Received: 22 June 2019 | Revised: 28 July 2019 | Accepted: 30 July 2019
DOI: 10.1002/ajim.23037

COMMENTARY

AMERICAN JOURNAL OF INDUSTRIAL MEDICINE WILEY

Artificial intelligence: Implications for the future of work

John Howard MD

US Department of Health and Human Services, Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health, Washington, District of Columbia

Correspondence
John Howard, MD, US Department of Health and Human Services, Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health, 395 E Street, S.W., Suite 9200, Washington, D.C. 20201.
Email: jhoward1@cdc.gov

Artificial intelligence (AI) is a broad transdisciplinary field with roots in logic, statistics, cognitive psychology, decision theory, neuroscience, linguistics, cybernetics, and computer engineering. The modern field of AI began at a small summer workshop at Dartmouth College in 1956. Since then, AI applications made possible by machine learning (ML), an AI subdiscipline, include Internet searches, e-commerce sites, goods and services recommender systems, image and speech recognition, sensor technologies, robotic devices, and cognitive decision support systems (DSSs). As more applications are integrated into everyday life, AI is predicted to have a globally transformative influence on economic and social structures similar to the effect that other general-purpose technologies, such as steam engines, railroads, electricity, electronics, and the Internet, have had. Novel AI applications in the workplace of the future raise important issues for occupational safety and health. This commentary reviews the origins of AI, use of ML methods, and emerging AI applications embedded in physical objects like sensor technologies, robotic devices, or operationalized in intelligent DSSs. Selected implications on the future of work arising from the use of AI applications, including job displacement from automation and management of human-machine interactions, are also reviewed. Engaging in strategic foresight about AI workplace applications will shift occupational research and practice from a reactive posture to a proactive one. Understanding the possibilities and challenges of AI for the future of work will help mitigate the unfavorable effects of AI on worker safety, health, and well-being.

KEYWORDS
artificial intelligence, decision support systems, machine learning, robotics, smart sensors

1 | INTRODUCTION

New employment arrangements, the pace of technological advances in the workplace, and changing workforce demographics have led international organizations,[1,2] national governments,[3-5] and private sector consultancies[6-11] to offer views about how the future of work will be affected by these trends. Emerging technologies—sensors, robotics, cyber-physical systems, cloud and quantum computing, advanced manufacturing, and Artificial intelligence (AI)—have captured most of the attention in future-of-work reports.[12-14] While the picture of what the far future of work will look like is not entirely clear, the role of AI in the workplace of the near future is becoming more integral in a firm's business strategy.[15]

AI will be a transformative influence across all industry sectors according to forecasts from the European Union,[16] China,[17,18] and the United States.[19,20] AI is expected to drive economic growth in a way similar to previous general-purpose technologies (GPTs).[21-23] In the 19th and 20th centuries GPTs, such as steam engines, railroads, electricity, electronics, and the Internet, have all had widespread impacts on social structures and the global economy.[24] While the prediction that AI will improve global economic welfare remains

Institution at which the work was performed: National Institute for Occupational Safety and Health.

speculative, recent advances in AI performance, especially in the areas of machine perception and cognition, have fueled optimism about AI's future economic role.[25]

Although still in their infancy, novel applications of AI in the workplace of the future raise important issues for occupational safety and health researchers, practitioners, employers, and workers. As AI-enabled applications are introduced in the workplace, occupational safety, and health professionals need to develop a better understanding about AI methods and their potential effects on work and workers. Maximizing the potential occupational safety and health benefits of AI applications, while minimizing any potential challenges, is critical as AI tools are introduced into the workplace.

The origins of AI, the use of machine learning (ML)methods—the most common AI application used today—and emerging AI applications embedded in physical objects like sensors and robotic devices, or operationalized in intelligent decision support systems (DSSs) are reviewed. Also reviewed are selected potential AI effects on automation and human-machine interactions. Engaging in strategic foresight[26] about AI workplace applications will shift occupational research and practice from a reactive posture to a proactive one[27] and will help mitigate unfavorable effects of AI on worker safety, health, and well-being.

2 | ORIGINS OF AI

AI is a large field of transdisciplinary science. The scientific disciplines that underlie AI include logic, statistics, cognitive psychology, decision theory, neuroscience, linguistics, cybernetics, and computer engineering.[28] From Charles Babbage, the inventor of the first mechanical computer in the 1850s, to Alan Turing, the father of the general-purpose programmable computer, who in 1950 was the first to ask "can machines think?"[29] the idea of machine intelligence equivalent to that of a human being has captured the imaginations of both computer scientists[30] and science fiction writers.[31]

The term "artificial intelligence" was first used in a proposal for a 1956 summer research workshop at Dartmouth College in New Hampshire. The workshop defined the "artificial intelligence problem" as one "of making a machine behave in ways that would be called intelligent if a human were so behaving."[32] Simply put, AI can be understood as an expansive general term that focuses on the use of computational methods to replicate human intelligence.

In 1950, Alan Turing proposed an operational test for machine intelligence. The Turing test measures the ability of a machine to exhibit intelligent behavior equivalent to or indistinguishable from that of a human. A computer "passes the test if a human interrogator, after posing some written questions, cannot tell whether the written responses come from a human or a machine."[29] The aim of the 1956 Dartmouth workshop was to develop a level of AI that could pass the Turing test—a level of machine intelligence that matches or exceeds human intelligence. To satisfy the Turing test, a computer needs to understand speech (natural language processing), be able to store what it knows or hears (knowledge representation), use that stored information to answer questions and draw conclusions (automated reasoning), and detect new patterns and adapt to new circumstances (ML).[28] Add two additional capabilities—computer vision and physical interaction—and the computer would satisfy what is known as the Total Turing test.[33,34] These six competencies now represent the major areas in the field of AI research and development.[28]

Machine competencies are divided into artificial general intelligence (AGI) or "strong" AI (actual thinking), and "narrow" or "weak" AI (simulated thinking).[28] Even though AGI is many decades away, futurists predict that when a machine is able to achieve AGI, an "intelligence explosion" will take place[35] and profound changes in human civilization would follow.[36] In the meantime, though, narrow AI—the type that is seen today—is beginning to deliver a suite of comprehensive AI services[37] through physical devices like sensors, robots, or through digital software applications enabling intelligent DSSs.

3 | MACHINE LEARNING

ML is a subdiscipline of AI that enables computers to learn from data. ML is an overarching term for several different methods to achieve AI,[38] and is the main driver of the growth in AI commercial applications.[39] ML has emerged as the chief AI tool to obtain cognitive insights, make predictions, and support decision-making from a computer.[40] ML represents a departure from earlier AI methods (expert systems) that operated by using an exhaustive set of logic rules, hand-coded in software, that attempted to anticipate all possible outcomes of a problem.[41] With ML, computers are able to infer their own rules using advanced software methods (algorithms).

While many of the algorithms used in ML have been used previously by statisticians, the recent generation of large amounts of digital data—images, texts, transactions, human and environmental sensing data ("big data")—that can be stored in the cloud rather than on-premises, and that can be analyzed faster and cheaper by graphical processing units, makes it possible to "train" machines to perform a task without being explicitly programmed to do so.[40] The various ML methods in current use include Internet searches, e-commerce, goods and services recommender systems, identification of images, image and speech recognition, sensor technologies, robotic devices, and cognitive DSSs.[42] All of these applications arise from several different ML methods that enable learning by a machine.[43]

3.1 | Supervised learning

Supervised learning uses a training data set, correctly labeled by a human expert, to find patterns and make predictions.[35] For example, training sets can be used to autocode large data sets of workers' compensation insurance claims to advance the science of occupational injury surveillance.[44] Using a supervised learning training data set, a radiographic image classification algorithm can learn the correct relationship between the input image, for example, an X-ray, and the output label, for example, lung cancer, and then apply that relationship to classify unlabeled images the computer has not seen before.[45]

3.2 | Unsupervised learning

Unsupervised learning does not use a prepared training set of data. Rather, unlabeled data are provided to the learning algorithm and the computer then describes the hidden structure of the data without human guidance, separating the data into clusters or groups.[46,47] For example, an unsupervised learning method can be used to target customers through clustering resulting in market segmentation.[48] While outputs from supervised learning may be more accurate than those from unsupervised learning, supervised learning is resource-intensive, as a training data set must be prepared by human experts.[49]

3.3 | Semi-supervised learning

Like other forms of ML learning, semi-supervised learning is an ML method to gain more understanding about the structure of a data set. Vast amounts of unlabeled data from images, voice, and text are currently being generated across industry sectors, but using supervised learning to classify unlabeled data is costly. However, when large amounts of unlabeled data are combined with a small amount of labeled data, the accuracy of an ML classification is improved and the costs of preparing the data set are reduced.[50] Speech recognition errors, for example, can be reduced by 22% by combining human and machine labeling of data using semi-supervised learning.[51]

3.4 | Reinforcement learning

Adapted from fundamental learning theory in psychology, reinforcement learning involves a training method based on rewarding desired behaviors and/or punishing undesired ones,[52] a form of sequential experimentation by a computer.[53] Reinforcement learning enables a computer to learn correct outcomes (behavior) through rewards and penalties using the trial and error method used by all humans.[54] In attempting to achieve a goal while interacting with a dynamic external environment,[45] a computer using reinforcement learning is generating its own training data through experimentation and optimization of the outputs.[39] Reinforcement learning is largely how AlphaGo learned its winning moves in playing Go with human competitors.[55] Reinforcement learning can be used with neural networks in autonomous vehicle technology, and in teaching a robot how to grasp objects it has never seen before.[56]

3.5 | Neural networks

Although neural networks are largely responsible for the recent surge in ML applications, the concept of a mimicking a network of neurons arose prior to the Dartmouth AI workshop in 1956.[57] In this in silico model of the brain, an artificial neural network is a computer program that "learns" not by using electrical signals like neuron activation, but by mathematically adjusting the probability weights between nodes in a number of successive layers so that the difference between the input and output layers narrows until the actual output of the network matches the desired output.[58-60]

In 1943, researchers suggested that multiple, interconnected layers of computer "neurons" that mimic the network of neurons and their synaptic connections found in the human brain could be trained to learn from data.[61,62] In 1958, the first example of a silicon neuron was created—the "perceptron."[63] In the 1960s, observations of the various optic cells found in a cat's visual cortex further inspired the concept of neural networks[64,65] used now for computer vision systems in autonomous vehicles.[66,67] By the late 1980s, the goal of replacing hand-engineering with trainable, multilayer networks were greatly aided by an acceptance of probability and decision theory,[68] research on the back-propagation algorithm,[69-71] the widespread availability of powerful parallel processors, and the emergence of big data.[62]

3.6 | Deep learning

Deep learning is a subset of neural networks that use multiple processing layers of interconnected neurons between input and output layers to recognize a pattern.[72,73] For example, input images are fed into a neural network and the neurons assign mathematical weights to different elements (pixels) of the image. A final output layer puts together all the pieces of information generated to identify the image. If the output is incorrect, the neural network notes the error and adjusts its neurons' weights. The network examines another image, repeats this step thousands of times, adjusting weights each time, narrowing the error rate until the network correctly identifies the image,[74,75] as a deep learning algorithm recently did in learning to recognize a cat without being trained on cat features.[76,77]

Deep learning algorithms have achieved significant success at image recognition,[77] speech recognition,[78] and natural language understanding.[79] These new ML technologies are just beginning to be applied in the workplace, chiefly in advanced sensors, robotic devices, and intelligent DSSs.

4 | AI WORKPLACE APPLICATIONS

4.1 | Sensor devices

Simple sensors such as end-of-life respirator indicators, personal dust monitors, and noise level meters are ubiquitous in the workplace and have been for many years. Advanced or "smart" sensors exhibit greater functionality than traditional sensors. Smart sensors can be surgically placed in the body (implantables); worn on the body or embedded safety clothing (wearables); or attached to a workplace object to monitor different parameters (placeables).[80-83] Any device or object with embedded sensors can be connected to the Internet, and to other similar devices, forming an Internet of Things (IoT). A cloud-based IoT platform can collect, integrate, and analyze data from a distributed industrial network of IoT sensors to improve the assessment of different workplace safety and health hazards.[84]

AI applications are being introduced into many different types of sensor technologies, across different industry sectors such as finance (high-frequency trading by ML); national security (intelligence analysis); health care (clinical decision-making); criminal justice (sentencing); insurance (fraud detection); and banking (loan evaluation).[23] What is getting most of the public attention is the use of emerging AI-enabled computer vision sensor technologies for facial recognition across many settings, including employment settings, and object detection by autonomous vehicles in the transportation industry.[85] Sensors using neural networks show promise in making control engineering systems smarter and more adaptive in industrial settings.[86] Advanced sensor devices are being equipped to use deep learning models to "sense" the environment in a manner similar to human visual and auditory perception.

Although research and development of advanced sensors have grown exponentially, challenges remain. For example, functionalizing robotic tactile perception is a sensor research frontier. Human dexterity has been hard to replicate in a robotic device, but new sensor research methods have been recently identified that may lead to the achievement of artificial touch systems.[87] In addition to various proprioceptive sensors that help prevent a robotic device from colliding with nearby human workers, newer sensors can be envisioned that can collect and report workplace exposure data on a continuous basis. Deploying sensors throughout a workplace makes the entire workplace, and everyone in it, data input for an AI-enabled DSS. Such a system can help occupational safety and health practitioner identify exposure trends in real-time and overtime. These sensor networks are at the heart of the emerging industrial IoT,[88] generating vast amounts of data from which occupational safety and health practitioner will have to extract value.

AI-enabled sensors can provide both promising benefits for the practice of occupational safety and health and potential challenges. Among the benefits could be the use of continuous data from workplace sensors for early intervention to prevent toxic exposures. Those data would allow practitioners to transition from the traditional reliance on slower episodic area or breathing zone sampling. Large data sets produced by a 24/7 sensor network, analyzed by ML-enabled algorithms, have the potential to improve surveillance of safety and health effects from AI, decrease uncertainty in risk assessment and management practices, and stimulate new avenues of occupational safety and health research. Also, AI-enabled virtual reality training can be used to create dynamic, high-fidelity immersive environments to simulate hazardous situations and enhance a worker's hazard recognition capabilities.[89]

Among the challenges is the privacy dilemmas associated with the use of AI-enabled sensor technology to monitor and track all aspects of worker performance.[90] More businesses are managing their workforces using sensor technology, cloud-based human resource systems, and ML-enabled data analytics in an approach called "people analytics."[91] While people analytics assists management in the business operations of recruitment, performance management, workforce planning, and retention, intrusive monitoring of employee behavior can lead to a loss of privacy,[92] feelings of depersonalization,[93] and heightened stress among workers.[12] Proposed best practices for employer-sponsored worker monitoring programs include using only validated sensor technologies; ensuring voluntary worker participation; ceasing data collection outside the workplace; disclosing all data uses; and ensuring secure data storage.[94]

4.2 | Robotic devices

Since the 1980s, robotic devices have been programmed to function in highly controlled environments, chiefly in automobile manufacturing plants, automating many tasks formerly performed by human workers.[60] Recently, there has been a shift from workplace robotic devices that do routine functions—automated robots—to the more advanced robots that are able to interact with people and their environment—autonomous robots. These newer AI-enabled robotic devices, called collaborative robots or "cobots".[95]

The presence of a cobot and a human worker in the same work area raises a number of safety issues, chiefly collision control. In 2016, the International Organization for Standardization (ISO) provided safety requirements to promote safe human-cobot collaboration. For industrial cobots equipped with AI-enabled sensors, the ISO recommended: (a) safety-related monitored stopping controls; (b) human hand guiding of the cobot; (c) speed and separation monitoring controls; and (d) power and force limitations.[96]

AI methods are also enabling one robotic device to learn from the experience of other robotic devices since the sensors in robotic devices can be connected to the cloud. The learning experience of one AI-enabled robotic device can be uploaded to all other connected robots by means of "cloud robotics."[97] When a safer method is discovered for a workplace process from the output of one robot, all robotic devices connected in the cloud can be upgraded to adopt the new method. Universal robotic upgradability in a cloud-connected network provides an operational learning advantage for robots over human learning which represents individually-dependent learning.[98]

4.3 | Decision support systems

Since the 1950s, firms have routinely used data management system analytics to drive business decision support. Firms that collect and store large amounts of data, who have robust computational capabilities, and in-house computer engineering expertise, are introducing AI to support financial, operational, and organizational risk decision-making.[99] AI applications can be used to mine knowledge from data for decision-making applications by using a DSS—a multipurpose informational AI-enabled tool.

The idea of using computers to aid decision-makers led to the use of technologies to support business decisions by leveraging data already stored in management information systems.[100-102] By the 1980s, expert systems that acquired the information directly from human domain experts and then transformed that information into machine-usable formats were introduced.[103] The process of knowledge acquisition using domain experts proved resource-intensive and DSSs were developed using newer ML methods such as deep learning neural networks.[104-106]

AI-enabled DSSs are now being used for decision-making across multiple industry sectors, especially in medicine.[107-110] The health care industry generates large amounts of data which provide ideal learning inputs for ML-enabled DSSs.[111] Clinical DSSs are touted as having the power to improve diagnostic accuracy,[112] and to assist physicians in comprehending complex relationships between scores of clinical variables.[104] To date, a number of studies using ML-enabled DSSs have shown progress in: (a) screening for lung cancer[113]; (b) detecting pulmonary tuberculosis[114]; (c) identifying diabetic retinopathy[115,116]; (e) diagnosing skin cancer[117]; (f) forecasting anticancer drug response in precision oncology treatments[118,119]; and (g) predicting cardiovascular risk factors from retinal photographs.[120] While these early research successes applying ML to large sets of medical data show great promise in enhancing the quality of health care, translating research findings into clinical advances remains a challenge.[121] For example, if an ML image classifier for melanoma skin cancer is trained only on light skin, the AI-enabled classifier will just perpetuate existing health disparities instead of being a tool to overcome them.[122]

DSSs may have a role in improving risk assessment and risk management strategies. Can AI-enabled DSSs prevent catastrophic events such as chemical plant explosions? Can AI-enabled DSSs aid in determining the optimal placement of firefighters during disasters like wildland fires? Can AI-enabled DSSs aid in making risk control decisions under conditions of uncertainty? Can AI-enabled systems recognize a near-miss even before human workers can recognize the "nearness" of the miss? Can AI-enabled systems offer effective risk prevention and mitigation recommendations for complex cumulative risks? Can AI-enabled systems take over control from a human to prevent a decision that will lead to severe injury or a fatality? These and other questions about AI and the future of work deserve the attention of the occupational safety and health community.

Concerns about ML-enabled DDSs, including algorithm transparency and algorithm bias, have arisen as they are introduced across industry sectors. The lack of methodological transparency inherent in ML methods ("black-box") can impair user trust in the outputs produced by a DSS.[123] Increasing the acceptability of DSSs could be achieved by developing interpretability modules to explain how DSS conclusions were reached in ways that are understandable to a human user.[124] Concerns have arisen that an over-reliance on ML "black-box" methods, as opposed to human experiential knowledge, can lead to the "de-skilling" of domain experts in the future.[125] For example, educational programs that train new safety and health practitioners to rely solely on "black box" AI-enabled risk management strategies can lead to aggregate skill loss for the safety and health profession.

5 | SELECTED AI IMPLICATIONS ON WORK

5.1 | Automation

AI-enabled robotic devices have the potential to increase the automation of industrial processes, resulting in technological job displacement.[126,127] Automation affecting employment is not new—many technological advances in the past have led to job destruction from automation.[128] For example, the agriculture sector has experienced significant negative employment shifts in the remote past and manufacturing more recently.[129] The employment effects of new technologies are complex. Job destruction and job creation can both result from the introduction of new technologies, but they may occur in varying proportions and at different times.[130] It is not clear whether job destruction or job creation will predominate as more AI-enabled technologies enter the workplace. In the meantime, the topic of technological job loss from automation is a much-discussed issue.[131-135]

Several estimates have been published about the extent to which job tasks could be automated across industry sectors. Studies by Oxford University[136] and by the McKinsey Global Institute[137] indicate that about half of all job tasks in the US economy could be automated with current AI-enabled technologies. However, not all studies agree that AI will be that much of a job eliminator. Some studies point to several economic, legal, or societal factors that could restrain a firm from adopting job-displacing AI technologies.[138] Fears of technological disruption by AI may be exaggerated,[139] as technology diffusion is often slow[140] which provides time for the new task and job creation to mitigate job loss from automation.[141,142]

5.2 | Human-machine interactions

The interaction of workers and machines has been a concern of ergonomists and systems engineers for many years. System controls which are not fully understandable to humans, or fully responsive in practice as they were in design, can lead to negative consequences. Managing risk as AI-enabled technologies are introduced to the workplace should start with a systems safety approach that focuses on system operation and controls[143] to ensure the reliability and safety of AI technologies enabling autonomous systems.[144]

The introduction of AI-enabled technologies in self-driving vehicles,[145] at a nuclear power plant,[146] or in the avionics systems of a jet airliner,[147,148] raises issues of how to manage the uncertainties associated with human-machine interactions with AI-enabled systems. For example, when human-machine interactions lead to serious injuries or fatalities, the task arises of assigning accountability for erroneous or conflicting sensor data, and/or limited human control over an automated or autonomous system.[149,150] In complex human-machine interactions, some approaches to accident analysis may be biased to safeguard "the integrity of the technological system, at the expense of the nearest human operator."[151]

Protecting an autonomous system operating under limited human control, and assigning blame to a human worker when a mishap occurs, is a potentially unfair way to assign accountability.[151] As more AI-enabled autonomous systems are introduced into workplaces outside of the airline and nuclear power industries, more interactions can be expected to occur between humans and complex systems using "black-box" AI algorithms. Safety management approaches that place responsibility on the nearest human worker involved in a complex human-machine interaction without a detailed analysis of the role of the autonomous system is a one-dimensional approach to safety.

6 | FUTURE OF WORK IS NOW

Uncertainty about how AI will shape the future of work parallel concerns about how AI may alter what it is like to be human.[152] AI-enabled applications that are beginning to enter the workplace need the attention of occupational safety and health practitioners, researchers, employers, and workers. When AI-enabled devices or systems are considered for introduction into the workplace, thorough preplacement safety and health review of their benefits and risks should be performed. A proactive approach to AI and its implications for the future of work require occupational safety and health professionals to develop strategic foresight to better anticipate and prepare for the possibilities and challenges of AI-enabled technologies on worker safety, health, and well-being.

CONFLICT OF INTERESTS

The author declares that there are no conflicts of interest.

DISCLOSURE BY AJIM EDITOR OF RECORD

John D Meyer declares that he has no conflict of interest in the review and publication decision regarding this article.

AUTHOR CONTRIBUTIONS

The author conceived and drafted the work; revised it critically for important intellectual content; gave final approval of the version to be published; and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

ETHICS STATEMENT

No ethics review nor informed consent was required as no human subjects research was involved.

DISCLAIMER

The findings and conclusions in this report are those of the author and do not necessarily represent the views of the National Institute for Occupational Safety and Health, the Centers for Disease Control and Prevention, or the US Department of Health and Human Services.

ORCID

John Howard http://orcid.org/0000-0002-1875-3516

REFERENCES

1. Global Commission on the Future of Work: Work for a Brighter Future. International Labour Organization. January, 2019. https://www.ilo.org/global/publications/books/WCMS_662410/lang--en/index.htm. Accessed June 21, 2019.
2. Stacey N, Bradbrook S, Reynolds J, Williams H. *Review of Trends and Drivers of Change in Information and Communication Technologies and Work Location. Foresight on New and Emerging Risk in OSH. European Agency for Safety and Health at Work*. Bilbao. Luxembourg: Publications Office of the European Union, 2018; 2019. https://doi.org/10.2802/807562. Accessed June 21.
3. Federal Ministry of Labor and Social Affairs, Germany. Re-imaging Work White Paper WORK 4.0; 2017. https://www.bmas.de/EN/Services/Publications/a883-white-paper.html. Accessed June 21, 2019.
4. Horton J, Cameron A, Devaraj D, Hanson RT, Hajkowicz SA. *Workplace Safety Futures. The Impact of Emerging Technologies and Platforms on Work Health and Safety and Workers' Compensation over the Next Twenty Years*. Canberra, Australia: Commonwealth Scientific and Industrial Research Organization (CSIRO); 2018. https://www.safeworkaustralia.gov.au/media-centre/news/future-work-health-and-safety. Accessed June 21, 2019.
5. Executive Order No.13859. Maintaining American Leadership in Artificial Intelligence. 84 *Fed. Reg.* 3967 (February 14, 2019). https://www.federalregister.gov/documents/2019/02/14/2019-02544/maintaining-american-leadership-in-artificial-intelligence. Accessed June 21, 2019.
6. Karoly LA, Panis C. *The Future at Work: Trends and Implications*. Santa Monica, CA: RAND Corporation; 2004. https://www.rand.org/pubs/research_briefs/RB5070.html. Accessed June 21, 2019.
7. World Economic Forum. The Future of Jobs: Employment, Skills, and Workforce Strategy for the Fourth Industrial Revolution. January, 2016. http://www3.weforum.org/docs/WEF_Future_of_Jobs.pdf. Accessed June 21, 2019.
8. Schwab K. *The Fourth Industrial Revolution*. New York, NY: Crown Publishing Group; 2017.
9. Volini E, Schwartz J, Roy I, et al. From jobs to super jobs. 2019 Global Human Capital Trends. April 11, 2019. https://www2.deloitte.com/insights/us/en/focus/human-capital-trends/2019/impact-of-ai-turning-jobs-into-superjobs.html. Accessed July 29, 2019.
10. Lund S, Manyika J, Segel LH, et al. The future of work in America: people and places, today, and tomorrow. McKinsey Global Institute. July 2019. https://www.mckinsey.com/featured-insights/future-of-work/the-future-of-work-in-america-people-and-places-today-and-tomorrow. Accessed July 29, 2019
11. Daugherty P, Wilson HJ Process Reimagined. Together, people and AI are reinventing business processes from the ground up. Accenture Research;2018. https://www.accenture.com/_acnmedia/PDF-76/Accenture-Process-Reimagined.pdf#zoom=50. Accessed June 21, 2018.
12. European Agency for Safety and Health at Work. OSH and the Future of Work: Benefits and Risks of Artificial Intelligence Tools in Workplaces. May 15, 2019. https://osha.europa.eu/en/tools-and-publications/publications/osh-and-future-work-benefits-and-risks-artificial-intelligence. Accessed June 21, 2019.
13. Stacey N, Ellwood P, Bradbrook S, et al. *European Agency for Safety and Health at Work. Foresight on New and Emerging Occupational Safety Risks Associated with Digitalisation by 2025*. Luxembourg:

Publications Office of the European Union; 2018. https://osha.europa.eu/en/tools-and-publications/publications/summary-foresight-new-and-emerging-occupational-safety-and-1. Accessed June 21, 2019.

14. Delponte L. *European Artificial Intelligence Leadership: the Path For An Integrated Vision*. Brussels: Policy Department for Economic, Scientific and Quality of Life Policies, European Parliament; 2018. http://www.europarl.europa.eu/RegData/etudes/STUD/2018/626074/IPOL_STU(2018)626074_EN.pdf. Accessed June 21, 2019.
15. Kiron D, Schrage M. Strategy for and with AI. *Sloan Manage Rev*. 2019;60(4):29-36. https://sloanreview.mit.edu/article/strategy-for-and-with-ai/. Accessed June 21, 2019.
16. European Commission. *Communication on Artificial Intelligence for Europe*. Brussels: European Commission; 2018. https://ec.europa.eu/digital-single-market/en/news/communication-artificial-intelligence-europe. Accessed June 21, 2019.
17. Barton D, Woetzel J, Seong J, Tian Q Artificial Intelligence: Implications for China. The McKinsey Global Institute. April 2017. https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/China/Artificial%20intelligence%20Implications%20for%20China/MGI-Artificial-intelligence-implications-for-China.ashx. June 21, 2019.
18. Lee K-F, Superpowers AI. *China, Silicon Valley and the New World Order*. New York, NY: Houghton Mifflin Harcourt; 2018.
19. White House. Office of Science and Technology Policy. Summary of the White House Summit for AI for American Industry. May 10, 2018. https://www.whitehouse.gov/wp-content/uploads/2018/05/Summary-Report-of-White-House-AI-Summit.pdf?latest. Accessed June 21, 2019.
20. White House. National Science & Technology Council. The National Artificial Intelligence Research and Development Strategic Plan: 2019 Update. June 21, 2019. https://www.nitrd.gov/pubs/National-AI-RD-Strategy-2019.pdf. Accessed July 29, 2019.
21. International Labour Organization. Safety and health at the Heart of the Future of Work: Building on 100 Years of Experience. Geneva, Switzerland; 2019. https://www.ilo.org/safework/events/safeday/WCMS_686645/lang--en/index.htm. Accessed June 21, 2019.
22. Manyika J, Bughin J The Promise and Challenge of the age of artificial intelligence. The McKinsey Global Institute, October 2018. https://www.mckinsey.com/featured-insights/artificial-intelligence/the-promise-and-challenge-of-the-age-of-artificial-intelligence. Accessed June 21, 2019.
23. West DM, Allen JR. *How Artificial Intelligence is Transforming the World*. Washington, DC: Brookings; April 24, 2018. https://www.brookings.edu/research/how-artificial-intelligence-is-transforming-the-world/. Accessed June 21, 2019.
24. Lipsey RG, Carlaw KI, Bekar CT. *Economic Transformations: general Purpose Technologies and Long-Term Economic Growth*. New York, NY: Oxford University Press; 2005.
25. Brynjolfsson E, Rock D, Syverson C. Artificial Intelligence and the Modern Productivity Paradox: a Clash of Expectations and Statistics. In: Agrawal A, Gans J, Goldfarb A, eds. *The Economics of Artificial Intelligence. An Agenda.* Chicago, IL: University of Chicago Press; 2019:23-59.
26. Hines A, Bishop P. Thinking About the Future: guidelines for Strategic Foresight. 2nd ed. Houston, TX: Hindsight; 2015.
27. Murashov V, Howard J. Essential features for proactive risk management. *Nat Nanotechnol*. 2009;4:467-470. https://www.nature.com/articles/nnano.2009.205.pdf. Accessed June 21, 2019.
28. Russell SJ, Norvig P. *Artificial Intelligence: A Modern Approach*. 3rd ed. Uttar Pradesh, India: Pearson Education Limited; 2015.
29. Turing AM. Computing machinery and intelligence. *Mind*. 1950;LIX(236):433-460. https://www.csee.umbc.edu/courses/471/papers/turing.pdf. Accessed June 21, 2019.
30. Jordan J. *Robots*. Cambridge, MA: MIT Press; 2016.
31. Asimov I, Frenkel KA. *Robots: Machines in Man's Image*. New York, NY: Harmony Books; 1985.
32. McCarthy J, Minsky ML, Rochester N, Shannon CE A proposal for the Dartmouth Summer Research Project on Artificial Intelligence. 1955. http://jmc.stanford.edu/articles/dartmouth.html. Accessed June 21, 2019.
33. Harnad S. Other bodies, other minds: a machine incarnation of an old philosophical problem. *Mind Mach*. 1991;1(1):43-54. https://link.springer.com/article/10.1007/BF00360578. Accessed June 21, 2019.
34. Schweizer P. The truly total Turing test. *Mind Mach*. 1998;8(2):263-272. https://doi.org/10.1023/A:1008229619541 Accessed June 21, 2019
35. Maini V, Sabri S Machine Learning for Humans. 2017. https://www.coursehero.com/file/32124967/Machine-Learning-for-Humanspdf/. Accessed June 21, 2019.
36. Kurzweil R. *Singularity is Near: When Humans Transcend Biology*. New York, NY: Penguin; 2005.
37. Drexler E Reframing Superintelligence. Comprehensive AI Services as General Intelligence. Technical Report #2019-1, Future of Humanity Institute, University of Oxford. https://www.fhi.ox.ac.uk/reframing/. Accessed June 21, 2019.
38. Mohri M, Rostamizadeh A, Talwalker A. *Foundations of Machine Learning*. 2nd ed. Cambridge, MA: MIT Press; 2018.
39. Taddy M. The Technological Elements of Artificial Intelligence. In: Agrawal A, Gans J, Goldfarb A, eds. *The Economics of Artificial Intelligence: An Agenda*. Chicago, IL: University of Chicago Press; 2019:61-87.
40. Jordan MI, Mitchell TM. Machine learning: trends, perspectives, and prospects. *Science*. 2015;349(6245):255-260. https://doi.org/10.1126/science.aaa8415 Accessed June 21, 2019
41. Haugeland J. *Artificial Intelligence: The Very Idea*. Cambridge, MA: MIT Press; 1985.
42. Davenport TH, Ronanki R. Artificial intelligence for the real world. *Harvard Bus Rev*. 2018. January-February.
43. Gershman SJ, Horvitz EJ, Tenenbaum JB. Computational rationality: a converging paradigm for intelligence in brains, minds and machines. *Science*. 2015;349(6245):273-278. https://doi.org/10.1126/science.aac6076 Accessed July 29, 2019
44. Myers A, Al-Tarawneh IS, Wurzelbacher S, et al. Applying machine learning to workers' compensation data to identify industry-specific ergonomic and safety prevention priorities: Ohio, 2001-2011. *JOEM*. 2018;60(1):55-73. https://doi.org/10.1097/JOM.0000000000001162 Accessed June 21, 2019.
45. Choy G, Khalilzadeh O, Michalski M, et al. Current applications and future impact of machine learning in radiology. *Radiology*. 2018;288(2):318-328. https://pubs.rsna.org/doi/10.1148/radiol.2018171820. Accessed June 21, 2019.
46. Hinton G, Sejnowski TJ. *Unsupervised Learning: Foundations of Neural Computation*. Cambridge, MA: MIT Press; 1999.
47. James G, Witten D, Hastic T, Tibshirani R. *An Introduction to Statistical Learning*. New York, NY: Springer Science; 2017.
48. Kelleher JD, Tierney B. *Data Science.* Cambridge, MA: MIT Press; 2018.
49. Ng A. What artificial intelligence can and can't right now. *Harv Bus Rev*. 2016. https://hbr.org/2016/11/what-artificial-intelligence-can-and-cant-do-right-now. Accessed June 21, 2019.
50. Chapelle O, Schölkopf B, Zein A. *Semi-supervised Learning*. Cambridge, MA: MIT Press; 2006.
51. Johnson K. Alexa scientists reduce speech recognition errors up to 22% with semi-supervised learning. *Venture Beat*. 2019. https://venturebeat.com/2019/04/04/alexa-ai-scientists-reduce-speech-recognition-errors-up-to-22-with-semi-supervised-learning/. Accessed June 21, 2019.
52. Thorndike E. *The Fundamentals of Learning*. New York, NY: Teachers College Bureau of Publications; 1932.
53. Varian H. Artificial Intelligence, Economics, and Industrial Organizations. In: Agrawal A, Gans J, Goldfarb A, eds. *The Economics of*

Artificial Intelligence: An Agenda. Chicago, IL: University of Chicago Press; 2019:399-422.
54. Sutton RS, Barto AG. *Reinforcement Learning: An Introduction*. 2nd ed. Cambridge, MA: MIT Press; 2018.
55. Moyer C How Google's AlphaGo beat a Go world champion. *The Atlantic Magazine*. March 28, 2016. https://www.theatlantic.com/technology/archive/2016/03/the-invisible-opponent/475611/. Accessed July 29, 2019
56. Knight W. Reinforcement learning: ten breakthrough technologies 2017. *MIT Technol Rev*. 2017. https://www.technologyreview.com/s/603501/10-breakthrough-technologies-2017-reinforcement-learning/. Accessed June 21, 2019.
57. Schmidhuber J. Deep learning in neural networks: an overview. *Neural Net*. 2015;61:85-117. https://arxiv.org/pdf/1404.7828.pdf. Accessed June 21, 2019.
58. McCulloch WS, Pitts W. A logical calculus of the ideas immanent in nervous activity. *Bull Math Biophys*. 1943;5(4):115-133. http://www.cs.cmu.edu/~./epxing/Class/10715/reading/McCulloch.and.Pitts.pdf. Accessed June 21, 2019.
59. Aggrawal CC. *Neural Networks and Deep Learning. A Textbook*. New York, NY: Springer; 2018.
60. Cockburn IM, Henderson R, Stern S. The Impact of Artificial Intelligence on Innovation: an Exploratory Analysis. In: Agrawal A, Gans J, Goldfarb A, eds. *The Economics of Artificial Intelligence: An Agenda*. Chicago, IL: University of Chicago Press; 2019:115-148.
61. Hebb D. *The Organization of Behavior: a Neuropsychological Theory*. New York, NY: Wiley; 1949.
62. Copeland M. What's the difference between artificial intelligence, machine learning, and deep learning. *Nvidia Blogs*. 2016. https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/. Accessed June 21, 2019.
63. Rosenblatt F. The perceptron: a probabilistic model for information storage and organization in the brain. *Psychol Rev*. 1958;65(6):386-408. https://www.ling.upenn.edu/courses/cogs501/Rosenblatt1958.pdf. Accessed June 21, 2019.
64. Wiesel TN, Hubel DH. Receptive fields of single neurons in the cat's striate cortex. *J Physio*. 1959;149:574-591. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1359523/pdf/jphysiol01247-0121.pdf. Accessed June 21, 2019.
65. Hubel DH, Wiesel TN. Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. *J Physio-London*. 1962;160:106-154. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1359523/pdf/jphysiol01247-0121.pdf. Accessed June 21, 2019.
66. LeCun Y, Bengio Y, Hinton G. Deep learning. *Nature*. 2015;521:436-444. https://doi.org/10.1038/nature14539 Accessed June 21, 2019.
67. Alpaydin E. *Machine Learning*. Cambridge, MA: MIT Press; 2016.
68. Pearl J. *Probabilistic Reasoning in Intelligence Systems: networks of Probable Inference*. San Francisco, CA: Morgan Kaufman; 1988.
69. Bryson AE, Ho Y-C. *Applied Optimal Control*. New York, NY: Taylor & Francis; 1975.
70. Rumelhart DE, Hinton GE, Williams RJ. Learning representations by back-propagating errors. *Nature*. 1986;323(6088):533-536. https://www.nature.com/articles/323533a0.pdf. Accessed June 21, 2019.
71. Hinton GE, Salakhutdinov RR. Reducing the dimensionality of data with neural networks. *Science*. 2006;313:504-507. https://doi.org/10.1126/science.1127647 Accessed June 21, 2019.
72. Goodfellow I, Bengio Y, Courville A. *Deep Learning*. Cambridge, MA: MIT Press; 2016.
73. Charniak E. *Introduction to Deep Learning*. Cambridge, MA: MIT Press; 2018.
74. Moawad A Neural networks and back-propagation explained in a simple way. February 1, 2018. https://medium.com/datathings/neural-networks-and-backpropagation-explained-in-a-simple-way-f540a3611f5e. Accessed June 21, 2019.
75. Clark L Google's artificial brain learns how to find cat videos. *Wired Magazine*, June 26, 2012. https://www.wired.com/2012/06/google-x-neural-network/. Accessed June 21, 2019.
76. Le QV, Ranzato M, Monga R, et al. Building high-level features using large scale unsupervised learning, *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*, Vancouver, BC; 2013 (pp. 8595-8598). https://doi.org/10.1109/ICASSP.2013.6639343. Accessed June 21, 2019.
77. Krizhevsky A, Sutskever I, Hinton G. ImageNet classification with deep convolutional networks. *Proceedings of Advances in Neural Information Processing Systems*. 2012;25:1090-1098. https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf. Accessed June 21, 2019.
78. Hinton G, Deng L, Yu D, et al. Deep neural networks for acoustic modeling in speech recognition: the shared views of four research groups. *IEEE Signal Proc Mag*. 2012;29:82-97. https://www.microsoft.com/en-us/research/wp-content/uploads/2016/02/HintonDengYuEtAl-SPM2012.pdf. Accessed June 21, 2019.
79. Hirschberg J, Manning CD. Advances in natural language processing. *Science*. 2015;349(6245):261-266. https://doi.org/10.1126/science.aaa8685 Accessed June 21, 2019.
80. Nag A, Mukhopadhyay SC, Kosel J. Wearable flexible sensors: a review. *IEEE Sens J*. 2017;17(13):3949-3960. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7931559&tag=1. Accessed June 21, 2019.
81. Bray H MIT Labor Shows Off Smart Treads That Can Send Messages, Change Color. *Boston Globe*. June 18, 2017. https://www.bostonglobe.com/business/2017/06/19/mit-lab-shows-off-smart-threads-that-can-send-messages-change-color/Kf8S15GtAWuZEc7TXprVkM/story.html. Accessed June 21, 2019.
82. Yang G-Z. *Implantable Sensors and Systems: from Theory to Practice*. New York, NY: Springer; 2018.
83. Metz R. The company embeds microchips in its employees, and they love it. *MIT Technol Rev*. 2018. https://www.technologyreview.com/s/611884/this-company-embeds-microchips-in-its-employees-and-they-love-it/. Accessed June 21, 2019.
84. Chui M, Loeffler M, Roberts R. The internet of things. *McKinsey Quarterly*. 2010. https://www.mckinsey.com/industries/high-tech/our-insights/the-internet-of-things. Accessed June 21, 2019.
85. Yurtsever E, Lambert J, Carballo A, Takeda K A survey of autonomous driving: common practices and emerging technologies. June 12, 2019. https://arxiv.org/pdf/1906.05113.pdf. Accessed June 21, 2019.
86. Sanders DA, Gegov A. Artificial intelligence for control engineering. *Control Eng*. 2013. https://www.controleng.com/articles/artificial-intelligence-tools-can-aid-sensor-systems/. Accessed June 21, 2019.
87. Sundaram S, Kellnhofer P, Li Y, Zhu J-Y, Torralba A, Matusik W. Learning the signatures of the human grasp using a scalable tactile glove. *Nature*. 2019;569:698-702. https://doi.org/10.1038/s41586-019-1234-z Accessed June 21, 2019.
88. Chalaka R, Venkatraman C, Badarinarayan H, Kinsey G Artificial Intelligence (AI) Delivering Breakthroughs in Industrial IoT. Hitachi, Ltd. September 19, 2017. https://www.hitachinext.com/en-us/pdfd/presentation/artificial-intelligence-delivering-breakthroughs-in-industrial-iot.pdf. Accessed June 21, 2019.
89. Bellanca JL, Orr TJ, Helfrich WJ, Macdonald B, Navoyski J, Demich B. Developing a virtual reality environment for mining research. *Min Metal Exploration*. 2019;36(4):597-606. https://doi.org/10.1007/s42461-018-0046-2 Accessed June 21, 2019.
90. Booth R. UK businesses using artificial intelligence to monitor staff activity. *The Guardian*. 2019. https://www.theguardian.com/technology/2019/apr/07/uk-businesses-using-artifical-intelligence-to-monitor-staff-activity. Accessed June 21, 2019.
91. Collins L, Fineman DR, Tsuchida A. People analytics: recalculating the route. 2017 human capital trends. *Deloitte Insights*. 2017. https://www2.deloitte.com/insights/us/en/focus/human-capital-trends/2017/people-analytics-in-hr.html. Accessed June 21, 2019.

92. Horvitz E, Mulligan D. Data, privacy, and the greater good. *Science*. 2015;349(6245):253-255. https://doi.org/10.1126/science.aac4520 Accessed June 21, 2019.
93. Harwell D As Walmart turns to robots, it's the human workers who feel like machines. *Washington Post*. June 6, 2019;1D. https://www.washingtonpost.com/technology/2019/06/06/walmart-turns-robots-its-human-workers-who-feel-like-machines/?utm_term=.b603806d8586. Accessed June 21, 2019.
94. Marchant GE. What are best practices for ethical use of nanosensors for worker surveillance? . *AMA J Ethics*. 2019;21(4):E356-E362. https://journalofethics.ama-assn.org/sites/journalofethics.ama-assn.org/files/2019-03/stas1-1904_0.pdf. Accessed June 21, 2019.
95. Vysocky A, Novak P. Human—robot collaboration. *MM Science Journal*. 2016;2016:903-906. https://doi.org/10.17973/MMSJ.2016_06_201611 June:903-906 Accessed June 21, 2019.
96. International Organization for Standardization. ISO/TS 15066:2016. Robots and Robotic Devices—Collaborative Robots. https://www.iso.org/standard/62996.html. Accessed June 21, 2019.
97. Kehoe B, Patil S, Abbeel P, Goldberg K. A survey of research on cloud robotics and automation. *IEEE T Autom Sci Eng*. 2015;12(2):398-409. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7006734. June 21, 2019.
98. Pratt GA. Is a Cambrian explosion coming for robotics? *J Econ Perspect*. 2015;29(3):51-60. https://pubs.aeaweb.org/doi/pdfplus/10.1257/jep.29.3.51. Accessed June 21, 2019.
99. Dhanrajani S Reimagining enterprise decision-making with artificial intelligence. *Forbes Magazine*. October 16, 2018. https://www.forbes.com/sites/cognitiveworld/2018/10/15/reimagining-enterprise-decision-making-with-artificial-intelligence/#186263462fd6. Accessed June 21, 2019.
100. Bonini CP. *Simulation of Information and Decision System in the Firm*. Englewood Cliffs, NJ: Prentice Hall; 1963.
101. Laudon KC, Laudon JP. *Information Management Systems: Managing the Digital Firm*. 15th ed. New York, NY: Pearson; 2018.
102. Pervan G, Willcocks L. Introduction to the special issue on decision support systems. *J Inf Technol*. 2005;20:65-66.
103. Jackson P. *Introduction to Expert Systems*. 3rd ed. Reading, MA: Addison-Wesley; 1999.
104. Phillips-Wren G. AI tools in decision support systems: a review. *Int J Artif Intell T*. 2012;21(2):1240005. https://www.worldscientific.com/doi/abs/10.1142/S0218213012400052. Accessed June 21, 2019.
105. Merkert J, Mueller M, Hubl M A survey of the application of machine learning in decision support systems. ECIS Completed Research Papers, 2015. https://aisel.aisnet.org/ecis2015_cr/133/. Accessed June 21, 2019
106. Shaikhina T, Khovanova NA. Handling limited datasets with neural networks in medical applications: a small-data approach. *Artif Intell Med*. 2017;75:51-63. https://doi.org/10.1016/j.artmed.2016.12.003 Accessed June 21, 2019.
107. Kononenko I. Machine learning for medical diagnosis: history, state of the art and perspective. *Artif Intell Med*. 2001;23:89-109. https://doi.org/10.1016/S0933-3657(01)00077-X Accessed June 21, 2019.
108. Shortliffe EH, Sepúlveda MJ. Clinical decision support in the era of artificial intelligence. *JAMA*. 2018;320(21):2199-2200. https://doi.org/10.1001/jama.2018.17163 Accessed June 21, 2019.
109. Hinton G. Deep learning—a technology with the potential to transform health care. *JAMA*. 2018;320(11):1101-1102. https://doi.org/10.1001/jama.2018.11100. Accessed June 21.
110. Topol E. *Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again*. New York, NY: Basic Books; 2019.
111. Ehteshami Bejnordi B, Veta M, Johannes van Diest P, et al. Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer. *JAMA*. 2017;318(22):2199-2210. https://doi.org/10.1001/jama.2017.14585 Accessed June 21, 2019.
112. Obermeyer Z, Emanuel EJ. Predicting the future—big data, machine learning, and clinical medicine. *N Engl J Med*. 2016;375(13):1216-1219. https://doi.org/10.1056/NEJMp1606181 Accessed June 22, 2019.
113. Ardila D, Kiralyap, Bharadwaj S, et al. End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography. *Nat Med*. 2019. https://doi.org/10.1038/s41591-019-0447-x Accessed June 21, 2019.
114. Lakhani P, Sundaram B. Deep learning at chest radiography: automated classification of pulmonary tuberculosis by using convolutional neural networks. *Radiology*. 2017;284(2):574-582. https://pubs.rsna.org/doi/pdf/10.1148/radiol.2017162326. Accessed June 21, 2019.
115. Gulsen V, Peng L, Coram M, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA*. 2016;316(22):2401-2410. https://doi.org/10.1001/jama.2016.17216 Accessed June 21, 2019.
116. Kanagasingam Y, Xiao D, Vignarajan J, Preetham A, Tay-Kearney M-L, Mehrotra A. Evaluation of artificial intelligence-based grading of diabetic retinopathy in primary care. *JAMA Network Open*. 2018;1(5):e182665-e182671. https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2703944 Accessed June 21, 2019.
117. Esteva A, Kuprel B, Novoa RA, et al. Dermatologist-level classification of skin cancer with deep neural networks. *Nature*. 2017;542(7639):115-118. https://doi.org/10.1038/nature21056 Accessed June 21, 2019.
118. Azuaje F. Artificial intelligence for precision oncology: beyond patient stratification. *NPJ Precision Oncology*. 2019;3(6):6. https://doi.org/10.1038/s41698-019-0078-1 Accessed June 21, 2019.
119. Tan M. Prediction of anticancer drug response by kernelized multitask learning. *Artif Intell Med*. 2016;73:70-77. https://doi.org/10.1016/j.artmed.2016.09.004 Accessed June 21, 2019.
120. Poplin R, Varadarajan AV, Blumer K, et al. Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. *Nat Biomed Eng*. 2018;2:158-164. https://doi.org/10.1038/s41551-018-0195-0 volume Accessed June 21, 2019.
121. Deo RC. Machine learning in medicine. *Circulation*. 2015;132(20):1920-1930. https://doi.org/10.1161/CIRCULATIONAHA.115.001593 Accessed June 21, 2019.
122. Adamson AS, Smith A. Machine learning and health care disparities in dermatology. *JAMA Dermatol*. 2018;154(11):1247-1248. https://doi.org/10.1001/jamadermatol.2018.2348 Accessed June 21, 2019.
123. Lahav O, Mastronarde N, van der Schaar M What is interpretable? Using machine learning to design interpretable decision-support systems. June 11, 2019. https://arxiv.org/abs/1811.10799. Accessed June 21, 2019.
124. Guidotti R, Monreale A, Ruggieri S, Turini F, Giannotti F, Pedreschi D. A survey of methods for explaining black box models. *ACM Comput Surv*. 2018;51(5):1-42. https://doi.org/10.1145/3236009. Accessed June 21, 2019.
125. Cabitza F, Rasoini R, Gensini GF. Unintended consequences of machine learning in medicine. *JAMA*. 2017;318(6):517-518. https://doi.org/10.1001/jama.2017.7797 Accessed June 21, 2019.
126. Brynjolfsson E, Mitchell T. What can machine learning do? Workforce implications. *Science*. 2017;358(6370):1530-1534. https://doi.org/10.1126/science.aap8062 Accessed June 21, 2019.
127. oja JK, Roth S, Westerlund L. Futures of robotics. Human work in digital transformation. *Int J Technol Manag*. 2017;73(4):176-205. https://doi.org/10.1504/IJTM.2017.10004003 Accessed June 21, 2019.
128. Acemoglu D, Restrepo P The wrong kind of AI? Artificial intelligence and the future of labor demand. March 5, 2019. https://economics.mit.edu/files/16819. Accessed June 21, 2019.
129. NCCI Insights. The economic outlook and its impact on workers compensation. June 2017. https://www.ncci.com/Articles/Pages/II_

Insights_QEB_Economic-Outlook-Impact-WorkersComp-Q3-2017.aspx. Accessed June 21, 2019.
130. Decker M, Fischer M, Ott I. Service robotics and human labor: a first technology assessment of substitution and cooperation. *Rob Auton Syst*. 2017;87:348-354. https://doi.org/10.1016/j.robot.2016.09.017 Accessed June 21, 2019.
131. Brynjolfsson E, McAfee A. *The Second Machine Age: Work, Progress, and Prosperity in Time of Brilliant Technologies*. New York, NY: W.W. Norton & Company; 2014.
132. DeCanio SJ. Robots and humans—complements or substitutes? *J Macroecon*. 2016;49:280-291. https://doi.org/10.1016/j.jmacro.2016.08.003 Accessed June 21, 2019.
133. Acemoglu D, Restrepo P. *The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment*. Washington D.C.: National Bureau of Economic Research; 2017. Working Paper 22252. Issued in May 2016, Revised in June. https://www.nber.org/papers/w22252. Accessed June 21, 2019.
134. Acemoglu D, Restrepo P Robots and Jobs: Evidence from U.S. Labor Markets. Washington, D.C.: National Bureau of Economic Research, Working Paper 23285. March 2017. https://www.nber.org/papers/w23285. Accessed June 21, 2017.
135. Autor D, Salomons A Is automation labor-displacing? Productivity growth, employment and the labor share. National Bureau of Economic Research, Working Paper No. 24871, August 2018. https://www.nber.org/papers/w24871.pdf. Accessed June 21, 2019.
136. Frey CB, Osborne MA. The future of employment: how susceptible are jobs to computerisation. *Technol Forecase Soc*. 2017;114:254-280. https://doi.org/10.1016/j.techfore.2016.08.019 Accessed June 21, 2019.
137. The McKinsey Global Institute. A Future That Works: Automation, Employment and Productivity. January 2017. https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Digital%20Disruption/Harnessing%20automation%20for%20a%20future%20that%20works/MGI-A-future-that-works_Full-report.ashx. Accessed June 21, 2019.
138. Arntz M, Greggory T, Zierahn U The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis. Organisation of Economic Cooperation and Development, Social, Employment and Migration Working Papers No. 189; 2016. https://doi.org/10.1787/5jlz9h56dvq7-en. Accessed June 21, 2019.
139. Atkinson RD, Wu J False Alarmism: Technological Disruption and the U.S. Labor Market, 1850-2015. Information Technology & Innovation Foundation, May 8, 2017. http://www2.itif.org/2017-false-alarmism-technological-disruption.pdf. Accessed June 21, 2019.
140. Cass O. *The Once and Future Worker. A Vision for the Renewal of Work in America*. New York, NY: Encounter Books; 2018.
141. Acemoglu D, Restrepo P. The race between man and machine: implications of technology for growth, factor shares, and employment. *American Economic Review*. 2018;108(6):1488-1542. https://pubs.aeaweb.org/doi/pdfplus/10.1257/aer.20160696. Accessed June 21, 2019.
142. Autor DH. Why are there still so many jobs? The history and future of workplace automation. *J Econo Perspect*. 2015;29(3):3-30. https://pubs.aeaweb.org/doi/pdfplus/10.1257/jep.29.3.3. Accessed June 21, 2019.
143. Leveson NG. Engineering a Safer World. *Systems Thinking Applied to Safety*. Cambridge, MA: MIT Press; 2011.
144. Darvish Rouani B, Samragh M, Javidi T, Koushanfar F. Safe machine learning and defeating adversarial attacks. *IEEE Security & Privacy*. 2019;17(2):31-38. https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=8677311. Accessed June 21, 2019.
145. Weise E, Marsh A Google self-driving van involved in crash in Arizona, driver injured (Update). *USA Today*, May 5, 2019. https://phys.org/news/2018-05-waymo-self-driving-car-collision-arizona.html. Accessed June 21, 2019.
146. Walker JS. *Three Mile Island: A Nuclear Crisis in Historical Perspective*. Berkeley, CA: University of California Press; 2004.
147. Clark N Report on '09 Air France Crash Cites Conflicting Data in Cockpit. *New York Times*, July 5, 2012. https://www.nytimes.com/2012/07/06/world/europe/air-france-flight-447-report-cites-confusion-in-cockpit.html. Accessed June 21, 2019.
148. German K FAA has no timetable for when Max 8 will fly again. *CNET*, June 10, 2019. https://www.cnet.com/news/boeings-737-max-8-all-about-the-aircraft-flight-ban-and-investigations/. Accessed June 21, 2019.
149. Cummings ML. Automation and accountability in decision support system interface design. *J Tech Stud*. 2006;32:23-31. https://doi.org/10.21061/jots.v32i1.a.4. Accessed June 21, 2019.
150. Sheridan TB, Parasuraman R. Human-automation interaction. *Rev Hum Fact and Ergo*. 2005;1(1):89-129. https://doi.org/10.1518/155723405783703082 Accessed June 21, 2019.
151. Elish MC. Moral crumple zones: cautionary takes in human-robot interaction. *Sci Tech Soc*. 2019;5:40-60. https://doi.org/10.2139/ssrn.2757236 Accessed June 21, 2019.
152. Pew Research Center. Artificial Intelligence and the Future of Humans. December 10, 2018. https://www.pewinternet.org/wp-content/uploads/sites/9/2018/12/PI_2018.12.10_future-of-ai_FINAL1.pdf. Accessed on June 21, 2019.

How to cite this article: Howard J. Artificial intelligence: Implications for the future of work. *Am J Ind Med*. 2019;1–10. https://doi.org/10.1002/ajim23037