than a purely economic, response concerning what kind of social safety nets should be in place to protect people from large, structural shifts in the economy. Absent mitigating policies, the beneficiaries of these shifts may be a small group at the upper stratum of the society.¹¹³

In the short run, education, re-training, and inventing new goods and services may mitigate these effects. Longer term, the current social safety net may need to evolve into better social services for everyone, such as healthcare and education, or a guaranteed basic income. Indeed, countries such as Switzerland and Finland have actively considered such measures. AI may be thought of as a radically different mechanism of wealth creation in which everyone should be entitled to a portion of the world’s AI-produced treasure.¹¹⁴ It is not too soon for social debate on how the economic fruits of AI-technologies should be shared. As children in traditional societies support their aging parents, perhaps our artificially intelligent “children” should support us, the “parents” of their intelligence.

As labor becomes a less important factor in production as compared to owning intellectual capital, a majority of citizens may find the value of their labor insufficient to pay for a socially acceptable standard of living.

¹¹³ For example, Brynjolfsson and McAfee, *Second Machine Age*, have two chapters of devoted to this (Erik Brynjolfsson and Andrew McAfee, *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, (New York: W. W. Norton & Company, Inc., 2014)) and Brynjolfsson, McAfee, and Spence describe policy responses for the combination of globalization and digital technology (Erik Brynjolfsson, Andrew McAfee, and Michael Spence, *Foreign Affairs*, July/August 2014, accessed August 1, 2016, <https://www.foreignaffairs.com/articles/united-states/2014-06-04/new-world-order>).

¹¹⁴ GDP does not do a good job of measuring the value of many digital goods. When society can’t manage what isn’t measured, bad policy decisions result. One alternative is to look at consumer surplus, not just dollar flows. As AI is embodied in more goods, this issue becomes more salient. It may look like GDP goes down but people have better well-being through access to these digital goods. See Erik Brynjolfsson and Adam Saunders, “What the GDP Gets Wrong (Why Managers Should Care),” *Sloan Management Review*, vol. 51, no. 1 (October 1, 2009): 95–96.

ENTERTAINMENT

AI will increasingly enable entertainment that is more interactive, personalized, and engaging. Research should be directed toward understanding how to leverage these attributes for individuals' and society's benefit.

With the explosive growth of the internet over the past fifteen years, few can imagine their daily lives without it. Powered by AI, the internet has established user-generated content as a viable source of information and entertainment. Social networks such as Facebook are now pervasive, and they function as personalized channels of social interaction and entertainment—sometimes to the detriment of interpersonal interaction. Apps such as WhatsApp and Snapchat enable smart-phone users to remain constantly “in touch” with peers and share sources of entertainment and information. In on-line communities such as Second Life and role-playing games such as World of Warcraft, people imagine an alternative existence in a virtual world.¹¹⁵ Specialized devices, such as Amazon’s Kindle have also redefined the essentials of long-cherished pastimes. Books can now be browsed and procured with a few swipes of the finger, stored by the thousands in a pocket-sized device, and read in much the same way as a handheld paperback.

Trusted platforms now exist for sharing and browsing blogs, videos, photos, and topical discussions, in addition to a variety of other user-generated information. To operate at the scale of the internet, these platforms must rely on techniques that are being actively developed in natural language processing, information retrieval, image processing, crowdsourcing, and machine learning. Algorithms such as collaborative filtering have been developed, for example, to recommend relevant movies, songs, or articles based on the user’s demographic details and browsing history.¹¹⁶

Traditional sources of entertainment have also embraced AI to keep pace with the times. As exemplified in the book and movie *Moneyball*, professional sport is now subjected to intensive quantitative analysis.¹¹⁷ Beyond aggregate performance statistics, on-field signals can be monitored using sophisticated sensors and cameras. Software has been created for composing music¹¹⁸ and recognizing soundtracks.¹¹⁹ Techniques from computer vision and NLP have been used in creating stage performances.¹²⁰ Even the lay user can exercise his or her creativity on platforms such as WordsEye, which automatically generates 3D scenes from natural language text.¹²¹ AI has also come to the aid of historical research in the arts, and is used extensively in stylometry and, more recently, in the analysis of paintings.¹²²

The enthusiasm with which humans have responded to AI-driven entertainment has been surprising and led to concerns that it reduces interpersonal interaction among human beings. Few predicted that people would spend hours on end interacting with a display. Children often appear to be genuinely happier playing at home on their devices rather than outside with their friends. AI will increasingly enable entertainment that is more interactive, personalized, and engaging. Research should be directed toward understanding how to leverage these attributes for individuals’ and society’s benefit.

115 Second Life, accessed August 1, 2016, <http://secondlife.com>; “World of Warcraft,” Blizzard Entertainment, Inc, accessed August 1, 2016, <http://us.battle.net/wow/en/>.

116 John S. Breese, David Heckerman, and Carl Kadie, “Empirical Analysis of Predictive Algorithms for Collaborative Filtering,” *Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence* (July 1998), accessed August 1, 2016, <http://arxiv.org/pdf/1301.7363.pdf>, 43–52.

117 Michael Lewis, *Moneyball: The Art of Winning an Unfair Game* (New York: W. W. Norton & Company, Inc., 2003); <http://www.imdb.com/title/tt1210166/>.

118 MuseScore, accessed August 1, 2016, <https://musescore.org/>.

119 Shazam, accessed August 1, 2016, <http://www.shazam.com/>.

120 Annie Dorsen, accessed August 1, 2016, <http://www.anniedorsen.com/>.

121 WordsEye, accessed August 1, 2016, <https://www.wordseye.com/>.

122 “Stylometry,” *Wikipedia*, last modified August 4, 2016, accessed August 1, 2016, <https://en.wikipedia.org/wiki/Stylometry>; <http://arxiv.org/pdf/1408.3218v1.pdf>.

Imagining the Future

The success of any form of entertainment is ultimately determined by the individuals and social groups that are its subjects. The modes of entertainment that people find appealing are diverse and change over time. It is therefore hard to predict the forms entertainment will take in the next fifteen years precisely. Nevertheless, current trends suggest at least a few features that the future entertainment landscape is likely to contain.

To date, the information revolution has mostly unfolded in software. However, with the growing availability of cheaper sensors and devices, greater innovation in the hardware used in entertainment systems is expected. Virtual reality and haptics could enter our living rooms—personalized companion robots are already being developed.¹²³ With the accompanying improvements in Automatic Speech Recognition, the Study Panel expects that interaction with robots and other entertainment systems will become dialogue-based, perhaps constrained at the start, but progressively more human-like. Equally, the interacting systems are predicted to develop new characteristics such as emotion, empathy, and adaptation to environmental rhythms such as time of day.¹²⁴

Today, an amateur with a video camera and readily-available software tools can make a relatively good movie. In the future, more sophisticated tools and apps will become available to make it even easier to produce high-quality content, for example, to compose music or to choreograph dance using an avatar. The creation and dissemination of entertainment will benefit from the progress of technologies such as ASR, dubbing, and Machine Translation, which will enable content to be customized to different audiences inexpensively. This democratization and proliferation of AI-created media makes it difficult to predict how humans' taste for entertainment, which are already fluid, will evolve.

With content increasingly delivered digitally, and large amounts of data being logged about consumers' preferences and usage characteristics, media powerhouses will be able to micro-analyze and micro-serve content to increasingly specialized segments of the population—down to the individual.¹²⁵ Conceivably the stage is set for the emergence of media conglomerates acting as "Big Brothers" who are able to control the ideas and online experiences to which specific individuals are exposed. It remains to be seen whether broader society will develop measures to prevent their emergence. This topic, along with others pertaining to AI-related policy, is treated in more detail in the next section.

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¹²³ Emoters, accessed August 1, 2016, <http://emoterbots.com/>.

¹²⁴ "Siri," Apple, Inc., accessed August 1, 2016, <http://www.apple.com/in/ios/siri/>.

¹²⁵ Ryan Calo, "Digital Market Manipulation," *George Washington Law Review* 82, no. 4 (2014): 995–1051.