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COMMENTARY

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Algorithms and the future of work

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Abstract

An *algorithm* refers to a series of stepwise instructions used by a machine to perform a mathematical operation. In 1955, the term artificial intelligence (AI) was coined to indicate that a machine could be programmed to duplicate human intelligence. Even though that goal has not yet been reached, the use of sophisticated machine learning algorithms has moved us closer to that goal. While algorithm-enabled systems and devices will bring many benefits to occupational safety and health, this Commentary focuses on new sources of worker risk that algorithms present in the use of worker management systems, advanced sensor technologies, and robotic devices. A new "digital Taylorism" may erode worker autonomy, and lead to work intensification and psychosocial stress. The presence of large amounts of information on workers within algorithmic-enabled systems presents security and privacy risks. Reliance on indiscriminate data mining may reproduce forms of discrimination and lead to inequalities in hiring, retention, and termination. Workers interfacing with robots may face work intensification and job displacement, while injury in the course of employment by a robotic device is also possible. Algorithm governance strategies are discussed such as risk management practices, national and international laws and regulations, and emerging legal accountability proposals. Determining if an algorithm is safe for workplace use is rapidly becoming a challenge for manufacturers, programmers, employers, workers, and occupational safety and health practitioners. To achieve the benefits that algorithm-enabled systems and devices promise in the future of work, now is the time to study how to effectively manage their risks.

KEYWORDS
algorithm, artificial intelligence, robotics, sensors

1 | INTRODUCTION

While the general concept of an algorithm has existed since antiquity,[1] the term "algorithm" originated with the Persian astronomer and mathematician, Muhammad ibn Musa al-Khwarizmi (c.780–c.850), known as the father of algebra.[2] His book on Arabic-Hindu numerals and arithmetic, *Al-Khwārizmī On the Hindu Art of Reckoning*, describes step-by-step methods for arithmetical calculation.[3] In the 12th century, a Latin translation of his book from the Arabic—*Algoritmi de numero Indorum*—began with the phrase *Dixit Algorizmi* ("Thus spake Al-Khwarizmi").[4] The English word "algorithm" was derived from the Latinization of Al-Khwarizmi's last name. In the present day, an algorithm refers to a series of precise, stepwise instructions used by a machine to perform a mathematical operation leading to the desired output.[5]

The modern era of algorithms began in the mid-19th century. In 1843, Ada Lovelace created an algorithm designed to calculate Bernoulli numbers, a sequence of rational numbers, on a *mechanical* machine designed by Charles Babbage to automate mathematical computations.[6] In 1937, Alan Turing developed a general-purpose computational device that could be programmed using algorithms.[7] A computer's power to perform cognitive tasks eventually led to the belief that human learning and reasoning could be duplicated by a machine.[8,9]

In the 1950s, a new scientific field of study called "artificial intelligence," or "AI" was born.[10] The term AI was used at first to describe the goal "…of making a machine behave in ways that would be called intelligent if a human being were so behaving."[11] Even though AI's goal was, and still is, to build a machine that can replicate human intelligence, there is little scientific agreement about what constitutes human intelligence.[12,13] The concept of computational rationality has been proposed as the one capability unifying human minds and computers.[14] While *strong* or *general* AI—machine intelligence equivalent to that of a human being—is a powerful cultural and social construct,[15] it is a goal that has yet to be achieved.[6] Yet it is undeniable that the use of sophisticated algorithms by computers across industry sectors has been moving cognitive science and data engineering closer to that goal.

2 | AI MODELS

As a sequence of mathematical operations, an algorithm can instruct a computer's transistors when to turn on and off. Using Boolean algebra where variables have values of true and false, various configurations of 0s ("off") and 1s ("on") are used by a computer's binary circuitry to process an algorithm's instructions. This electromechanical process is understood as "computer reasoning."[16] To operationalize an AI method or model, algorithmic instructions must be written in a programming language that a computer understands, such as Python, C++, Java, Ruby, R, or others.[17] Over the past several decades, two major approaches to emulating human reasoning and decision-making by machine intelligence have been developed.

2.1 | Expert system model

As the first successful applications of AI, expert systems were introduced in the 1970s and gained widespread popularity in the 1980s and 1990s.[18] Designed to capitalize on prior human knowledge, expert systems involved the use of hard-coded, rules-based algorithms in a system that mimicked the decision-making ability of a human expert in a particular area of knowledge.[19] In an expert system, domain experts develop a knowledge base and inference rules that can be used by an inference engine to deduce new information using condition ("IF") and consequence ("THEN") rules.[20] Known as symbolic AI models or good old-fashioned AI (GOFAI),[20,21] expert systems had early successes but eventual limitations. Representing an entire field of human knowledge with a finite set of rules requires a lot of effort on the part of domain experts.[22] Often, domain experts cannot always fully explain their reasoning, which makes engineering a knowledge base and inference rules challenging.[23] As any knowledge base grows, more rules must be added. Expert systems have no procedures to generate rules automatically; they must be updated manually, which takes time and resources.[24] A new AI model that can learn and rapidly adapt to new data and conditions was needed.[17]

2.2 | Machine learning method

A major shift in AI models occurred when traditional expert systems were superseded by data-driven machine learning.[23] Machine learning algorithms learn and improve from "experience" by exploiting large sets of "training data" provided by a human agent, discerning patterns not coded in advance by that agent but derived inductively without being explicitly programmed to do so.[23,25] Unlike an expert system that derives answers from rules and data, machine learning develops rules from data and answers.[26] Even though machine learning is a subfield of AI, the term machine learning has become synonymous with AI.

2.2.1 | Deep learning and neural networks

Deep learning has become the dominant subfield of machine learning to generate data-driven decision outputs. Deep learning is particularly appropriate for problems where data are complex and large training data sets are available.[27] Deep learning utilizes *artificial neural networks* to help machines sense and perceive the world around them.[28]

Artificial neural networks are engineered systems modeled on the human brain's intraconnected system of neurons.[29] The precise physical structure of the neuron was first described by Santiago Ramón y Cajal in 1889, and knowledge about how it achieves its computational complexity through electrochemical physiology continues to accumulate today.[30] For example, in training an artificial neural network to mimic the computations of a simulated biological neuron, an electronic neural network requires between five and eight layers of interconnected artificial neurons to represent the operational complexity of a *single* biological neuron.[31]

Like neurons that are connected by synapses, a network of engineered neurons can be trained to solve problems using a suite of algorithms. One of these—the backpropagation algorithm—has emerged as a critical algorithm to improve the accuracy of a feed-forward neural network in achieving the desired outcome.[32,33] The backpropagation algorithm trains the neural network by performing a backward pass through the engineered network after each forward pass, adjusting the connection weights in the network to reduce the mathematical difference between the actual output and the desired output.[32] Numerical *weights* are applied to the data inputs in a neural network that mimic the excitatory or inhibitory role of synapses in the brain.[34] To each weight is applied a numerical *bias* to indicate the tendency for the neuron to fire (higher bias) or not to fire (lower bias).[27] The backpropagation algorithm operates on the system of weights and biases that influence the desired outputs of the artificial neuron.[5]

2.2.2 | Machine learning algorithms

Scores of different machine learning algorithms are now available to meet the data needs of real-world applications. Effective machine learning models depend on both the quality of input data and the performance of the algorithms used in the application.[23] Generally, machine learning algorithms can be categorized into four types based on the major categories of machine learning: supervised; unsupervised; semisupervised; and reinforcement learning.[35,36]

Supervised machine learning models use labeled data sets to train algorithms that classify data or predict outcomes accurately. In supervised learning, algorithms such as support vector machine (SVM), naïve Bayes; K-nearest neighbor; decision trees, random forests; and linear and logistic regression are commonly used. In *unsupervised machine learning models*, unlabeled data sets are analyzed and clustered to discover hidden patterns in data groupings without the need for human intervention. These models use algorithms such as K-means, Markov decision process, principal component analysis, Gaussian mixture modeling, and backpropagation [in neural networks]. *Semi-supervised machine learning models* are models in which a small amount of labeled data is combined with a large amount of unlabeled data during training. These models use algorithms such as self-training, co-training, generative methods, mixture models, semisupervised SVM, and graph-based modeling. *Reinforcement machine learning models* use an approach where the algorithm learns through trial-and-error in an interactive environment using feedback from its own actions to maximize outcome rewards. In reinforcement learning, algorithms such as Q-learning, temporal difference, and deep adversarial networks are common.[35–37]

Ever more complex algorithms are leading to scientific and cybersecurity advances. For example, a novel neural network machine learning approach called *AlphaFold* incorporates physical and biological knowledge about protein structure, leveraging multi-sequence alignments into the design of the deep learning algorithm, to predict the structures of some 200 million proteins from 1 million species.[38] The European Bioinformatics Institute's *AlphaFold Protein Structure Database*[39] has ushered in the new era of "digital biology."[40]

Another example involves classical encryption algorithms which use large numbers and their prime factors to secure sensitive data (e.g., "integer factorization algorithms"). These existing encryption standards could be at risk from an attack by a quantum computer that might be capable of efficiently factoring very large numbers.[41] To mount a digital defense against such a future threat, new "quantum-resistant" encryption standards are needed.[42] The National Institute for Standards and Technology (NIST) staged several competitions to encourage the development of new encryption-protective algorithms.[43,44]

3 | ALGORITHMS IN THE WORKPLACE

Deep neural learning algorithms have led to dramatic advances in speech recognition through natural language processing, visual object recognition by means of computer vision, and new pharmaceutical drug discovery through bioactivity prediction and de novo molecular design.[45,46] Machine learning algorithms are powering various occupational safety and health applications across several industry sectors.[47] Algorithm applications are found in manufacturing[48,49]; construction[50]; agriculture[51]; extractive mining[52]; retail[53]; and public governance.[54] Data-driven insights powered by algorithm-enabled systems and devices can be conceptualized as future-of-work tools in occupational safety and health that may one day tell you *what* happened (*descriptive systems*) and *why* it happened (*diagnostic systems*); forecast what will happen (*predictive systems*); support decision-making based on present and future conditions (*prescriptive systems*); and take physical actions (*semi-autonomous* and *autonomous systems*).[55–58]

Like other systems and devices used in the workplace, algorithm applications can have many potential benefits, but they may also pose risks to society[59] and workers.[60,61] Enthusiasm over the expected benefits of integrating algorithms into workplace equipment, processes, conditions, and human management systems should be tempered by a full awareness and understanding of their risk profile. Understanding the risks and benefits of algorithm-enabled workplace systems should be based on a comprehensive risk evaluation.[62]

Risks posed by algorithm-enabled systems generally originate in three areas: (1) errors and biases in the *input* or training data; (2) flaws in the design of the *algorithm* or mistakes in coding the algorithm into a programming language; and (3) *user* disregard of an algorithm's limitations or underlying assumptions, leading to an inappropriate application or incorrect interpretation of system outputs or decisions.[63] The increasing complexity of proprietary algorithms—especially self-learning algorithms which can change their decision logic during operation—make it difficult for designers, manufacturers, and users to gain an operational understanding about how an algorithm works.[64,65] Lack of algorithmic transparency can be a major impediment to the assessment and control of new occupational safety and health risks.[62] As algorithmic decision-making is increasing in various societal systems,[66] and in worker management systems, advanced sensor technologies, and robotic devices,[47] attention is focused on ways to attain greater algorithm transparency.[67–69]

3.1 | Algorithmic management

Close physical supervision has been the traditional way that employers have monitored their workers. Employers can now monitor workers by means of video surveillance; track a worker's physical movements through geolocation algorithms; monitor an employee's use of email, social media, and web browsing; assess a worker's productivity, level of engagement, propensity to leave the organization, and adherence to workplace safety behaviors.[70–72] These new data-driven approaches to human resources management are referred to as "people analytics" and are touted as helping employers make better decisions.[73]

Algorithmic management techniques can collect and store worker data on a continuous basis, potentially without express purpose or worker disclosure.[74] In some algorithmic management technologies, the observer of the worker and the decision-maker can both be nonhuman agents.[75–77] Algorithmic worker management systems can process collected data to produce a decision output and send that decision to a human or a machine to reward, discipline, or terminate a worker.[60,72]

Algorithmic management is especially pervasive in the gig economy,[78–80] but digital surveillance and management technologies are also seen across other industry sectors.[81,82] New algorithmic technologies have the potential to significantly transform organizational control by affecting the employer–employee relationship.[83] When the organization, not the worker, is the primary beneficiary of algorithm-enabled tools,[84] and where bureaucratic control of the workplace is at stake, individual strategies of resistance to collective organizing—*algoactivism*—can emerge.[83] The diffusion of algorithmic management systems will affect the future of work but may do so in unintended and undesirable ways.[85]

3.1.1 | "Digital Taylorism" and loss of worker autonomy

Algorithmic-enabled productivity and performance systems often represent a type of management control without worker consent when surveillance is not prospectively disclosed to workers.[61] When algorithms are given power over a worker's job, and when the worker has no information or understanding of what data the algorithm is collecting, how the data are being used, and for what purpose, workers report feelings of powerlessness.[86,87] This is not surprising since under algorithmic management workers often have no meaningful interaction with their "digital supervisor."[75,88]

Shift allocation algorithms, delivery route algorithms, warehouse workers movement algorithms, continuous performance algorithms, and other work productivity algorithms are being applied not only to manufacturing workers, but also to service workers, knowledge workers, warehouse workers, and even to first-line supervisors.[87] The new forms of algorithmic management resemble the "scientific management" of Frederick Taylor.[89] This new "digital Taylorism" can be associated with the erosion of worker autonomy, work intensification, psychosocial stress, and a decline in worker well-being.[90–92]

3.1.2 | Data persistence and erosion of worker privacy

Workers have an interest in controlling information about themselves and preventing their employers from knowing "private" things about them without their consent. While the limits of what is private about a worker under algorithmic management are currently uncertain, the presence of large amounts of information about a worker within an algorithmic-enabled system does present a potential security risk. If a nonauthorized person gains access to stored data, a worker's expectation of privacy can be violated.[93] Since increased cloud computing capacity has decreased the costs of data storage, data about a worker, once created, may persist indefinitely.[94] Furthermore, algorithmic-generated data could be repurposed without a worker's knowledge and, if it falls into the wrong hands, may damage a worker's privacy interests.

3.1.3 | Algorithmic bias and discriminatory outcomes

Algorithms that are used to automate organizational management systems may produce discriminatory outcomes that can reproduce and reinforce society's historical age, racial and ethnic, and gender biases, among others.[60,95] Algorithmic bias occurs when an algorithmic-enabled system's outputs advantage or disadvantage some individuals or groups more than others without a justified reason for the disparate impacts.[96] The source of bias can arise from historical proclivities contained in the training data[97] or from algorithm design choices.[98] Reliance on indiscriminate data mining may reproduce forms of discrimination set in motion by previous decision-makers[99] and may lead to occupational inequalities in hiring, retention, and termination, primarily adversely affecting minority workers.[96,100] By implementing algorithmic bias detection and mitigation procedures—*algorithmic hygiene*—and subjecting algorithms to extensive testing before use, consequential decisions negatively affecting workers can be lessened.[96,101,102]

3.2 | Advanced sensor technologies

Sensors are at the heart of technology-managed work as they provide the data inputs for algorithmic controls. Advanced sensor technologies are being commercialized and entering the workplace as new exposure science tools.[103] There are three types of sensors: (1) *placeable sensors* are sensors that can be located around the workplace or fixed to tools or equipment; (2) *wearable sensors*, attached to worker's clothing or a hard hat, or woven into clothing such as electronic textiles, or epidermal sensors attached directly to a worker's skin; and (3) *implantable sensors*, which can be inserted into the skin via microneedles, embedded as microchips, or directly ingested.[104]

Advanced sensor technologies using miniaturized algorithm-embedded microprocessors have the potential to greatly accelerate advances in occupational exposure science by continuously sensing the ambient work environment for hazardous substances or a worker's proximity to known hazards.[105] Wearable and placeable sensors, linked wirelessly and capable of communicating with each other, can be deployed in the workplace as a network system for multihazard safety and health applications.[106] Sensor networks used to detect and monitor hazardous exposures either in the military[107] or in the civilian workplace,[108] to prevent adverse incidents[109] or conversely to promote worker health,[110] can also raise worker concerns over intrusive worker surveillance, algorithmic bias, and violation of personal privacy.[101]

Furthermore, as the algorithmic complexity of a multisensor workplace network increases, operational risks to the network also increase, which require methods that maintain the network's functional integrity.[92] A sensor integrated into a complex software program with multiple algorithms that are operating mechanical equipment may provide erroneous data arising from technical glitches or cybersecurity failures and risk the safety of the machinery operators and others.[104] The most dramatic example of a sensor operating outside of design parameters involved the angle-of-attack (AoA) sensor embedded in a complex operational system on Boeing's 737 Max aircraft. The AoA sensor sent faulty data to the Maneuvering Characteristics Augmentation System (MCAS) software, which caused the horizontal stabilizers to repeatedly pitch the airplanes down, overwhelming the pilots and causing them to lose control of the aircraft.[111]

3.3 | Robotics

Algorithms are critical components of all robotic devices. From an AI architectural perspective, robotic devices can be physically-embodied robots or digital-decision assistants. Robots exhibit three major functions: they sense, plan, and act. Algorithms are involved in all three of these essential robotic functions. Perceptual *sensing* interprets (through algorithms) input signals from sensors detecting light, sound, location, navigation, position, proximity to other objects, movement speed, acceleration, and other data.[112] Robotic motion *planning* is accomplished by the integration of a suite of traditional planning algorithms, classical machine learning algorithms, optimal-value reinforcement learning algorithms, and policy-gradient learning algorithms.[113] These perceptual, interactive algorithms enable an intelligent robotic device to interact with humans or move around in physical space.[114] *Acting* by physical robots is performed through effectors powered by batteries, electric motors, or pneumatics.[112] Digital-assistant robotic devices produce data-based decisions and have been touted as safety assistants that can play an active role in mitigating worker risk.[115]

Traditional robotic devices operate separately from workers, but recently mobile-arm manipulators and other newer robotic devices, working alongside human workers, have been introduced into the workplace. Collaborative robots, or "cobots," combine the dexterity, flexibility, and problem-solving skills of human workers with the strength, endurance, and precision of mechanical robots.[116] Cobots can reduce safety risks and augment productivity, but they can pose a robot-human collision risk from unexpected actions by the robot or the human worker, and through inattention by the human worker.[101] Internet or intranet security risks affecting algorithmic controls or degradation of sensors designed to protect nearby human workers could result in cobot malfunction and increase the risk of injury.[117]

As with algorithmic management systems, work intensification may occur when a robotic system under algorithmic control causes a mismatch between a human worker's physical or cognitive capabilities and work demands. When robotic systems are designed to maximize productivity without adequately considering the impact on human workers' performance, their risk profile increases. While the integration of robotics into work processes promises many productivity benefits, workers may face the risks of work intensification[118] and job displacement[119] from their use.

4 | GOVERNANCE

4.1 | Risk management

Introduction of algorithm-enabled AI systems and devices for workplace use is accelerating faster than algorithm-specific risk assessment and risk management strategies can be developed.[47,120] When integrated into workplace systems, algorithms can present a unique taxonomy of risks that may not be addressed in an organization's traditional occupational safety and health risk management approaches.[62] New methods are needed to detect biases in input data, find design errors in proprietary algorithms, and ensure that output decisions are logically derivative of the input data.[63] The risks arising from invasive surveillance, algorithmic bias, loss of autonomy and privacy, inaccurate decision outputs, and work intensification should be added to existing risk assessment and management approaches. Workers should also have latitude and method to challenge algorithm-generated decisions.[121]

In the case of algorithm-enabled decision systems, the risk control strategy characterized by a human review of algorithmic outputs, called "humans-in-the-loop," is touted as an effective risk management tool.[102,122] However, humans may not be that effective at algorithmic oversight.[71] Many algorithms are inherently opaque and therefore difficult to audit.[123] Advanced skills in mathematics and computer science are often needed to understand exactly *how* an algorithm produced a particular output and *why* it did so.[124,125] Analogous to the twin approaches to workplace safety management based on person versus system error, algorithmic safety management depends on close examination of all "upstream" factors—input data and algorithm design—to prevent "downstream" risks.[126]

4.2 | Legislation and regulation

Challenges to the development of effective risk management for systems whose performance is guided by algorithms, and concerns about the potential economic, political, and social costs of the commercialization of AI technologies, have led to proposals in Europe and the United States to regulate their development and use.[127] Regulating algorithm-enabled systems will be a challenging task as algorithms are already integrated into a great variety of AI systems, in machines from commercial aircraft to Internet search engines, and in devices from advanced sensors to industrial robots.[128]

The European Commission (EC) in April of 2021 submitted a draft proposal for a European Union (EU) regulatory framework for AI —The European Union Artificial Intelligence Act.[129] The Act imposes regulatory burdens only when the AI system is likely to pose high risks to fundamental rights or safety.[130] In the United States, the

Algorithmic Accountability Act of 2022 was introduced in Congress in February of this year.[131] The Algorithmic Accountability Act directs the Federal Trade Commission (FTC) to promulgate regulations that require any covered entity to conduct impact assessments regarding algorithm-enabled decision-making, especially those that implicate an "augmented critical decision process."[132]

Algorithm governance is also being developed by US executive branch agencies. In February 2019, Executive Order 13859 directed the White House Office of Management and Budget (OMB) to provide guidance to all federal agencies on regulatory and non-regulatory approaches to AI as well as ways to reduce barriers to the development and adoption of AI technologies.[133] In a November 2020 memorandum, OMB directed federal agencies to provide their regulatory compliance plans by May 2021 consistent with a 2019 NIST's federal engagement plan for AI technical standards.[134,135]

In 2022, NIST developed a second draft of a framework to better manage algorithm risks to individuals, organizations, and society.[136] The NIST *Artificial Intelligence Risk Management Framework* has been developed as a consensus-based, collaborative process and is intended for voluntary use to improve the ability to incorporate trustworthiness considerations into the design, development, use, and evaluation of AI products, services, and systems.[137] Executive branch agencies like the Food and Drug Administration (FDA) and the Department of Transportation (DOT) have already been incorporating algorithm considerations into their regulatory schemes for medical device software and autonomous vehicles.[138]

Regulatory approaches have also been proposed by the private sector. One approach proposes establishing a government agency that would certify the safety of algorithm-enabled systems and use legal incentives to compel designers, manufacturers, and sellers to ensure safe algorithms and internalize the costs of algorithm-associated harms.[139] Another proposes the equivalent of the FDA to oversee the registration of an algorithm before it is used commercially, just as patents undergo review before a limited monopoly is granted the patent owner.[140]

Algorithm-enabled AI systems are maturing quickly, but international and national legislative, regulatory, and voluntary proposals move at a very slow pace. As the autonomous performance of algorithms that serve in a decision-making role in society and in the workplace increases, attention has been drawn to liability concerns and whether legal sanctions can play a role in accountability for algorithmic harms.[141,142]

4.3 | Legal accountability

Can algorithm-enabled management systems, advanced sensor technologies, or robotic devices with machine learning capabilities be held legally accountable for their output decisions or actions? For a worker injured in the course of employment by an algorithm-enabled robotic device, the answer is clear in that an employer's workers' compensation insurance provides medical benefits to the injured worker. Outside of an undisputed work-related injury, legal actions that a worker may take, like alleging that the algorithm is a defective product, is an unsettled legal issue.[143]

Outside of the workplace, who bears the legal responsibility for an injury when a machine learning algorithm in an autonomous device performs a negligent action independent of human supervisory control?[144] Advanced robotic devices operating deep learning algorithms may take account of new information collected during their operation and adjust their "behavior" in ways unforeseen by the algorithm designers, data collectors and trainers, system architects or device manufacturers, software programmers, operators, or final users.[141] Currently, there is no settled legal approach to assigning legal liability in the case of robot injuries or fatalities.[145,146] As algorithms take on more decision-making roles in society and at the workplace, they will continue to challenge the existing principles of legal accountability.

5 | CONCLUSION

In the future of work, algorithms will provide many beneficial applications in occupational safety and health. While algorithm-enabled systems and devices may reduce sources of human error and enhance worker safety and health, algorithms may also introduce new sources of risks to worker well-being. Determining that an algorithm is safe for use in a worker management system, in advanced sensor technologies, in robotic devices, and in other workplace systems, tools and machinery will challenge the risk assessment and management capabilities of algorithm designers and software programmers, algorithm-enabled equipment manufacturers, employers, workers, and occupational safety and health practitioners. To ensure that the benefits of algorithm-enabled systems and devices have a prominent place in the future of work, now is the time to study how to effectively manage their risks.

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The author contributed all concepts for the article, provided references, wrote drafts, and the final form of the manuscript. The author approved the final version submitted to the American Journal of Industrial Medicine.

CONFLICTS OF INTEREST

The author declares that there are no conflicts of interest.

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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 U.S. Department of Health and Human Services.

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