

COMMENTARY

Artificial intelligence: Implications for the future of work

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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 consultancies⁶⁻¹¹ 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

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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 foresight²⁶ about AI workplace applications will shift occupational research and practice from a reactive posture to a proactive one²⁷ 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 scientists³⁰ 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 place³⁵ 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 services³⁷ 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 cancer¹¹³; (b) detecting pulmonary tuberculosis¹¹⁴; (c) identifying diabetic retinopathy^{115,116}; (e) diagnosing skin cancer¹¹⁷; (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 DSSs, 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 University¹³⁶ and by the McKinsey Global Institute¹³⁷ 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 slow¹⁴⁰ 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 controls¹⁴³ 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.

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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.

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