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Data and Algorithms in the Workplace: A Primer on New Technologies

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1. Introduction

The COVID-19 pandemic has intensified an already urgent discussion about the future of work and the role technology will play in shaping that future. Media reports have highlighted new technologies designed to monitor workers' health and health-related behavior, and widespread employer adoption of remote worker monitoring tools.[1] Other reports have focused on the potential for automation and long-term job displacement to accelerate as a result of the conditions created by the pandemic.[2] Although these reports feature new COVID-related technologies, many are simply the latest application of data-driven technologies developed over the past decade. This working paper explores existing and emerging data-driven technologies and their various applications in the workplace.

Researchers and worker advocates have begun to explore data-driven systems and their implications for workers and society. Their research reports provide an excellent foundation for understanding various trends involving data-driven technologies in the workplace.[3] For example, Coworker.org and The Century Foundation published an article highlighting the growing trend of datafication in the workplace.[4] Upturn published a report outlining different technologies used in the hiring process and their implications for gender and racial equity in employment.[5] And Data & Society has published several reports covering workplace monitoring and algorithmic management on labor platforms and in traditional employment relationships.[6] This important research has shed light on different aspects of worker data collection and data-driven systems and how they operate in the workplace.

Building on these foundational reports, the purpose of this paper is to provide worker organizations and policymakers with a framework for understanding the broad range of data collection strategies and algorithmic systems currently in use or being developed for the workplace. Specifically, the focus here is on understanding the technologies themselves, the context in which they evolved, how they operate, and their potential applications in the workplace. This paper draws on research and analysis focused on specific technologies and the technology industry. Sources include the industry and technology consulting press, technology vendor materials, patent applications, academic research, reports from social research and advocacy institutes, popular media coverage of technology systems and vendors, as well as participation in conferences and meetings focused on computer science, artificial intelligence technologies, and the "future of work" more broadly.

To be clear, this type of technology-focused research is only one component of what will be required to understand the full scope of technological change emerging today. A full research agenda will need to include the perspectives of workers as well as those of employers, and an analysis of the technology production supply chain — which firms are producing new technologies for a given industry, who is funding them, who decides what gets developed in the labs, and so forth. Most important, we urgently need more research on how new technologies affect workplaces and workers (especially in terms of race and gender equity), and the factors driving variation in firms' decisions about technology adoption.

Before moving on, it is important to emphasize that this paper describes emerging technologies; as such it may to a certain extent reflect technology developers' aspirational efforts to advance a product rather than technologies in widespread use among employers. Thus, inclusion of a particular technology or practice in this report is not an indication of its prevalence or likelihood of adoption. That said, some of the technologies discussed in this paper have been in use for some time and are currently widely deployed by employers. Regardless of whether the technologies are in the early stages of development or widely deployed by employers, some of these technologies have elicited concern among various stakeholders. This points to the need to generate a clear framework for assessing and governing the use of proposed technologies. It also highlights the importance of expanding institutional capacity to shape the trajectory of technology innovation.

2. Background: The data-driven firm

Over the past few decades, information and communication technologies (ICTs) have become ubiquitous in the U.S.[7] Today, 90 percent of U.S. adults use the internet, 4 out of 5 own a smartphone, and three-quarters own or use a computer.[8] Computers and other digital technologies now mediate most economic transactions and facilitate an increasing amount of social interactions, generating a digital record of each transmission.[9] Recognizing the economic value of this digital transmission data, firms have developed new business models based on these digital technologies and the stream of data they generate – a process often referred to as digitalization.[10]

Internet technology platforms such as Facebook and Google were among the first to adopt data-driven business models, using data extracted from user's digital interactions as a core source of economic value. After initially offering their services (e.g., email, search engine, social media platform) for free, these companies leveraged their user data to personalize advertisements to individuals and dramatically increase the returns on advertising campaigns. In short, they monetized the insights extracted from the collection and analysis of user data.[11]

Another important outcome of the proliferation of digital data ("big data") is the wave of innovations in data analysis and computer technologies based on algorithms. Improvements in the capacity of computers to store and process data, combined with the increased volume of and access to digital data, have enabled researchers and technology developers to achieve dramatic advances in artificial intelligence (AI) research.[12] The resulting data-driven algorithms underlie many of the technological advances of the past decade.[13] In fact, a crucial contributing factor to the success of the technology platforms mentioned above is their ability to analyze digital data streams and deploy that analysis in a technological system. The systems consist of data-mining, predictive analytics, and machine learning algorithms that identify and segment users into micro-categories of consumers for personalized, targeted advertising.[14] Together, increased volumes of data and the development for new systems for analysis of that data constitute the core of the digital transformation of the economy.

Emerging and traditional businesses have begun to follow the lead of these early innovators by digitalizing business processes and adopting data-driven business strategies (often referred to as "data monetization" in the business press).[15] According to business consultants, firms can derive value from data through three different strategies:[16]

- **Raw data**: selling existing sources of data
- **Insights**: analyzing data to arrive at business insights to support decision-making
- **Data-driven "intelligent" technologies**: using data to develop and operate technologies based on computer algorithms that have the capacity to make automated decisions or take actions that further business objectives

Although selling raw data is one form of revenue generation, analyzing data to develop insights or new data-driven technologies often produces more value for firms. Internally, firms can use insights derived from data or data-driven technologies to control business variables and thereby increase productivity, decrease costs, or increase sales revenues, for example. Firms can also sell or share data-driven insights or technologies as a service to other businesses (a topic discussed below).

3. Types and uses of worker data

Data analytics used in the context of business decisions are not new. Dating back to the 1800s, the finance and insurance industries began to analyze available data to determine prices and underwriting for insurance policies.[17] In the early 1900s scholars began to apply data collection and analysis to work processes and workers. Frederick Taylor's time-and-motion studies tried to maximize workplace productivity and efficiency through precisely timed measurements of worker tasks; his work became the foundation for industrial engineering and production strategies.[18] And Hugo Munsterberg conducted psychological experiments and testing to glean insights about workers in order to solve "problems related to economic efficiency" in the workplace. His innovations evolved into human resource psychometric strategies, such as the assessment and measurement of behavior, attitudes, and personality traits.[19]

Throughout history, efforts to derive value from worker and workplace data, such as those described above, have often led to technological innovations and dramatic changes in the workplace. Today, however, efforts to derive value from these data and data-driven technologies have increasingly become a core business strategy. This section highlights three dimensions of the data-driven workplace:

- Data collection by firms and the types of worker data collected
- Strategies firms use to collect data
- Evolution of data-driven technologies in the workplace

3.1. Types of worker data

While firms initially focused on consumer data in their digital strategies, they are increasingly also looking to worker data as a source of economic value.[20] Firms can generate significant value by collecting data about workers' activities and using that information in data-driven technologies designed with the intent of decreasing operating costs, improving workforce decision-making, and increasing workforce efficiency or productivity. Table 1 shows different types of worker data collected by firms.

Table 1. Types of worker data collected by firms

Historical data • Credit report • Criminal record • Employment and salary history • Education history, professional licenses • Driving record • Health screening, drug and alcohol test results • Participation in volunteer activities • Consumer activity	Workplace activities and interactions data • Presence and location: timeclock, at desk, in building • Coworker interactions • Smartphone use, Wi-Fi access, instant messaging • Bathroom access and usage • Body movements • Safety habits
Biometric data • Fingerprint, palmprint, earprint • Finger and palm geometry • Facial geometry, expressions • Tone of voice • Iris or retina scan • Body language, walking gait	Job activity data • Computer activity: system login, keystrokes, screenshots, application use • Internet activity: email content, web searches • Machine interactions: handheld devices, industrial machines, robots, wearables • Customer service interactions: calls, sales, claims • Business transactions and transfers • Driving: vehicle location (GPS), acceleration, braking patterns, route, accidents and near misses, behaviors while driving and in vehicle, conversations
Health and wellness data • Heart rate and respiration • Exercise activity • Sleep patterns • Movement/activity level • Menstruation and pregnancy tracking	Evaluation data • Customer ratings and reviews • Peer reviews • Performance reviews • Employee surveys, sentiment
Cognitive and behavioral data • Questionnaire/survey responses • Cognitive function assessment results • Personality test results • Skill test performance • Virtual and augmented reality device use	Digital footprint • Social media activity • Web presence: blogs, online forum participation, website registrations • Job board activity

As this table illustrates, firms collect an extensive array of data about prospective and current workers. They may collect data on their own employees, and/or they may contract with a business service provider or other third-party firm to collect data on their workforce. Some types of data, such as criminal background checks, have been collected by employers for decades.[21] More recently, employers have embraced other types of data collection, such as biometric or health and wellness data, as new sensor-based technologies have become available.[22] It is important to note that some types of worker data collection are still rare, such as walking gait recognition. However, this may change as firms continue to develop technological capacities and applications. For example, some observers have suggested that gait recognition and other biometric recognition technologies could grow in popularity with increased regulation of facial recognition technologies.[23]

3.2. Data collection strategies

With the turn toward the digital economy, many firms have focused on identifying new sources of data and new data collection strategies. Digitalizing business operations and automating existing data collection are often the first steps towards digitalization for traditional firms. This can entail transitioning existing data collection systems (e.g., personnel management, point of sale) into a cloud-based or networked computer system to aggregate data sources.[24] The increased demand for data among firms has also led to innovation in technologies designed to collect data.

The data collection strategies and technologies listed in this section illustrate the various methods that firms use to gather as much information as possible to develop a full picture of the workplace (see Table 2). Firms often use parallel strategies to collect data about customers. Many uses of data in the workplace often combine information about the wider environment in which a firm operates – such as customer behaviors and sentiment, or traffic – with worker data; this is often one of the distinguishing features of more sophisticated workplace technologies.[25]

Table 2. Firm strategies for worker and workplace data collection

Mechanism for collecting data	Type of data captured
External data acquisition	
• Private data sources: purchasing data from data brokers and business service providers • Public data sources: accessing government data sets and publicly available information from the internet	Individual data: digital profiles, social media profiles, background reports, behavioral scores (e.g., credit reports), DMV records, voting records, property reports, court filings, criminal records, professional licenses; environmental context data: weather, labor market data, industry and market trends, local event data
Digital and AI-enhanced electronic monitoring systems	
• Computer and network systems: metadata, system logs, system surveillance software (keystroke logging, continuous screenshot capture and digital recording) • Video: surveillance cameras, vehicle dash cameras, on-demand video interviews, cameras embedded in devices, digital video recordings, computer vision algorithms using biometric and facial recognition • Audio: microphones embedded in phone systems and other devices, natural language processing algorithms using speech recognition	Computer use and access to applications or programs; files accessed, downloaded, printed, or copied to a USB-connected device; content and message details of internal and external communications; social media activity and online browsing history using work computers and personal devices; work activities, behaviors, interactions, conversations; transactions in the workplace, at workstations or sites, in vehicles, on company property
Human-generated content	
• Questionnaires, surveys, and behavioral assessments: employee engagement surveys, employee satisfaction surveys, personality tests or inventories, training retention assessments • Computer-based games: cognitive assessments, competency or aptitude assessments, knowledge and skill tests • Reviews and ratings: business reviews (e.g., Yelp, Glassdoor), peer reviews, customer feedback ratings and surveys • Other: job applications, resumes, chatbot interviews, chatbot interactions with HR portal	Behavioral data; cognitive data such as math, logic, and reasoning skills; content knowledge; interests, attitudes, opinions; job experience; customer and worker satisfaction; employment history
Sensors embedded in equipment and devices	
• Internet of Things (IoT): sensors embedded in products connected to the internet or workplace facilities' wireless communication network • Workplace equipment and devices: sensors or instrumentation embedded in smartphones, handheld devices, industrial machines, vehicles, timeclocks, access panels, and other devices • Wearables, smartwatches, and fitness trackers: sensors embedded in a wristband, watch, ID badge, ring	Location, movement or motion, speed, proximity, body orientation, human interactions, heart rate, respiratory rate, activity levels, environment around human or machines, temperature, vibration

External data acquisition

Firms often acquire data from external sources.[26] For example, firms may pull data from government compiled datasets that provide information related to labor markets, weather, industry and market trends, or local events. These publicly available datasets play an important role in workplace algorithms designed to optimize work activities to the business context, a topic discussed in greater detail later in this paper. Other public datasets provide information about individuals, which employers may access for information about employees (e.g., DMV records, criminal convictions, professional licenses).

Firms may also purchase data from private data sources including data brokers and other business service providers.[27] These suppliers create background reports for employers by aggregating data from a variety of sources including government agencies, credit agencies, and private businesses. Some third-party data providers compile digital profiles on individuals through web-crawling and data-mining techniques designed to extract data from websites (e.g., social media platforms, website registrations, participation on forums, blogs, media coverage).[28] Firms often purchase these data reports from third-party companies, rather than collect and analyze these data internally. However, as the value of data increases, more firms may choose to increase their internal capacity for data gathering and analysis.[29]

Digital and AI-enhanced electronic monitoring systems

Digital and AI-enhanced electronic monitoring systems are another strategy that firms can use to collect data. For decades, employers have electronically monitored workplaces and workers. With the initial adoption of computers and other ICTs, employers began to monitor computer and internet activity using computer metadata, system logs, and monitoring software to collect data on employees' digital activities.[30] Early forms of electronic monitoring, entailing closed-circuit video cameras and audio recordings, have evolved into networked systems that enable employers to remotely monitor workplaces in real-time and to capture high quality digital data streams that can be easily reviewed and analyzed.[31] Many of these strategies are quite common among employers. According to a 2007 survey conducted by the American Management Association and the ePolicy Institute, two-thirds of companies surveyed monitored workers' internet activity, nearly half monitored workers using video cameras, and over one-third monitored email.[32]

With advances in AI research, digital audio and video content can now be analyzed by algorithms that allow computers to recognize and interpret humans and their activities. Early forms of electronic monitoring technologies, such as analog closed-circuit video camera and audio recordings, did not generate digital data that could be easily analyzed. For example, although employers could monitor and record workplace activities with video cameras, they could only watch the live video feed, or playback the videotape recording, to glean information about the activities. However, advances in machine learning algorithms have enabled computers to interpret audio and visual content and translate the information into digital data for further analysis.[33] For instance, Presto Vision – a restaurant technology service provider – recently tested a system in Outback

Steakhouse restaurants that analyzes the video surveillance footage of the dining room to detect the amount of time servers spend at a table interacting with customers.[34] Similarly, some transportation companies have installed vehicle camera systems to monitor and collect data on driving behaviors, in-cab activities, and vehicle incidents. These systems can detect if the authorized driver is behind the wheel (using facial recognition), whether the driver's eyes are closing more than normal, or if the driver uses their phone or wears their seatbelt.[35]

AI-enhanced technologies can also interpret the content of audio recordings or real-time conversations, using speech recognition algorithms to interpret and translate the content of the conversation into a digital transcript.[36] Call centers use these systems to generate a digital transcript of phone conversations, and to conduct sentiment analysis of a customer's tone of voice and inflections to detect if they are angry or exhibiting other emotions.[37]

Human-generated content

Firms also collect data directly from workers and customers. Employers have always collected some data directly from workers, such as job applications or self-evaluations for personnel files. However, starting in the 1990s, firms increasingly began administering tests to job applicants in the form of IQ tests, personality and interest inventories, and performance simulations.[38] By 2015, employers administered tests to an estimated 60 percent of workers, as job applicants and/or as employees.[39] As the human resource management field has continued to incorporate data analytics (or "people analytics"), the demand for worker data has grown, in particular for information that measures workers' perceptions, attitudes, thoughts, and feelings.[40] Employers also collect cognitive and behavioral data using job skill and aptitude assessments as well as orientation and training modules.[41] For example, Pymetrics, a leading hiring technology service provider, administers online games to job candidates to collect data from applicants.[42] Firms have also begun to directly solicit customer ratings and reviews to assess customer satisfaction with workers' performance.[43]

Sensor-based data acquisition technologies

The increase in demand for data among firms and technologists has provided a powerful incentive for technology developers to design technologies specifically for data collection, leading to multiple innovations in sensor-based data acquisition technologies. Firms are increasingly adopting these sensor-based technologies to collect worker data.[44]

Sensors detect, measure, and transmit information about the environmental context surrounding the sensor and/or physical and behavioral characteristics of a human wearing the sensor. They can capture precise measurements of the physical environment and can discern human characteristics, activities, and interactions with machines and devices. There are multiple types of sensors, each measuring different types of information.[45] Some common types of sensors used in the workplace and the information they detect include:

- Accelerometer: detects acceleration, vibration, tilt; used to determine movement and speed
- Gyroscope: detects orientation and tilt, used to identify the direction of a device
- Magnetometer: detects magnetic fields, compass orientation (north pole)
- GPS instrumentation: communicates with satellites to determine location on the earth, used to determine location on map and other spaces (e.g., an office or warehouse)
- Infrared, light-emitting diode (LED), radio-frequency identification (RFID): detects location and proximity (how close the device is to other object/humans)
- Light sensor: detects ambient light levels
- Pedometer: detects the amount of steps
- Pressure: detects touch
- Microphone: detects sound
- Camera: detects visual information
- Biometric: captures and then detects physiological or behavioral traits

Sensors can be embedded in a variety of objects. The most common forms of sensor-based data acquisition technologies used in the workplace are: Internet of Things (IoT), wearables, smartwatches and fitness trackers, workplace equipment and handheld devices, and personal devices (e.g., smartphones).

Internet of Things (IoT) refers to objects with embedded sensors that detect information on a continuous basis and transmit the data to the internet and/or in-house wireless communication network.[46] IoT devices can send and receive information from other devices within the network, enabling seamless data collection and transfer between devices. The broad definition of IoT includes all of the “smart” devices listed in the sensor and instrumentation category whereas the narrow definition of an IoT device often refers to internet-connected household products, such as televisions, speakers, or computer printers. One IoT start-up, Beam Technologies, partners with employers to offer an internet-connected toothbrush as part of a dental insurance plan.[47] The Beam toothbrush collects data on toothbrushing activity to the company and to an app, allowing the company and users to evaluate brushing patterns and activity. The company offers variable insurance premium rates depending on the user’s behavior.[48]

Wearables are a subcategory of IoT devices that can be worn by people as a wristband, watch, armband, ring, or ID badge.[49] Wearables can include location tracking sensors, barcode scanners, microphones, and other types of sensors. For example, one company, Humanyze, uses “sociometric” ID badges embedded with a microphone, accelerometer, Bluetooth, and infrared sensors to collect data about an individual employee’s location, speech patterns, bodily movements and orientation, posture, and interactions with other employees.[50] These accessories collect, transmit, and analyze data in the same way as an IoT product, but often include haptics –

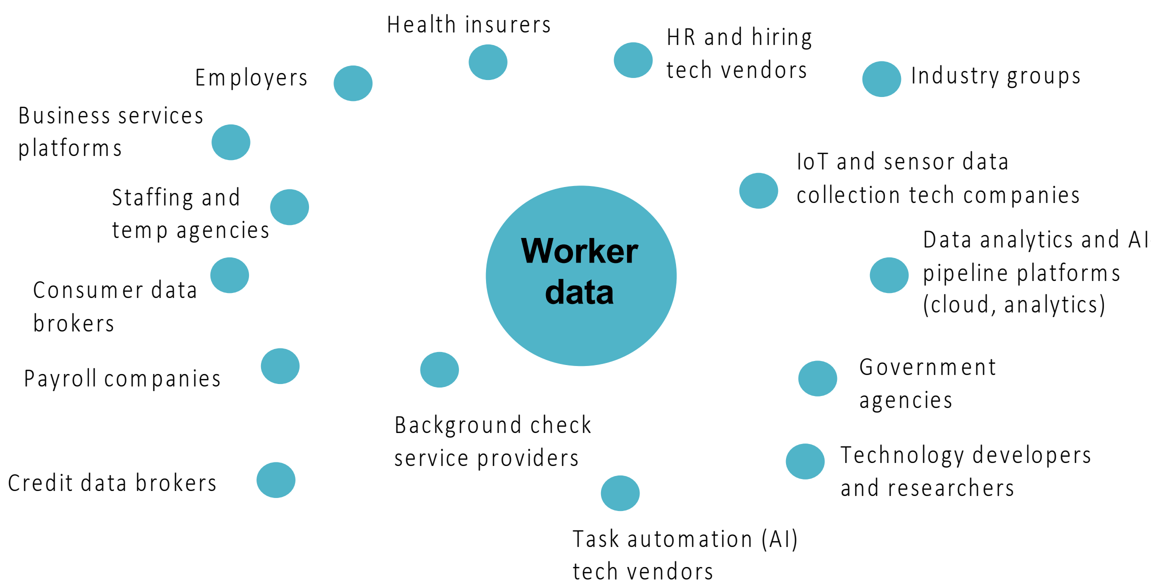
sensations (e.g., vibrations) produced in the device – or other mechanisms that enable a computer to communicate and interact with the wearer of the device.[51] Other types of wearables include exoskeletons, virtual reality (VR) headsets, and smart glasses.[52] Smartwatches and fitness trackers are a subcategory of wearables that collect and track health data as well as other types of data.[53]

Equipment and handheld devices can be considered IoT if they have embedded sensors or instrumentation and transmit data through a communication network. Vehicles enabled with GPS and other location-based tracking devices, handheld scanners, industrial machines with interfaces and a communication infrastructure are all examples of equipment and devices with embedded sensors. For example, UPS trucks include both GPS instrumentation for location tracking and over 200 sensors embedded in the delivery trucks that detect data on things like idling time, seatbelt use, back-ups, and door openings.[54] Personal devices (e.g., smartphones, tablets) can also collect and convey a variety of data, such as location data, data entered by employees in apps downloaded on the phone, and data collected by sensors in the phone (most smartphones are equipped with the full list of sensors included above).[55] Identity authentication systems can incorporate sensors to detect human characteristics. For example, recent innovations in attendance and time tracking systems include scanners that detect biometric data, such as fingerprints, and other personally identifiable information.[56] Industrial machines can also include embedded sensors that detect human activities and interactions. For example, Prolacs – a company that produces laundry monitoring, management, and control systems for industrial laundries and laundromats – includes a variety of sensors in their machine control panels that detect the current status of each machine (e.g., running, on pause, cancellations, idling), and productivity counts.[57]

3.3. The ecosystem of worker data and data-driven technologies

As firms have shifted toward data monetization strategies, worker data has become a key source of value for a host of different types of companies.[58] While data brokers have long played a key role in collecting data from individuals, an extensive ecosystem of firms that collect and process worker data has emerged over the past few decades. Some of these firms have been in the business of collecting worker data for a long time, such as payroll companies and employment screening companies.[59] However, technology vendors and related firms in the technology development supply chain have increasingly become involved in worker data collection and analysis.[60] Figure 1 highlights some of the different types of firms involved in the worker data ecosystem.

Figure 1. Ecosystem of businesses involved with worker data



The relationships between some of the firms in this ecosystem are fairly straightforward, but others are not. Some of the different types of inter-firm relationships involving worker data include:

- Sales fees or subscription service
- Joint ventures and sharing agreements
- Membership in a mutual database
- Data and analytics technology services
- Subsidiaries, mergers, and acquisitions

Firms can enter into subscription service agreements in addition to directly purchasing worker data (e.g., when an employer hires a firm to complete a background check on a job candidate). For example, many employers pay Equifax to process (and fight) workers' un-employment claims and to provide a "verification service" that supplies worker data to a variety of other firms, such as creditors, property management companies, social service agencies, and other employers seeking pre-employment screenings.[61] As part of this relationship, employers provide Equifax with their current employees' work history and personal income information on a weekly basis. The Equifax Work Number database contains data for nearly one-third of the workforce in the US.[62]

Alternatively, employers may pay a membership fee to join a mutual association that compiles an industry-based database of workers. For example, nearly two decades ago a few background screening companies created retail theft databases based on data from employer reports of employee shoplifting, theft, or fraud – including alleged thefts that never resulted in legal action such as an arrest, criminal prosecution, or conviction. These membership-based databases are legal despite class action lawsuits and investigations by the Federal Trade Commission (FTC) for failing to comply with the Fair Credit Reporting Act (FCRA). In 2012, the FTC issued a civil penalty of $2.6 million against one of the companies, HireRight, for multiple violations against the FCRA, and in 2014, another company, LexisNexis, faced a class action lawsuit in a Pennsylvania court for violating the FCRA with their Esteem retail theft database.[63] LexisNexis suspended operations of their Esteem database under the lawsuit settlement terms, but HireRight continues to host the National Retail Mutual Association retail theft database, which included more than 130 retail company members as of 2016.[64]

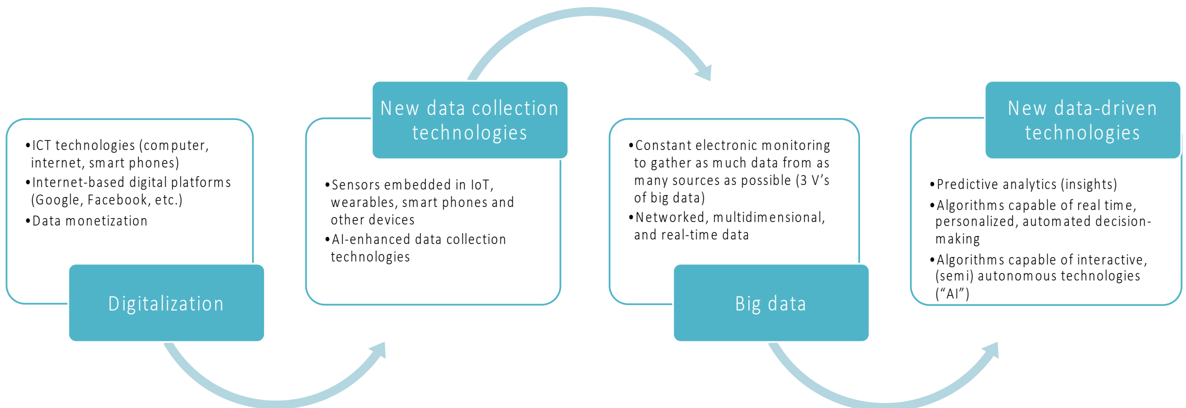
The rising importance of data and data-driven technologies has motivated firms to develop new data-sharing and transfer arrangements, expanding the worker data ecosystem even further. Some of these arrangements entail employers providing technology vendors with raw employee data in return for business insights or data-driven technologies. In some cases, the technology vendor collects individual worker data and may share either individual-level or aggregate data with the employer. For example, Hirevue, a hiring technology vendor, collects employee data directly and shares the data with employers.[65] In contrast, Humanyze, a workplace analytics company, collects individual-level worker data to analyze social interactions and organizational effectiveness, but does not share the individual-level data with employers.[66]

As the data-driven technology landscape has continued to evolve, firms have also started to offer new data storage and analytics services for a wide range of clients.[67] For example, IBM offers a variety of cloud-based services (such as advanced data storage, processing, and analytics capacities) that enable firms to use the IBM Watson algorithmic system platform to build AI-enabled technologies like chatbots and virtual assistants.[68] Firms can store their data on the IBM Cloud and combine their dataset with IBM datasets and with data from other firms using their system.[69] Firms may also acquire or merge with other firms in order to gain access to their datasets, analytics capabilities, or data-driven technologies; mergers and acquisitions are common among technology firms.[70]

3.4. The evolution of data collection and data-driven technologies

The previous section illustrates the various strategies firms use to gather as much information as possible, including using AI-enhanced and sensor-based data collection technologies that enable firms to collect continuous streams of large volumes of data from a wide variety of sources. As the sophistication of data collection technologies has increased, firms have also enhanced their ability to extract more insights from these data, and to develop and deploy more data-driven algorithms. Figure 2 illustrates the pipeline of data gathering and analysis, from digitalization and data collection to the creation of data-driven technologies.

Figure 2. The cycle of innovation in data-driven technologies



There is an iterative relationship between data collection and data-driven technologies – digitalization has led to new demands for data, which in turn has led to technological innovations designed to collect new types of data. The availability of big data has in turn led to innovations in computer algorithms, which have begun to surface in new technologies in the workplace over the past decade. Electronic monitoring and data collection practices are only a starting point for how firms glean value from worker data. The full value of worker data for employers comes from how the data can be used in the workplace, by generating new insights, developing technologies that automate decision-making, or by laying the foundation for intelligent machines capable of interacting with workers and completing work tasks.

4. Algorithms in the workplace

Data-driven algorithms underlie many technological changes in the workplace. This section provides a definitional overview of algorithms and explores algorithmic technologies in greater detail.

4.1. What are algorithms?

Algorithmic systems are not new, but their role in society has changed with the introduction of the internet and the expansion of the digital economy. An algorithm, in its simplest form, is a set of rules, in computer programming code, for solving a problem or performing a task. Computers are able to complete tasks independently by following the instructions outlined by the algorithm. The simple version of algorithms has been around for decades and is still the most common form in use today. It is not "intelligent," but can automate a task, such as sending an automatic email response to inform people that you are on vacation. Computer programmers refer to this type of algorithm as “by-hand” or “rule-based” algorithms. You could compare it to a cookbook recipe; the algorithm is simply following a set of commands dictated by the programmer.[71]

Recent advancements in AI research have resulted in much more sophisticated algorithms that combine math, statistics, and computer programming code that enable computers (machines) to learn and adapt to new information (data), and, ultimately, to accomplish a specific objective.[72] These learning algorithms – also referred to as machine learning, deep learning, or neural networks – enable computers to complete a specific task without a human programmer explicitly writing the rules for how the computer should complete the task. In fact, these algorithms often extend beyond human capacity for comprehension, becoming opaque even to the human programmer.[73]

Although the new learning algorithms are better able to mimic human intelligence in narrow contexts, AI researchers caution that these recent technological advances have not fully achieved general artificial intelligence.[74] Nevertheless, algorithmic systems have achieved a degree of intelligence, enabling machines to interact with humans and their environment or to make decisions without any human intervention.[75] The more advanced versions of these algorithms accomplish tasks and make decisions by mimicking human capacities to reason, learn, and recognize visual objects, text, speech, and sentiment.[76] The capabilities of this type of algorithm vary widely. A software program designed to identify credit card fraud is a simple example of this type of algorithm. Robots with the capability to navigate city streets include a more advanced version of this type of algorithm – one designed to mimic human capabilities to perceive and adapt to its environmental context.

This report uses the generic term algorithm to refer to both its basic and more advanced forms, but the majority of the technological systems described in this paper run on the more advanced machine learning algorithms.

4.2. Algorithm objectives and design decisions

Regardless of the level of intelligence of an algorithm, a crucial thing to understand is that humans make decisions about the objective and design of the algorithm. Some common objectives underlying algorithms used in the workplace include reducing uncertainty in management decisions, identifying potential risks that might incur business costs, optimizing and automating scheduling or work process decisions, maximizing worker productivity, automating production tasks, or improving workplace safety.

For example, the underlying objective for many algorithms used in the hiring process is to reduce uncertainty in hiring decisions.[77] Hiring employees entails costly decisions in the context of imperfect information – the employer does not know whether a potential job candidate will become a star employee or quit shortly after getting hired. To reduce this type of uncertainty, some hiring technology developers design algorithms to predict which subset of job candidates will likely become high-performing, successful employees. Technology developers have designed another type of algorithm to optimize work schedules for frontline workers. The objective for these scheduling optimization algorithms is to identify the most efficient staffing schedule – in terms of lowest hourly labor cost – to align with the timing of customer demand patterns.[78]

In designing algorithms, computer programmers make decisions about how to define the objective, which factors to consider, how much value to place on each factor relative to other factors, and what data to use.[79] These choices shape the design and implementation of algorithms. Design choices reflect the values and assumptions of the technology developer, and ultimately those of the firm paying for the product or hiring the programmer to create the product. For instance, in the hiring technology example, the programmer must decide how to define a successful employee and which data to use as a measurement to represent this definition. For these hiring algorithms, developers often rely on questionnaires or games administered to workers that aim to measure personality characteristics with the assumption these characteristics are an indication of an individual's potential productivity or value as an employee.[80]

The importance of design choices

Technology developers and those who deploy technologies make decisions that have consequences – intended or unintended – for the people who interact with the technology. Design decisions determine the outcomes of the technology, who benefits from those outcomes, and who is potentially harmed. By default, "algorithms tend to be myopic," meaning that they focus narrowly on factors specified in the design (model) and data provided to the model.[81] The technology developer's choices in which factors to prioritize, or their failure to specify all relevant factors, can result in unanticipated consequences. An example of unintended consequences of design decisions is Uber's autonomous vehicle design. In 2018, one of Uber's test vehicles accidentally killed a pedestrian in Tempe, Arizona. By many accounts, Uber's leadership made a series of decisions that likely contributed to the failure of the autonomous vehicle to stop for the pedestrian in the street. Rather than prioritize an extremely cautious strategy for stopping the vehicle when faced with unknown objects in its path (potentially a less enjoyable ride, with more vehicle braking), Uber decided to prioritize a smooth ride for the passenger.[82]

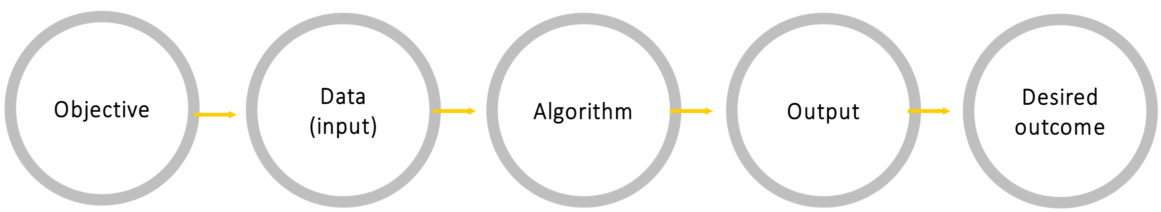
Scheduling optimization systems provide another example of the unintended consequences of design decisions associated with algorithms. The primary objective of these systems is to generate the most efficient workforce schedule considering multiple factors, such as seasonal sales patterns, local events, predicted customer demand, local weather predictions, and worker availability.[83] Many of these systems are designed to generate schedules in 15-minute increments and can adjust in real-time based on the most recent data available.[84] If employers and programmers do not include factors that take into consideration workers' schedule preferences and the coherence of the assigned schedule, these algorithms can result in a variety of negative consequences for workers, such as highly variable, unpredictable, and discordant schedules.[85] For instance, Starbucks recently made news due to their use of a scheduling algorithm with the tendency to generate "clopening" shifts in which an employee is scheduled to close at night and open first thing in the morning.[86]

These systems involve a series of human-made choices in the design stage that reflect the values and assumptions of the designers, and those from whom they seek (or neglect to seek) input. The choices made by humans in the design and implementation of an algorithm are as crucial to consider when evaluating these systems as the technological capability of an algorithm itself.

4.3. Algorithmic systems: transforming data into desired outputs

Given a specific task objective, algorithms enable a computer to transform data inputs into desired outputs.[87] In other words, the algorithm enables the computer to analyze information (the input data) in order to extract insights about the data and make predictions or decisions based on the data (the output). Figure 3 provides a basic and non-exhaustive illustration of an algorithmic system's workflow.

Figure 3. Simplified algorithmic system lifecycle



The algorithmic process: transforming data inputs into desired outputs

The process by which a computer algorithm transforms data inputs into outputs for a given task entails multiple steps. Each of these steps includes varying degrees of human involvement.[88] First, given a specific task objective (as defined by a human) the computer system must have access to information (data inputs) about the task at hand and the context surrounding that task. Data can be collected and entered manually by humans, automatically gathered from the internet or private data sources, or, in the case of more advanced algorithmic systems, data collection can be automated via sensor technologies that enable the machine to perceive the physical or digital task environment (including human interactions) to collect information in real-time.[89]

Second, the algorithm analyzes and interprets the data inputs in order to produce the desired output for the task. The procedure for performing the task can be outlined in code by a human programmer, using a basic if-then logic for what the computer should do given the data meets certain conditions. Alternatively, in the case of learning algorithms, the human programmer determines the type of learning algorithm to complete the task, but the computer develops its own rules for how to perform the task by learning from the data introduced into the system, either through examples in the data or from experience.[90] Regardless of the learning approach used, the algorithm enables the machine to develop a model, or knowledge about the relationships in the data, and then uses this knowledge to perform the task.

Third, based on its analysis of the data, the algorithm generates output in the form of a prediction or decision. Depending on the type of task objective, the output can take the form of a prediction score reflecting the probability of future outcomes, classification of data, flag or alert of anomalous data points, or categorization of data points. The algorithmic system output could even be part of a series of decisions about the next action to take (either a recommendation for a human to implement or command for a machine).[91] Each of these types of outputs – predictions, decisions, or recommendations – sets the course for further action by a human or machine, which, when implemented, completes the task objective for the algorithmic system.

Types of analytical tasks algorithms perform

Algorithms perform different types of analytic tasks or procedures in order to solve a problem.[92] Some of the basic types of analytical tasks or logical procedures that machine learning algorithms perform include:

- Prediction: analyzing historical data patterns to predict or forecast the likelihood of future events, behaviors, or outcomes
- Classification: identifying or predicting which category new information (e.g., visual object, text, audio) belongs in, based on categories previously defined by human programmers
- Pattern detection: identifying relationships and unusual events or patterns in the data
- Categorization: identifying clusters of data points (e.g., people or objects) and categorizing them into groups or segments within the dataset

Analytic tasks form the basis of more complex technological systems that combine machine learning algorithms with other types of technologies and that are increasingly common in the workplace.[93] These include the following technologies:

- Computer vision: analysis of visual information (static images or video streams) to recognize images, objects, activities or events, individual faces, intentions
- Speech perception: analysis of audio information (e.g., phone calls, conversations) to recognize speech
- Natural language processing: analysis of written and spoken language to recognize and classify words, and to interpret and generate written and spoken language
- Emotion recognition: analysis of audio (e.g., tone of voice) or visual (e.g., facial expressions) data to detect the emotional state of humans
- Sentiment analysis: analysis of text for emotional tone to classify attitudes or opinions (e.g., positive, negative, neutral)

These technological advances have enabled machines to perceive the physical environment; to interpret human activities, behaviors, and language; to reason and make logical decisions; and to interact with humans and their environment.

4.4. General application of algorithms in the workplace

Algorithmic technologies have numerous applications common in everyday life and in the workplace. These applications can be grouped into three general categories: 1) statistical insights, 2) automated decision-making systems, and 3) interactive machines (described in Figure 4 below). These categories are not mutually exclusive.[94] In fact, each of the systems builds upon the previous type of system – i.e. machines that make decisions or interact with humans and the physical environment must also make predictions about factors (human actions, environmental conditions) that are unknown to the machine and that might influence the machine's decisions or actions.[95]

Figure 4. Applications of algorithmic systems

Statistical insights	• Forecast or predict future events or behaviors • Classify and categorize data • Identify patterns and anomalies in the data
Automated decision-making systems	• Optimize and automate decisions • Personalize recommendations • Prescribe courses of action to take
Interactive machines	• Perceive and monitor humans and the digital and physical environment • Interact with humans and the digital and physical environment • Automate human activities – virtual assistants, chatbots, robots, autonomous vehicles

Statistical insights are perhaps the most prevalent application of algorithms in the workplace.[96] Firms use these algorithms to solve the problem of incomplete information and uncertainty in decision-making.[97] In their most basic form, this application of algorithms relies on statistical techniques like regression analysis or causal analysis forecasting to analyze historical data in order to predict the probability of a future event or behavior happening.[98] For instance, employers use these algorithms to make predictions about whether a job candidate is likely to be a productive employee or to quit.[99] In addition to predictive analytics, other algorithms attempt to identify or discover patterns in the data. For example, algorithms might look for anomalies in sales transaction data to identify potentially fraudulent activities and predict future fraud.[100] A common application of statistical insight algorithms is to assist or augment managerial decision-making about workers.

Managers may receive the algorithmic “insights” about workers in the form of scores, ranking, alerts, flags, segmentation categories, delivered via a manager-facing dashboard.[101]

Automated decision-making systems are a more advanced application of algorithms. These algorithms build upon prediction functions to arrive at a decision about the course of action to take next.[102] Business consultants often refer to this application of algorithms as prescriptive analytics – meaning the algorithm is designed to identify the optimal process for a task, to make a decision, and to prescribe a course of action, given a desired objective and a wide variety of variables.[103] These algorithms shape the labor process or worker behaviors to align with the business context and to conform to the employer’s preferred parameters and choice architecture. One form of this type of algorithm is designed to optimize work schedules, matching when and where workers work.[104] A second form of these algorithms make decisions about the optimal procedure or course of action to take to complete a task, directing workers to complete tasks in a specific manner or order, or structuring the work context in a way that limits workers’ discretion for how to complete a task.[105] A third form of this type of algorithm makes personalized recommendations (in the form of nudges) to influence or manipulate workers to make desired decisions or to behave in a certain way.[106] Each of these applications draw from a wide range of business context data and worker data to arrive at the optimal or recommended course of action. Rather than assist managers with insights to make decisions about workers, this class of algorithms is designed to automate managerial tasks more fully.[107] Many observers refer to this group of algorithms as “algorithmic management.”[108]

Interactive machines are the most advanced application of algorithms in the workplace. Interactive (or “intelligent”) machines build on the capabilities of prediction and decision-making, but these algorithms enable machines to interact with humans or the environment, and to some extent act autonomously.[109] This group of algorithms is what most people think of as AI. Interactive algorithms enable a machine to perceive sensory data from the physical or digital environment or object of analysis, to interpret the information based on existing knowledge derived from available data, and to take action in the environment. Interactive machines operate in real-time, perceiving the environment or object of analysis, and adapting and responding to new information in order to interact with humans or move around in physical space. They are often designed to complete a domain-specific work task.[110] The algorithms draw from domain-specific data to provide information to the worker to assist or augment their ability to complete a particular task, and in some cases to automate the task entirely. Interactive machines can be physically embodied in hardware (robotics or other physical machines), operate as virtual machines, or function as software embedded in computers and devices.[111] Robots, self-driving vehicles, virtual chatbots, digital assistants, and diagnostic systems are all examples of interactive machines used in the workplace. Due to their ability to automate specific job tasks, interactive machines are the technologies that have generated much of the concern about automation and worker job displacement. Notably, intelligent machines have the capability of automating tasks carried out by both frontline managers and workers.

5. Examples of how employers can use algorithms in the workplace

This section provides concrete examples that illustrate how employers use different algorithmic systems in the workplace. Table 3 groups employers' uses of algorithms into four functional areas of business operations that involve frontline workers (workers that are directly engaged in the firm's production of goods or services):[112]

Table 3. Functional areas of business operations

Human resource management	Organization of work	Workforce management	Production of goods and services
• Recruitment and hiring • Risk assessment • Education and training • Health and safety • Performance evaluation	• Scheduling workers • Coordinating work activities	• Directing workers • Manipulating workers	• Assisting and augmenting worker tasks • Work task substitution

Most of the specific examples discussed below are products offered by third-party technology service providers. In some cases, the examples are the result of a partnership between a technology start-up and a large employer to implement a specific technology in their companies. While some of the technologies and technology vendors discussed here are well-established (or at least cite a long list of clients), it is unclear the extent to which some of these technologies have been adopted in the workplace, of if they are still aspirational efforts from technology developers.

5.1. Human resource management

Over the past ten years, the human resources (HR) field has actively embraced data analytics (or "people analytics" in HR industry terminology).[113] HR technology vendors and in-house data scientists increasingly use algorithms to make predictions about who should see job ads, who might be productive employees, whom to hire, whom to promote, who may quit or commit fraud, and whom to fire.[114] Technologies designed for the hiring phase of the HR process are one of the fastest growing areas of HR technology development.[115] Josh Bersin, an HR consultant, has compiled a database of over 1,400 HR technology vendors.[116] Practitioners and technology designers have also begun to develop algorithmic applications for other aspects HR management, including performance evaluation, risk assessment, education and training, and health and safety.[117]

5.1.a. Recruitment and hiring

Third-party technology service providers and in-house HR departments have developed a wide range of algorithms to assist or automate aspects of the recruitment and hiring process. Hiring workers is expensive. On average, firms spend over $4,000 to hire a new employee.[118] One reason why hiring employees is so costly is because of the amount of time and work it takes to actually hire someone, which involves several distinct phases.[119] The following are some examples of functions that data-driven technologies may assist in different phases of the hiring process:

- **Worker sourcing and recruiting**: job description text analysis, micro-targeting and behavioral targeting job advertisements, personalized job recommendations, predictive matching for job candidates and employers, data-mining and predictive headhunting for potential job candidates
- **Job candidate screening**: chatbots screening for minimum job qualifications; analyzing resumes and application text; testing and assessing candidate aptitude, skill, and personality
- **Interviewing job candidates**: interview scheduling via chatbot; speech, sentiment, and facial expression analysis of video interviews
- **Job candidate selection**: predicting job candidate "fit" with an employer's desired employee characteristics or definition of high performers; data-mining public online data to build job candidate digital profiles; background checks using automated content analysis techniques to parse and classify text and images; profiling candidates based on digital footprint and social media activity; predicting likelihood of salary offer acceptance; predicting potential candidate job performance, honesty, or likelihood to violate workplace policies, commit fraud, or quit

Firms design these systems in an effort to reduce the amount of time it takes to hire, the costs incurred to hire, and the uncertainty in deciding who to hire.[120] Employers want to know if the job candidate is likely to perform well or whether they are likely to quit after a short period of time, and technology developers design systems that attempt to solve this problem of uncertainty. Increasingly, technology vendors are also designing systems to solve the problem of lack of diversity in the workforce, though the extent to which they are able to do so remains unclear and contested.[121]

The algorithms used in the hiring process fall primarily in the predictive data analytics category, but HR technology vendors are increasingly deploying interactive machine algorithms designed to sense and interpret workers and their behaviors (e.g., chatbots, expression analysis, sentiment analysis). Job candidates may never interact with a human during the initial application process, and instead engage entirely with chatbots and automated systems that process applications or resumes, and filter workers.

The use of algorithms has historically focused on the recruiting and screening phases, but algorithms are increasingly being used in the interview phase of the hiring process. According to

Bersin, video assessments are the fastest growing area for HR hiring expenditures. In a 2016-2017 HR survey conducted by Sierra-Cedar, 55 percent of participating companies indicated that they are increasing investment in video interviewing and assessment.[122] Although these automated systems may not make the final decision about whom a company should hire, they do make automated decisions about which job candidates to exclude from the pool of applicants.[123] Table 4 provides an overview of the services offered by one hiring technology company, HireVue, which evaluates job candidates' "employability" by combining predictive algorithms with more complex algorithms designed to recognize and interpret candidates' facial expressions and behaviors.[124] HireVue's system combines multiple types of algorithmic systems into one product.

HireVue has developed a multifaceted algorithmic system to assess and predict which job candidates will be "high performing" employees. HireVue collects data via on-demand video interviews and psychometric games. Using their own webcam-equipped computer, smartphone, or tablet, job candidates record a video interview responding to a series of questions presented via video clips from HireVue employees.[125] The job candidate can practice their responses by deleting and re-recording their answers to each question before moving on to the next question. Depending on the employer's preference, some questions may entail a written rather than video response. Job candidates also complete a series of short psychometric games. According to Hirevue, the data points derived from the video content measure "social intelligence (interpersonal skills), communication skills, personality traits, and overall job aptitude" whereas the data from the game-based assessments measure "cognitive attributes like analysis, decision-making, reasoning, and problem-solving skills."[126] Hirevue may also administer the video and game assessments to the company's current employees who hold the same position.

HireVue's algorithmic model pulls data from the current employee assessment results and job performance evaluations, or generic models for common job positions.[127] Using this model, the algorithm analyzes the job candidate video and game assessment results in an effort to predict which job candidates are most likely to become successful employees – i.e. those who align most closely with the employer's evaluation of which current employees fit its criteria of a successful employee.[128] From this analysis, the algorithm generates an "insight score" of 0 to 100 for job candidates, and provides the list of job candidates and their scores to employers.[129] HireVue's algorithm can automatically reject job candidates who do not meet a predefined employer threshold for the job position.[130]

Table 4. HireVue

Objective	Data used & data collection strategy	Analytic techniques	Output
• Reduce costs for hiring workers • Identify candidates most likely to be productive and to "fit" with the company culture and workforce	• Behavior, facial expressions, word choice, tone of voice recorded during video interview • Responses and performance on "game-based" cognitive assessments	• Speech recognition • Natural language processing • Sentiment analysis • Facial expression analysis • Emotion recognition • Machine learning • Predictive statistics	• "Insight score" of 0 to 100 percent • Ranked list of job candidates based on scores • Video interviews

5.1.b. Risk assessment

Firms also use data and algorithms to assess workplace risks. As with hiring algorithms, risk assessment algorithms often provide "insights" to managers to help them make decisions about workers. Types of risk assessment algorithms include:

- **Security and risk assessment**: predicting employee likelihood to quit their job; predicting employee likelihood to engage in fraudulent activities; flagging potentially fraudulent activities or high-risk transactions; analyzing employee sentiment to identify "toxic workers," "toxic managers," disgruntled workers, or potential union organizers; and monitoring worker social media activities for brand management
- **Health and wellness monitoring**: predicting employee health costs, potential hospitalizations and emergency rooms visits, risk of developing health conditions

Technology developers design risk assessment algorithms to help firms preempt potential scenarios that might incur costs or negative outcomes for their brand. The design objectives for these algorithms can be to reduce or avoid costs and liability due to fraud, employee turnover, worker organizing, negative public perception of company, higher health insurance premiums related to poor employee health, or lower productivity due to lost work related to illness. Fraud detection systems are one example of risk assessment algorithms.[131] These applications use learning algorithms to analyze data from employee transactions and interactions in order to identify relationships and patterns in the data. Once the algorithms learn the normal relationships in the data, the system can analyze incoming data to detect abnormal patterns or outliers and then flag the activity or send an alert to managers.

Other algorithms used for risk assessment can detect employee burnout or negative comments about the company by analyzing data from emails, internal messaging systems, or social media.[132] These systems can detect employee sentiment (negative, positive, neutral tone) in the context of discussion among employees by using natural language processing algorithms trained to recognize predefined themes or words in the text. Managers can then make decisions about how to address the employee or situation identified by the algorithmic system, based on the information it provides.

Another example of a risk assessment application is a "flight risk" algorithm that predicts the likelihood an employee will leave their job. Some companies use these algorithms to preempt high-performing employees from quitting. Bloomberg, Hewlett-Packard, and IBM, along with many other firms, have developed these algorithms to evaluate their workforces.[133] Some of the data variables in these models include motivation and work-life balance, commuting time, amount of time spent traveling for work, salary, frequency of raises, number of job rotations, performance ratings, employee personal and professional development, sociodemographic and geographic data, and labor market trends. These algorithms generate a score for each employee that the employer can use as a basis for deciding who to promote, and to whom to provide raises or work opportunities.[134]

Algorithms for risk assessment can also automate machine decisions and implement actions. For example, in an internal meeting at Facebook, developers suggested that their internal messaging system (Facebook Workplace) could be enabled to automatically block employee posts on topics such as unionization.[135] Applications designed to decrease employee health risks and related costs are another example of risk assessment systems.[136] Many firms incorporate wearable electronic fitness trackers into their workplace wellness programs in an effort to reduce health care costs and increase productivity. These trackers often include algorithms that analyze employee physical activity data and nudge employees to engage in physical activity to improve health outcomes, and in some cases reward them for doing so.[137] One objective of introducing fitness trackers may be to encourage employees to track their health activities and improve their health, but employers may also receive monetary benefits from insurance companies and third-party vendors by sharing the employee health data collected.[138]

5.1.c. Education and training

Training and education technologies appear to be an area of growth in the HR technology field.[139] Two examples of education and training strategies enabled by algorithms include:

- **Job simulation**: situating workers into job context or work environment, often through virtual reality (VR), or immersive computer-generated worlds that draw from sensory algorithms
- **Training personalization**: using prediction techniques to gauge and tailor training to individual knowledge and skills

Algorithmic systems can help simulate workplace environments and job conditions that enable workers to roleplay scenarios and practice interactions.[140] The systems often collect worker data from employee records and learning modules and combine these data with machine perception technologies (e.g., computer vision, natural language processing). They then identify employee behavioral characteristics and provide feedback – typically in the form of social recognition or nudges – to tailor the learning experience to the individual worker. For example, Walmart recently partnered with STRIVR and Occulus Go to introduce VR headsets for employee training on a variety of work tasks, such as customer relations, restocking, and deli operations.[141] Walmart also uses the headsets to assess an employee's potential to be successful as a manager.[142]

Algorithmic systems can also provide personalized and adaptive learning environments tailored to the specific employee's skills and learning needs.[143] This type of personalization predicts the learner's needs and preferences, drawing from learner behaviors, job history, personality insights, and career goals. Like the job simulation systems, these systems can rely on data collected directly from the employee or through their interactions with intelligent machines. For example, Filtered Magpie offers an algorithmic system that employs a chatbot to interact with employees in order to collect information and to identify skills gaps among employees.[144]

Table 5 describes the key functions and features of Tailspin Virtual Human, a VR interactive training system that is composed of multiple algorithms used to interpret and respond to a worker's behavior. Talespin is customer service training system that combines VR with a variety of intelligent machine capabilities into a training technology that mimics human interaction. According to the company's literature, the objective of the system is to help workers improve their soft skills for interacting with customers, such as cold calling, overcoming objections, building rapport with customers, communicating product knowledge, identifying customer needs, customer service complaints, and technical support.[145] Employees wear a VR headset that places them in an immersive simulated environment with a "virtual human." Using natural language processing, speech recognition, text-to-speech translation, sentiment analysis, and emotion analysis, the virtual reality character attempts to interpret employee behaviors as well as mimic the body language, behaviors, and expressions of a human in order to converse with the employee and respond to the employee's behaviors.[146] Talespin offers modules to simulate different types of jobs, including a training simulation to help managers practice firing employees. [147] Employers receive employee training data and analytics to track employee interactions with the platform and to use for performance evaluations.[148]

Table 5. Talespin Virtual Human

Objective	Data used & data collection strategy	Analytic technique	Output
• Train workers to develop "soft skills" for customer service interactions	• Virtual reality (VR) device sensors track employee interaction with training modules including facial expressions, body movement and eye gaze	• Natural language processing • Speech recognition • Text-to-speech • Sentiment analysis • Emotion analysis	• Training scores • Recorded employee training interactions

5.1.d. Health and safety

A few firms have begun to develop algorithms to improve workplace safety and health. Two types of applications that use algorithms to address health and safety risks in the workplace include:

- **Worker behavior monitoring:** identifying poor ergonomics or employee fatigue
- **Workplace environmental health and safety hazard prevention**: identifying hazardous situations, toxic fumes, high temperatures; and locating employees in at-risk environments

Some of these technologies use wearable sensors and learning algorithms to detect and predict risk of injury. For example, one company, StrongArm Technologies, has developed a system that uses wearable sensors to monitor and collect data on employee movements and then processes this data with a machine learning algorithm to generate an injury risk score for each worker based on the extent to which an employee's movement aligns with proper ergonomic principles. Based on this risk score the system can send haptic feedback (i.e. the sensor buzzes) to the employees if they are not conforming to proper ergonomic practices. The employer can access a wide range of data analytics including safety behavior data for each employee.[149]

Other technologies use sensors embedded in location tracking devices (e.g., wearables with radio-frequency identification (RFID) chips) to enable machines to track workers within or outside of the workplace. For example, the Enseo Madesafe panic button attempts to provide hotel workers and other service workers a means to alert security in threatening situations. The technology includes a handheld device embedded with a location tracking sensor and a small panic button along with network receivers and a computer monitor for building security. When an employee presses the panic button, it emits a radio signal that triggers an algorithm to notify security of the worker's location. Although the Enseo system has the capacity to enable real-time monitoring and data analytics reports for each worker's device, they do offer the option for maintaining worker privacy by only showing the worker location if they activate the panic button.[150]

Some construction and mining companies use machine perception algorithms (e.g., computer vision) that monitor workers and the workplace environment for safety reasons. For instance, one construction company uses computer vision to analyze job site photos, scan them to identify safety hazards (e.g., workers not wearing protective equipment), and correlate the images with the company's accident records.[151] Other technologies combine computer vision algorithms designed to interpret the workplace environment with location tracking sensors embedded in wearable devices (e.g., helmets, jackets, tool belts, wristbands, etc.) to locate workers within that context. An example of this type of system is Toolbox Spotter; the key features of this system are described in Table 6.

Toolbox Spotter is an algorithmic system designed to increase safety in industrial settings with heavy equipment, such as in construction, rail, logistics, mining, and manufacturing. The system uses video cameras attached to equipment to collect visual data on the worksite. Computer vision and deep learning algorithms process the visual data to identify objects or people in the blind spot of heavy equipment operators.[152] Specifically, the system tracks the speed at which a person is walking and predicts the likelihood the equipment and person will intersect.[153] If the system determines there is a hazard, it alerts the person at risk of getting hit as well as the equipment operator. Each worker will receive a notification through vibrations in a wristband along with flashing lights at the worksite. The technology can also automatically disable the equipment to avoid injuring the person.

Table 6. Toolbox Spotter

Objective	Data used & data collection strategy	Analytic technique	Output
• Prevent heavy machinery from hitting people or objects on a worksite	• Video cameras attached to equipment capture data on worker activities and objects at a worksite • Wearable location tracking sensors	• Computer vision • Deep learning • Object recognition	• Notifications via vibrations in a wristband, flashing lights, or automatic vehicle disabling features

5.1.e. Performance evaluation

Employers can also use algorithms for HR processes to evaluate worker or organizational performance. Some of the different functions of algorithmic systems and technologies for performance evaluation include:

- **Individual level monitoring and performance evaluation**: analyzing productivity measures relevant to the job, such as units produced, talk time, calls answered, email volume and timing, participation in meetings; identifying high performers; profiling workers to identify potential leaders; assessing worker development and lifetime value; and segmenting the workforce based on efficiency or productivity rates
- **Organizational network analysis (ONA) of workforce interactions:** analyzing team, department, or unit level social dynamics to identify patterns in workplace interactions that contribute to higher productivity levels; identifying abusive interactions and poor management techniques; identifying the most valuable and connected workers who bridge teams, encourage collaboration, or serve as information hubs within an organization; identifying bottlenecks in communication or communication disconnects; identifying productive teams and team dynamics; and identifying compatibility among workers

For both types of performance evaluation algorithms, AI-enabled electronic monitoring technologies allow firms to collect data on employee activities at a micro level to quantify work activities. For example, sensors embedded in wearables, badges, IoT, and workplace equipment enable these systems to collect data on a variety of interactions in the workplace, including conversations, movement, workflow activities, and device usage.[154] These systems often include a second layer of algorithms that use these data to analyze individual productivity or to identify social relationships and patterns within the workplace for organizational learning. As in the case of algorithms used to hire workers, these algorithmic systems can provide managers with information to make decisions about workers or workplace processes to increase productivity or to encourage "high value" employees to remain engaged in the workplace.[155] In some cases, these algorithms can automate managerial tasks, as in the case of Amazon's algorithm that fired workers with low productivity levels.[156]

Enaiable is an example of an application of an algorithm designed to evaluate individual performance by providing managers with a performance score for workers.[157] Enaible's Trigger-Task-Time module captures data on an employee's daily workflow with software embedded on computers and other IT systems (e.g., internal messaging, email, phone systems, CRM systems, etc.). The system collects data on the time of day, order of work activity, and duration of tasks, among other factors. Using these data, a machine learning algorithm builds a behavioral profile for each employee by learning the patterns for what triggers the employee to complete tasks and the amount of time it takes for them to finish the task. Enaible's system then generates a "productivity score" between 0 and 100 for each employee. Managers can use the scores to compare employees or evaluate an employee's productivity in relation to their typical behavior.[158] The Enaible system also provides managers with recommendations for tasks to automate within an employee's workflow, and it aggregates information on how much time employees spend in meetings, or reading and sending emails, and how these activities correlate with company profits.[159]

Humanyze is an example of a company deploying organizational network analysis (ONA) to detect patterns in workforce interactions.[160] The key features of Humanyze are outlined in Table 7. Humanyze aspires to provide employers with insights about the social dynamics of their organization. The system provides analysis on team inclusivity and interaction patterns, such as who dominates conversations or patterns of email communications between managers and employees representing different demographic groups (e.g., women, people of color).[161] Humanyze uses "sociometric" ID badges embedded with a microphone, accelerometer, Bluetooth, and infrared sensors to collect data about an individual employee's "proximity to another person, direct face-to-face interaction, location, individual speech patterns, conversational turn-taking patterns, orientation, body movement patterns, and posture patterns."[162] The badges capture speech and speech patterns of both the person wearing the badge and other people who interact with the person wearing the badge. For instance, the badge microphone gauges voice tones and identifies the extent to which workers participate in meetings. The accelerometers measure worker body language and can track movements such as "how often you push away from your desk."[163] Data from the badges are combined with metadata collected from email and calendars, phone activity, and instant messaging. Raw data are collected on local servers and then transported to Humanyze for analysis, using a combination of social network analysis, voice analysis, and body language analysis.[164]

As part of the terms of service with employers, Humanyze provides employers with a dashboard containing anonymized and aggregated reports of the team and organizational-level analysis. The reports attempt to analyze and compare teams or organizational interaction patterns that contribute to individual level performance metrics such as "productivity, job satisfaction, employee engagement, and drive."[165] This analysis is also provided to employees to show how they compare to others in the workplace. At the individual level the Humanyze system analysis provides "real time information about the user's communication, social signaling, and interaction patterns," such as movement and energy levels, time spent listening, speaking at the same time, interrupting, or dominating the conversation, and interactions with different social groups (e.g., gender, job status).[166]

Table 7. Humanyze

Objective	Data used & data collection strategy	Analytic technique	Output
• Identify organizational and team interaction patterns and their relationship to performance metrics	• ID badges embedded with a microphone, accelerometer, Bluetooth, and infrared sensors that detect proximity to another person, direct face-to-face interaction, location, individual speech patterns, conversational turn-taking patterns, orientation, body movement patterns, and posture patterns • Metadata collected from email and calendars, phone activity, and instant messaging	• Machine learning • Social network analysis • Voice analysis • Body language analysis	• Dashboard for employers featuring anonymized and aggregated report with the team and organizational level analysis on team inclusivity and interaction patterns • Individual level analysis for employees

5.2. Organization of work

Algorithms designed to optimize workforce scheduling and the coordination of work activities are another application of algorithms in the workplace.[167] Technology developers design workforce optimization algorithms with the objective of improving organizational performance in terms of increased productivity and efficiency, or increased customer satisfaction and loyalty. In general, these algorithms draw from information about the business context to predict what is likely to happen in the future, or to identify constraints or potential options for a business process. These algorithms often automate decisions and generate a prescribed course of action for humans to implement. Thus, workforce optimization algorithms automate managerial scheduling and work coordination decisions. For workers, these machine decisions often dictate when, where, and how they complete tasks.

5.2.a. Scheduling workers

Over the past decade, many retail and service employers have adopted workforce scheduling algorithms to help generate worker schedules. As noted above, technology developers typically design scheduling optimization algorithms to identify the most efficient (lowest cost) staffing schedule to align with the timing of customer demand patterns.[168] These algorithms draw on a variety of data to predict customer demand, make decisions about the most efficient workforce schedule to meet that demand, and generate workers' schedules accordingly.[169] Many of these systems generate schedules in 15-minute increments, adjusting in real-time based on the most recent data available, and publish updated worker schedules directly to an app. As described previously, these systems often produce erratic and irregular schedules for individual workers. Percolata (described in Table 8 below) is one example of a retail scheduling optimization technology that combines a variety of data to predict shopping traffic and automatically generate work schedules.

Percolata has developed a scheduling program with the goal of increasing worker productivity in retail.[170] The system uses sensors – WiFi access and motion detectors – along with video cameras and microphones to measure in-store customer traffic. The WiFi sensors detect the "electronic fingerprints of mobile electronic devices" based on device access to store WiFi systems and use the duration of stay to distinguish between customers and employees.

Percolata's staff-planning platform combines data from in-store customer traffic patterns (flow, volume, and types of customer) with data on weather, marketing calendars, sales history, website traffic, occupancy history, third-party data, and local events to predict future shopping traffic. Using machine learning models, Percolata's system attempts to match employee availability to the predicted shopper forecast to generate optimal schedules to meet shopper traffic patterns. Percolata also assigns schedules based on employee productivity scores to place the "most capable employees" during peak customer traffic times. The algorithm calculates and ranks employees (and combinations of employees) based on sales productivity, which is calculated by the ratio of sales divided by customer traffic for each worker. Notably, the Percolata system generates schedules with an "optimal" mix of workers to maximize sales in 15-minute increment time slots throughout the day, with the potential to result in erratic schedules for workers. Employees and managers can access and make scheduling changes in real-time through mobile apps.

Table 8. Percolata

Objective	Data used & data collection strategy	Analytic technique	Output
• Optimize workforce scheduling for sales employees	• WiFi sensors detect the "electronic fingerprints" of customers and employees based on their mobile device access to store WiFi systems • Employee schedule availability • Data on in-store customer traffic patterns, weather, marketing calendars, sales history, website traffic, occupancy history, third-party data, local events	• Predictive analytics • Machine learning	• Automated schedules • Employee "shopper yield" score and rank based on sales productivity • Employee optimum productivity profiles • Store "shopper yield" score

5.2.b. Coordinating work activities

A second type of workforce optimization algorithm automates work task coordination. This type of algorithm coordinates business operations by matching, in real-time, workers to work tasks or workers to clients/customers. For instance, transportation network company platforms (TNCs) coordinate drivers and customers in real-time with algorithms that processes customer demand, trip duration, pick-up and drop-off location, and a variety of constraints such as traffic, driver availability, among others.[171] Uber has designed its algorithm to minimize the time it takes to match customers to drivers, in order to maximize the trips enroute at any given time and, therefore, revenue per hour for the company.[172]

Some of these systems incorporate a wide array of factors to optimize logistics or operations. For example, the UPS Orion system optimizes driver routes to minimize fuel costs and maximize driver efficiency and customer service.[173] The telematics system combines driver data from GPS and over 200 sensors embedded in delivery trucks with traffic, weather, and customer requests to determine driver routes in real-time.[174] The system enables customers to add pick-ups throughout the day and re-routes drivers accordingly.[175]

Another example of an optimization algorithm for workforce coordination is Afiniti, described in Table 9. Afiniti is a technology vendor that has designed an algorithm to optimize call center services through customer service personalization – essentially matching call center agents with customers based on personality – in order to maximize sales and customer satisfaction.[176] Afiniti collects comprehensive data on both employees and customers for their call center clients. For employees, they administer an employee survey for new hires that covers their likes/dislikes, hobbies, and interests. Afiniti also compiles data from call center employee records, such as gender, marital status, child status, and home neighborhood, along with employee performance evaluation data. They also collect call center customer data including demographic characteristics, location, credit score, purchasing history, social media, and other online behaviors.

Afiniti analyzes the customer data with a deep learning algorithm to segment customers into groups of customer subtypes. Using this information, Afiniti develops a machine learning algorithmic model that uses the customer subtype data and the call agent data to match the customer with specific call agents. The Enterprise Behavioral Pairing algorithm predicts which call agent on duty will most likely succeed in achieving business objectives (sell, support, retain, upsell, etc.) based on the customer subtype and the call agents' characteristics. Afiniti also analyzes historic call data in order to determine patterns of successful behavioral interactions between customers and call agents.

Table 9. Afiniti Enterprise Behavioral Pairing

Objective	Data used & data collection strategy	Analytic technique	Output
• Optimize call center customer service by pairing call center agents with customers based on personality characteristics	• New hire employee survey collects data on likes/dislikes, hobbies and interests (music, fitness, sports) • Employee records: gender, marital status, child status, home neighborhood, performance evaluations • Purchased or compiled customer data including demographic characteristics, location, credit score, purchasing history, social media, and other online behaviors.	• Deep learning algorithm for segmenting customer subtypes • Machine learning for predicting and best match between customer and call agent	• Automated call routing • Insight into patterns of successful customer service interactions

5.3. Workforce management

The next category of workplace algorithms includes those that directly engage with the labor process itself. Although the line between algorithms designed to optimize schedules or allocate work and algorithms designed to manage workers in the production process is a little blurry, there is a distinct difference between the two types of algorithms. Workforce management algorithms focus on directing workers to complete a work task – they delineate what task needs to be done, how the task should be done, and in what order tasks should be completed. Work scheduling and coordination algorithms, on the other hand, focus on optimizing and predicting who should work, when they should work, and in some cases where they should work. There is, of course, some overlap in these processes, and some systems incorporate multiple features. However, it is important to distinguish the different problems these algorithms are designed to solve in order to clarify the different types of functions they carry out. One type of algorithm involves planning, scheduling, and coordinating the workforce; the other involves directing, guiding, motivating worker activities and behaviors.

The algorithms in this section are often referred to as "algorithmic management," based on their use to shape or control worker behaviors. Some analysts have also equated the process of using algorithms to control workers as a form of "digital Taylorism" after Frederick Taylor's time and motion studies that enabled managers to fine-tune worker tasks and exert greater control over task execution. [177] This is the same underlying idea behind algorithmic management.

However, as multiple scholars have noted, it is helpful to distinguish between the directly controlling workers and manipulating workers.[178] Algorithms that directly control workers' structure their task environment and restrict the decision architecture around their activity, while algorithms that manipulate workers attempt to influence or motivate their decisions and behaviors using psychological strategies based in HR management research.[179] The subsection below highlights these different strategies for managing worker production tasks.

5.3.a. Directing workers

Algorithms designed to direct worker activities and behaviors prescribe a course of action that aligns with the employer goals (which often entails maximizing productivity or service quality), in an effort to ensure that workers complete tasks in the desired manner. These algorithms draw from data collected on workers and work tasks via sensor technologies that communicate information between workers and a computer network in real-time. Using this data stream, algorithms generate automated management decisions to direct, guide, and order workers' specific job tasks. Workers often receive personalized feedback about their activities via a computer dashboard, mobile device, or wearable sensors. The machine operates to restrict workers' discretion in physical or digital space through real-time managerial oversight and task direction.[180]

Instacart's system for in-store shoppers is an example of an algorithm that delineates tasks and task order. The system draws from an "aisle mapping" database that delineates where each item is in a store and then provides workers with an ordered pick list to completing the shopping tasks.[181] A task verification system confirms the task completion when a worker pulls an item off the shelf and places it in the cart. Electronic visit verification (EVV) technologies for home care workers operate in a similar way, but with more emphasis on task monitoring and verification due to state policies designed to curb Medicaid fraud.[182]

Amazon has developed multiple systems designed to micro-manage workers, one of which includes real-time feedback mechanisms designed to control worker activities and modify worker behaviors. A few years ago, Amazon filed a patent application for an algorithmic system to direct warehouse workers' product picking activities.[183] The proposed system includes ultrasonic devices located throughout the warehouse for each inventory item location, and sensors embedded in wristbands worn by workers that collect real-time data on their hand movements and location in the warehouse. Amazon's patent proposed to triangulate the pick list (list of items to retrieve for fulfilling orders) for items in a customer order with an item's inventory location in the warehouse and the worker's hand location. The ultrasonic devices would send signals based on matching the proximity of the inventory item sensor with the sensor embedded in the worker's wristband. If the worker attempted to grab an item from the wrong inventory item bin, the system would send a haptic (vibration) signal back to the worker's wristband to let them know they made the wrong decision. To date, it is not clear whether Amazon plans to adopt this system in its warehouses. Amazon has, however, introduced robots that deliver products to workers who stand in-place at a caged-in workstation. Rather than attempting to shape workers' picking decisions, the robots control the distribution and flow of products and set the pace of work (like an assembly line).[184]

Other systems provide workers with directions for next steps to take to complete a task or recommendations for desired behaviors. One technology vendor, Cogito, is an example of an algorithmic system designed to provide call center workers with behavioral guidance and recommendations.[185] This system is described in Table 10. Cogito designs technology systems to help call centers improve customer service and efficiency with real-time employee guidance devised to shape employee behaviors. It monitors and records conversations and other interactions between call center employees and customers. Their algorithmic system uses machine learning, voice recognition, and natural language processing in order to detect and analyze the speech of both the employee and the customer. Using these data, the algorithmic system analyzes customer sentiment and call center agent behavior patterns, energy levels, interruptions, degree of empathy, level of participation, tone of voice, and speaking pace in order to provide real-time guidance to nudge employees to adjust their behaviors accordingly.

On a dashboard, call agents receive notifications, or cues, coaching them to express more empathy, pace the call more efficiently, or exude more confidence and professionalism. Supervisors also have access to a dashboard that enables them to identify problematic situations and intervene if necessary. The dashboards also provide managers with a "customer experience score" based on the worker's call analysis, along with predictive and prescriptive insights regarding customer churn, call efficiency, employee performance, and sales conversions. Managers may apply this information to make decisions about employees or future job candidates.

Table 10. Cogito

Objective	Data used & data collection strategy	Analytic technique	Output
• Provide coaching and call guidance to improve customer service and call efficiency	• Electronically monitors employee phone call interactions with customers	• Machine learning • Natural language processing • Voice recognition • Predictive analytics • Sentiment analysis	• Employee dashboards with real-time cues, call guidance, nudges, and customer call experience scoring • Supervisor real-time dashboard with service issue alerts and customer call experience scoring • Manager insight reports: customer churn, call efficiency, employee performance, and sales conversion

5.3.b. Manipulating workers

The second version of workforce management algorithms are designed to influence rather than dictate worker decisions. These technologies combine Taylorist insights about micro-monitoring the work process with behavioral economics and industrial and organizational psychology, both focused on human cognition and motivation strategies.[186] Like the algorithms used to direct workers' job activities, these algorithms track workers and collect workplace data in real-time in order to provide personalized feedback to workers. However, instead of directing workers to do specific tasks in a particular order and at a particular time, these algorithms use psychological strategies such as incentives and penalties to prompt individuals to modify their behavior to align with the goals of the firm:

- Incentives are a type of nudge that uses differential rewards based on desired behaviors (in lieu of basic remuneration for labor provided) in the form of badges, points, or public workplace displays ranking employees (leaderboards).
- Penalties are a type of nudge that uses threats to discourage undesired behaviors; threats may involve potential exclusion from a work platform, poor ratings from customers or clients, or automatic firing for falling below desired productivity levels

Technology developers increasingly embed these behavior modification strategies into games, which the industry refers to as "gamification."[187] These systems simulate virtual games by providing points and badges for behaviors that align with a company's goals.[188] Some systems take the game one step further by simulating competitions among participants (users) by publishing rankings on leaderboards.[189] Ian Bogost, a philosophy professor and game designer, refers to gamification as "exploitationware" because the basic objective is to extract value from workers under the veneer of a game.[190] System designers often use these strategies to link employee behaviors and activities with a firm's desired outcomes in terms of pace of work or quantity of work.[191]

Platforms are well-known for using incentives and penalties to shape worker behaviors.[192] Uber uses "surge pricing" incentive schemes to encourage drivers to drive during peak demand times and in certain locations.[193] The company also sets targets for drivers and sends notifications about promotional rates to drivers to encourage them to continue driving.[194] On the other hand, drivers can receive penalties for cancelling or declining dispatches while logged into the system, and in some cases the drive will be dropped from the platform. A key feature of these systems is the arms-length approach to management.[195] Instead of a human manager attempting to directly control workers' activities in person, these systems allow for management from afar – i.e. management by machine. The true source of managerial direction is invisible. This is important for the platform economy, where the platform companies have historically avoided hiring workers as employees under the premise that they should be classified independent contractors instead.

Strategies for manipulating worker behaviors extend beyond the platform economy. Firms use gamification to shape worker behaviors in terms of pace of work or quantity of work in other types of industries as well. For instance, the technology vendor NCR includes gamification features in some of its grocery industry cashier scanning systems to increase the pace of scanning.[196] Some companies simulate competitions among employees by publishing employee productivity rankings on leaderboards throughout the workplace. For example, several years ago Disneyland hotels introduced productivity leaderboards into their hotel laundry facilities to pit workers against one another in an effort to increase productivity. Employees referred to the system as "the electronic whip," which ultimately led to bad press for the hotel, and Disney eventually dropped the system.[197]

Amazon has developed perhaps the most publicized gamification system in recent history. Some of Amazon's warehouse operations use gamification strategies and productivity leaderboards to increase worker productivity. Using sensors embedded in the product scanners to collect data on worker movement and number of items picked, the system mirrors the real-time data collected on their physical labor into virtual space in the form of video games. As workers pick products for shipping, their actual productivity numbers power their progress in a game visualization. The games (PicksInSpace, Dragon Duel, CastleCrafter, Mission Racer) each have a different game scape, but the goal is the same: to increase employee efficiency and productivity.[198] For example, Mission Racer, a sports car racing game, shows race cars moving around a virtual track, pitting employees against each other based on their productivity scores. Employees receive rewards in the form of points, badges, and "swag bucks," which they can use to buy Amazon branded products.[199]

5.4. Production of goods and services

The final application of algorithms in the workplace is the most often discussed category in recent debates about the future of work. This category includes the use of intelligent machines to automate work tasks. Work task automation falls within two different types of activities:[200]

- **Machines assisting and augmenting workers**: machines provide decision support or supplemental task automation to enable workers to complete work tasks (i.e. human and machine share the job task)
- **Machines substituting partially or wholly for workers**: machines partially or fully automate core human tasks

Algorithmic technologies used in the production context can provide workers with information to support decision-making, enabling workers to complete work tasks more easily or quickly. For example, a medical diagnostic system can provide decision support to technicians and doctors by using large datasets of medical images files to make predictions regarding the diagnosis of a disease. Other algorithmic systems operate as interactive machines that can substitute human labor to complete a work task independently. Examples of this type of system include software virtual assistants or chatbots, as well as physically embodied intelligent machines such as self-driving vehicles and industrial robots (sometimes referred to as "cobots").[201]

Technology developers often design these technologies with the objective of increasing labor productivity and/or reducing labor costs. For the most part these technologies are domain-specific, meaning that they are designed for specific industries and in many cases for specific workplaces. For example, Amazon has designed robots specifically for the purpose of moving goods within a warehouse.[202] Like Amazon, Walmart has been at the forefront of introducing new technologies in the workplace; their janitorial robots are an example of interactive machine designed to automate a production task as a substitute for human labor. The key features of these machines are described in Table 11.

Walmart partnered with a robotics company, Brain Corp, to introduce their Auto-C Autonomous cleaners in multiple stores across the US. The purpose of these robots is to assist the janitorial staff with floor cleaning tasks. [203] The basic operation of the machines entails multiple steps. First, the robot uses cameras and sensors to perceive the task environment, including objects and humans in its path. After interpreting and analyzing the environment, the robot arrives at a decision about what action to take (move forward or stop). If the robot concludes there are no obstacles, the machine moves forward, scrubbing aisles along the route. It is important to note that the so-called "autonomous" floor scrubber is not actually fully autonomous; employees still need to assist and supervise the cleaning robot by mapping the route and preparing the floor for cleaning. To carry out these tasks an employee must ride along on the robot like a riding lawn mower.

Table 11. Walmart Auto-C Autonomous cleaner

Objective	Data used & data collection strategy	Analytic technique	Output
• Complete janitorial floor cleaning tasks	• Cameras and other sensors to perceive the store environment • LiDAR for navigation	• Machine learning algorithm	• Robotic hardware • Aisle cleaning action

The example of Walmart's janitorial robot draws attention to a few important points about automation. First, technologies described as autonomous often operate along a continuum of technological capacities and levels of automation, with varying degrees of human involvement. Second, technologies that assist and augment worker capacities may also play a role in automated systems. For example, some vehicles operated by humans have auto-braking systems that engage if a driver swerves out of their lane or is about to collide with another object. This same technology is a component of vehicles further along the continuum toward full automation.[204] Third, as intelligent machines move along the continuum toward more fully autonomous machines, the relationship between the worker and the machine shifts from the machine assisting the worker to the worker assisting the machine.

In other words, even the most technically autonomous systems are never fully independent from social systems. Humans play a role in their design, development, and their ability to operate in the social and physical world. Behind the scenes, human workers train these systems to help them understand and operate within the human world.[205] In one sense, although a machine may complete the actual job task, the human labor involved in completing the task has simply shifted to another group of workers who enable the machine to complete the task. Workers also provide back-up support and often serve as a scapegoat when these systems fail.[206]

6. Next research directions

The purpose of this working paper is to provide worker organizations and policymakers with a framework for understanding data collection strategies and algorithmic systems currently in use or being developed for use in the workplace, with an emphasis on low-wage industries. As this paper outlined, data collection strategies, in particular sensor and AI-enhanced technologies, potentially enable monitoring and data collection on nearly every dimension of the digital and physical work environment: what happens, how it happens, and the context in which it is happening. Every location can be tracked, and every worker action, interaction, and transaction can be captured and recorded. These new technologies enable data collection on workers at an unprecedented, granular level of detail. Moreover, the extensive nature of some of these data collection strategies extend well beyond the workplace, blurring the work-life boundaries between employers and workers.

The algorithmic systems enabled by the scale and scope of worker data collection have a wide variety of capabilities and technological applications in the workplace. These systems can make predictions to help managers make decisions about workers or automate managerial decisions, delineating when, where, and how workers complete tasks. Data-driven technologies can also provide information to workers to assist or augment their ability to complete a task, and in some cases to automate workers’ tasks entirely. As a result, these new data collection strategies and algorithmic systems have significant implications for workers and present new challenges for advocates and policymakers.

Understanding the technological capacities and processes of data collection and algorithmic systems is a first step in responding to these challenges. The next step is to investigate the actual adoption and implementation of new technologies by employers, and the effects of these technologies on jobs and workers. Crucially, this will require research that brings in worker perspectives as a key source of information about how these technologies are actually playing out in the workplace.

We are only starting to understand the potential effects these new data-driven technologies can have on jobs and workers. Emerging research points to negative effects on working conditions and workers, and to the potential for these technologies to exacerbate socio-economic inequalities.[207] For example, some of the potential harms identified by researchers include:

- Bias and discrimination against people of color, immigrants, and women due to biased data inputs and analytic processes
- Unpredictable schedules resulting from scheduling optimization systems
- Decreased worker power and autonomy and increased stress resulting from constant electronic monitoring and algorithmic management
- Deskilling and lower wages as jobs become more controlled and restricted
- Work speed-up resulting from algorithmic systems designed to increase productivity
- Workplace stress and bodily injury resulting from speed-up and increased interactions with machines
- Job insecurity resulting from technologies designed to replace workers and increase workforce fissuring
- Employment and labor law violations enabled by these technologies (e.g., wage theft, misclassification)
- Increasing ability for employers to prevent or punish worker organizing and union activity
- Inaccurate or unsubstantiated predictions or decisions made by algorithmic systems

Issues of equity are a central concern with data-driven technologies that rely on historical data because historical patterns of discrimination may be reflected in data and then become encoded in technology, which in turn reproduces those patterns in their technological outputs. The analytic processes in the algorithms themselves can give rise to bias in these systems as well. However, bias in the data and algorithmic systems is not the only source of discriminatory outcomes; employment patterns in industries and occupations where firms are experimenting with data and algorithms represent another way that these technologies can affect equity. All of these factors have far reaching implications for historically marginalized groups, such as workers of color, women, and immigrant workers.

However, the outcomes of these new technologies are not pre-determined or inevitable. Many data-driven technologies have the potential to be used in ways that benefit both workers and employers.[208] Data-driven technologies could potentially be used to:

- Enable workforce participation among elderly and disabled communities by increasing the accessibility for human and computer interactions (e.g., with voice commands or computer vision systems)
- Identify racial and gender bias and discrimination in the workplace by analyzing data on workplace decisions and social dynamics to detect patterns of discrimination
- Increase workers' skills and advance their position in the workplace by using technology to augment and support their work, freeing them from more menial or repetitive tasks
- Create predictable and flexible schedules using algorithmic systems that include information about workers' preferences
- Reduce health and safety risks via monitoring and risk detection systems

- Identify employment and labor law violations by monitoring and tracking activities in the workplace

In short, the effects of data-driven technologies are not a given. In many cases, negative effects are not inherent in the technology itself, but instead result from decisions made by firms in the design process and in the implementation of the technology in the workplace. We therefore need more research exploring variation in technology design and adoption practices by firms, focusing on identifying the sources of that variation (i.e. regulations, worker voice, firm or industry norms, etc.). We also urgently need research that looks at variation in how the productivity gains resulting from technology adoption are distributed within a workplace. Investigating these questions will help us better understand how to encourage the development and adoption of data-driven technologies that protect and empower workers and that enhance equity in the workplace.

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Endnotes

[1] For example, see media coverage about a Microsoft and United Health screening app, see Finley, D. (2020, May 18). Microsoft and UnitedHealth Group are rolling out a coronavirus screening app to US employers. *Business Insider*. Retrieved from https://www.businessinsider.com/microsoft-unitedhealth-launch-coronavirus-return-to-work-app-2020-5 and Cooley, B. (2020, May 22). Microsoft and UnitedHealth Group launch workplace health app. *CNet*. Retrieved from https://www.cnet.com/health/microsoft-and-unitedhealth-group-launch-workplace-health-app/. Also, see media coverage about Amazon's social distancing AI, see Simonite, T. (2020). Amazon touts AI for social distancing amid worker complaints. *Wired*. Retrieved from https://www.wired.com/story/amazon-touts-ai-social-distancing-worker-complaints/ and Vincent, J. (2020, June 16). Amazon deploys AI 'distance assistants' to notify warehouse workers if they get too close. *The Verge*. Retrieved from https://www.theverge.com/2020/6/16/21292669/social-distancing-amazon-ai-assistant-warehouses-covid-19. For media coverage regarding widespread monitoring, see Allyn, B. (2020, May 13). Your Boss Is Watching You: Work-From-Home Boom Leads to More Surveillance. *NPR*. Retrieved from https://www.npr.org/2020/05/13/854014403/your-boss-is-watching-you-work-from-home-boom-leads-to-more-surveillance; Golden, J., & Chemi, E. (2020, May 13). Worker monitoring tools see surging growth as companies adjust to stay-at-home orders. *CNBC*. Retrieved from https://www.cnbc.com/2020/05/13/employee-monitoring-tools-see-uptick-as-more-people-work-from-home.html; and Chyi, N. (2020, May 12). The workplace-surveillance technology boom. *Slate*. Retrieved from https://slate.com/technology/2020/05/workplace-surveillance-apps-coronavirus.html. Also see Public Citizen. (2020). *Workplace privacy after Covid-19*. Retrieved from https://www.citizen.org/article/workplace-privacy-after-covid-19/ and Rodriguez, K., & Windwehr, S. (2020, September 10). Workplace Surveillance in Times of Corona. *Electronic Frontier Foundation*. Retrieved from https://www.eff.org/deeplinks/2020/09/workplace-surveillance-times-corona.

[2] See Ding, L., & Molina, J. S. (2020). *"Forced Automation" by COVID-19? Early Trends from Current Population Survey Data*. Retrieved from https://www.philadelphiafed.org/-/media/community-development/publications/discussion-papers/discussion-paper_automation.pdf; MIT Technology Review Insights. (2020). *Covid-19 and the Workforce: Critical workers, productivity, and the future of AI*. *MIT Technology Review*. Retrieved from https://www.technologyreview.com/2020/04/30/1000888/covid-19-and-the-workforce-critical-workers-productivity-and-the-future-of-ai/; and Muro, M., Maxim, R., & Whiton, J. (2020). The robots are ready as the COVID-19 recession spreads. Retrieved from https://www.brookings.edu/blog/the-avenue/2020/03/24/the-robots-are-ready-as-the-covid-19-recession-spreads/.

[3] In addition to the reports listed below, see Rogers, B. (2019). *Beyond Automation: The Law & Political Economy of Workplace Technological Change* (Vol. June). Retrieved from https://rooseveltinstitute.org/wp-content/uploads/2020/07/RI_Beyond-Automation_Working-Paper.pdf; Levy, K., & Barocas, S. (2018). Refractive surveillance: Monitoring customers to manage workers. *International Journal of Communication*, *12*, 1166–1188. Retrieved from https://ijoc.org/index.php/ijoc/article/viewFile/7041/2302; Sánchez-m=Monedero, J., & Dencik, L. (2019). The datafication of the workplace. *Data Justice Project, Cardiff University*, 1–46. Retrieved from https://datajusticeproject.net/wp-content/uploads/sites/30/2019/05/Report-The-datafication-of-the-workplace.pdf; Christin, A. (2020). What Data Can Do: A Typology of Mechanisms. *International Journal of Communication*, *14*(0), 20.; and Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, *14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174.

[4] Adler-Bell, S., & Miller, M. (2018). *The Datafication of Employment*. *The Century Foundation*. Retrieved from https://tcf.org/content/report/datafication-employment-surveillance-capitalism-shaping-workers-futures-without-knowledge/.

[5] Bogen, M., & Rieke, A. (2018). *Help wanted: An examination of hiring algorithms, equity, and bias*. Washington D.C. Retrieved from https://www.upturn.org/reports/2018/hiring-algorithms/.

[6] Mateescu, A., & Nguyen, A. (2019). *Explainer: Workplace Monitoring & Surveillance*. *Data & Society Research Institute*. Retrieved from https://datasociety.net/library/explainer-workplace-monitoring-surveillance/ and Mateescu, A., & Nguyen, A. (2019). Explainer: Algorithmic Management in the Workplace. *Data & Society Institute*,

(February), 1–15. Retrieved from https://datasociety.net/library/explainer-algorithmic-management-in-the-workplace/.

[7] Weiser, M. (1991). The computer for the 21st century. *Scientific American*, *265*(3), 94–105.

[8] Schaeffer, K. (2019). U.S. has changed in key ways in the past decade, from tech use to demographics. Retrieved from https://www.pewresearch.org/fact-tank/2019/12/20/key-ways-us-changed-in-past-decade/.

[9] Varian, H. R. (2010). Computer Mediated Transactions. In *The American Economic Review* (Vol. 100, pp. 1–10); Zuboff, S. (2015). Big other: Surveillance capitalism and the prospects of an information civilization. *Journal of Information Technology*, *30*(1), 75–89.

[10] For a full discussion on digitalization, see: National Academies of Sciences Engineering and Medicine. (2017). *Information technology and the U.S. workforce: Where are we and where do we go from here? Information Technology and the U.S. Workforce: Where Are We and Where Do We Go from Here?* Washington, DC: The National Academies Press. Also, see Varian, H. R. (2014). Beyond big data. *Business Economics*, *49*(1), 27–31.; European Commission. (2019). *The Impact of the Digital Transformation on EU Labor Markets*; and, for a brief description of digitalization, see Bloomberg, J. (2018). Digitization, Digitalization, And Digital Transformation: Confuse Them At Your Peril. *Forbes*. Retrieved from https://www.forbes.com/sites/jasonbloomberg/2018/04/29/digitization-digitalization-and-digital-transformation-confuse-them-at-your-peril/#2f6b3b2c2f2c

[11] Varian, H. R. (2010). Computer Mediated Transactions. In *The American Economic Review* (Vol. 100, pp. 1–10); Varian, H. R. (2014). Beyond big data. *Business Economics*, *49*(1), 27–31.

[12] AI research draws from a variety of fields including math, computer science, statistics, robotics, among others.

[13] See National Academies of Sciences Engineering and Medicine. (2017). *Information technology and the U.S. workforce: Where are we and where do we go from here?* Washington, DC: The National Academies Press. Retrieved from https://www.nap.edu/catalog/24649/information-technology-and-the-us-workforce-where-are-we-and.

[14] Varian, H. R. (2010). Computer Mediated Transactions. In *The American Economic Review* (Vol. 100, pp. 1–10); Varian, H. R. (2014). Beyond big data. *Business Economics*, *49*(1), 27–31.

[15] Gottlieb, J., & Rifai, K. (2017). *Fueling growth through data monetization*. *Mckinsey & Company*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/fueling-growth-through-data-monetization; Gandhi, S., Thota, B., Kuchembuck, R., & Swartz, J. (2018). Demystifying data monetization. Retrieved from https://sloanreview.mit.edu/article/demystifying-data-monetization/; Opher, A., Chou, A., Onda, A., & Sounderrajan, K. (2016). *The Rise of the Data Economy: Driving Value through Internet of Things Data Monetization*. *IBM Corporation*.

[16] Gandhi, S., Thota, B., Kuchembuck, R., & Swartz, J. (2018). Demystifying data monetization. Retrieved from https://sloanreview.mit.edu/article/demystifying-data-monetization/

[17] Isson, J. P., & Harriott, J. I. (2016). *People Analytics in the Era of Big Data: Changing the way you attract, acquire, develop, and retain talent*. Hoboken: Wiley.

[18] Taylor, F. W. (1919). *The principles of scientific management*. New York: Harper & Brothers Publishers.

[19] Munsterberg, H. (1913). *Psychology and industrial efficiency*. Boston: Houghton Mifflin Company.

[20] See Adler-Bell, S., & Miller, M. (2018). *The Datafication of Employment*. *The Century Foundation*. Retrieved from https://tcf.org/content/report/datafication-employment-surveillance-capitalism-shaping-workers-futures-without-knowledge/.

[21] For example, the US government began to conduct FBI criminal background checks for federal employment in 1954. Since then criminal background checks have expanded to employment beyond government employees. For a comprehensive analysis of FBI criminal background checks for employment, see Neighly, M., & Emsellem, M. (2013). *Wanted: Accurate FBI background checks for employment*. Retrieved from http://www.nelp.org/page/-/SCLP/2013/Report-Wanted-Accurate-FBI-Background-Checks-Employment.pdf?nocdn=1.

[22] For examples, see: Ajunwa, I., Crawford, K., & Schultz, J. (2017). Limitless worker surveillance. *California Law Review*, *105*(3), 735–776.; Ajunwa, I. (2018). Algorithms at work: Productivity Monitoring Platforms and Wearable Technology as the New Data-Centric Research Agenda for Employment and Labor Law. *Saint Luis University Law Journal*, *63*(21), 21–54.; Bersin, J., Mariani, J., & Monahan, K. (2016). *Will IoT technology bring us the quantified employee? The Internet of Things in human resources*. Retrieved from http://www2.deloitte.com/us/en/pages/tech-nology-media-and-telecommunications/topics/the-internet-of-things.html.

[23] For example, see Thomas, E. (2019, September). New surveillance tech means you'll never be anonymous again. *Wired*. Retrieved from https://www.wired.co.uk/article/surveillance-technology-biometrics; Holmes, A. (2019, October). Facial recognition is on the rise, but artificial intelligence is already being trained to recognize humans in new ways — including gait detection and heartbeat sensors. *Business Insider*. Retrieved from https://www.businessinsider.com/ai-training-beyond-facial-recognition-gait-detection-heartbeat-sensors-2019-10; Kang, D. (2018, November 6). Chinese 'gait recognition' tech IDs people by how they walk. *AP News*. Retrieved from https://apnews.com/article/bf75dd1c26c947b7826d270a16e2658a.

[24] For a description of the multistep process of digital transformation and data integration in firms, see Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B., & Sethupathy, G. (2016). *The Age of Analytics: Competing in a Data-Driven World*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-age-of-analytics-competing-in-a-data-driven-world.

[25] Levy, K., & Barocas, S. (2018). Refractive surveillance: Monitoring customers to manage workers. *International Journal of Communication*, *12*, 1166–1188. Retrieved from https://ijoc.org/index.php/ijoc/article/viewFile/7041/2302.

[26] Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B., & Sethupathy, G. (2016). *The Age of Analytics: Competing in a Data-Driven World*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-age-of-analytics-competing-in-a-data-driven-world

[27] For more information about the data brokerage industry see: Reike, A., Yu, H., Robinson, D., & von Hoboken, J. (2016). *Data brokers in an open society*. London: Upturn & Open Societies Foundation. Retrieved from https://www.opensocietyfoundations.org/uploads/42d529c7-a351-412e-a065-53770cf1d35e/data-brokers-in-an-open-society-20161121.pdf; Christl, W. (2017). *Corporate surveillance in everyday life: How companies collect, combine, analyze, trade and use personal data on billions*. Vienna: Cracked Labs. Retrieved from https://crackedlabs.org/dl/CrackedLabs_Christl_CorporateSurveillance.pdf. For information about the employment background check industry see: Cerullo, M. (2019, June 28). What everyone should know about employer background checks. *CBS NewsNews*. Retrieved from https://www.cbsnews.com/news/what-job-candidates-should-know-about-employer-background-checks/; Gordy, C. (2012, April). When Background Checks Violate Civil Rights. *The Root*. Retrieved from https://www.theroot.com/when-background-checks-violate-civil-rights-1790884189.

[28] For more information on social media profiling practices used to determine employability, see Madden, M., Gilman, M., Levy, K., & Marwick, A. (2017). Privacy, Poverty and Big Data: A Matrix of Vulnerabilities for Poor Americans. *Washington University Law Review*, *95*(1), 053–125.

[29] See Bersin, J., & Gretczko, M. (2015). People data everywhere: Bringing the outside in. Retrieved from https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2015/people-data-everywhere-human-capital-trends-2015.html?:2el:3dc:dup1137:eng:cons:hct15.

[30] For examples of computer metadata collection, see Sánchez-Monedero, J., & Dencik, L. (2019). The datafication of the workplace. *Data Justice Project, Cardiff University*, 1–46. Retrieved from https://datajusticeproject.net/wp-content/uploads/sites/30/2019/05/Report-The-datafication-of-the-workplace.pdf; Nord, G. D., McCubbins, T. F., & Nord, J. H. (2006). E-monitoring in the Workplace: Privacy, Legislation, and Surveillance Software. *Communications of the ACM*, *49*(8), 73–77; and Ciocchetti, C. A. (2011). The Eavesdropping Employer: A Twenty-First Century Framework for Employee Monitoring. *American Business Law Journal*, *48*(2), 285–369. For a discussion about use of metadata for electronic monitoring in general, see Bernal, P. (2016). Data gathering, surveillance and human rights: recasting the debate. *Journal of Cyber Policy*, *1*(2), 243–264. https://doi.org/10.1080/23738871.2016.1228990.

[31] See Ludwig, S. (2018, April 12). Pro's and Cons for IP vs. Analog Video Surveillance. *Security Magazine*. Retrieved from https://www.securitymagazine.com/articles/88854-pros-and-cons-for-ip-vs-analog-video-surveillance and Mesenbrink, J. (2004, February 1). Video Surveillance: IP Video Caters to Restaurants. *Security Magazine*. Retrieved from https://www.securitymagazine.com/articles/77787-video-surveillance-ip-video-caters-to-restaurants-1.

[32] The ePolicy Institute. (2007). 2007 Electronic Monitoring & Surveillance Survey. Retrieved from http://www.epolicyinstitute.com/2007-survey-results. Also, for more information on employer electronic monitoring practices, see: Collier, L. (2019). *Workplace surveillance*. *Sage Business Researcher*.

[33]See Kambies, T., Mittal, N., Roma, P., & Sharma, S. K. (2017). *Dark analytics: Illuminating opportunities hidden within unstructured data*. *Deloitte Insights*. Retrieved from https://www2.deloitte.com/us/en/insights/focus/tech-trends/2017/dark-data-analyzing-unstructured-data.html. Also, for a description of computer vision, video analysis and interpretation, see National Academies of Sciences Engineering and Medicine. (2017). *Information technology and the U.S. workforce: Where are we and where do we go from here?* Washington, DC: The National Academies Press. Retrieved from https://www.nap.edu/catalog/24649/information-technology-and-the-us-workforce-where-are-we-and.

[34] See Matsakis, L. (2019, October). At an Outback Steakhouse Franchise, Surveillance Blooms. *Wired*. Retrieved from https://www.wired.com/story/outback-steakhouse-presto-vision-surveillance/. Also see Vincent, J. (2020, June 16). Amazon deploys AI 'distance assistants' to notify warehouse workers if they get too close. *The Verge*. Retrieved from https://www.theverge.com/2020/6/16/21292669/social-distancing-amazon-ai-assistant-warehouses-covid-19.

[35] See, for example: Smartdrive, https://www.smartdrive.net/solutions/smartchoice-program-video-safety/; idrive https://idriveglobal.com/technology/; and Lytx https://www.lytx.com/en-us/fleet-management/dash-cam.

[36] See Beswick, J. (2020, March 30). Converting call center recordings into useful data for analytics. Retrieved from https://aws.amazon.com/blogs/compute/converting-call-center-recordings-into-useful-data-for-analytics/ and Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P., & Malhotra, S. (2018). *Notes from the AI frontier: Insights from hundreds of use cases*. Retrieved from https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Notes%20from%20the%20AI%20frontier%20Applications%20and%20value%20of%20deep%20learning/Notes-from-the-AI-frontier-Insights-from-hundreds-of-use-cases-Discussion-paper.ashx.

[37] See Simonite, T. (2018, March 19). This Call May Be Monitored for Tone and Emotion. *Wired*. Retrieved from https://www.wired.com/story/this-call-may-be-monitored-for-tone-and-emotion/; Shacklett, M. (2020, March 11). How improved sentiment analysis in voice- based communications can help increase sales. *Tech Republic*. Retrieved from https://www.techrepublic.com/article/how-improved-sentiment-analysis-in-voice-based-communications-can-help-increase-sales/; and Marinac, T. (2020). *A Guide to Call Center Sentiment Analysis | Calabrio A Guide to Call Center Sentiment Analysis*. Retrieved from https://www.calabrio.com/wfo/customer-interaction-analytics/call-center-sentiment-analysis/.

[38] Lunenburg, F. C. (2011). The Art and Science of Personnel Selection: The Use of Tests and Performance Simulations. *International Journal of Management, Business, and Administration*, *15*(1), 1–5. Retrieved from http://www.nationalforum.com/Electronic Journal Volumes/Lunenburg, Fred C. The Art & Science of Personnel Selection-Tests and Perf Sim.-IJMBA (DONE).pdf. For a discussion on employer use of personality tests, see O'Neil, C. (2016, September 1). How algorithms rule our working lives. *The Guardian*, pp. 1–10. Retrieved from https://www.theguardian.com/science/2016/sep/01/how-algorithms-rule-our-working-lives; Pasquale, F. (2015). The Black Box Society. *The Black Box Society*; Newman, N. (2017). Reengineering Workplace Bargaining: How Big Data Drives Lower Wages and How Reframing Labor Law Can Restore Information Equality in the Workplace. *University of Cincinnati Law Review*, *85*, 693–760.

[39] Meinert, D. (2015, June). What do personality tests really reveal? *HR Magazine*. Retrieved from https://www.shrm.org/hr-today/news/hr-magazine/pages/0615-personality-tests.aspx

[40] See Falletta, S. (2014). In Search of HR Intelligence: Evidence-Based HR Analytics Practices in High Performing Companies. *People & Strategy*, *36*(4), 28–37 and Isson, J. P., & Harriott, J. I. (2016). *People Analytics in the Era of Big Data: Changing the way you attract, acquire, develop, and retain talent*. Hoboken: Wiley.

[41] See Bogen, M., & Rieke, A. (2018). *Help wanted: An examination of hiring algorithms, equity, and bias*. Washington, D.C. Retrieved from https://www.upturn.org/reports/2018/hiring-algorithms/ and Arellano, C., DiLeonardo, A., & Felix, I. (2017). *Using people analytics to drive business performance: A case study*. *McKinsey Quarterly*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/using-people-analytics-to-drive-business-performance-a-case-study.

[42] Pymetrics, https://www.pymetrics.ai/.

[43] Rosenblat, A., Barocas, S., Levy, K., & Hwang, T. (2016). Discriminating Tastes: Customer Ratings as Vehicles for Bias. *Intelligence.Datasociety.Net*, (October), 1–21. Retrieved from https://datasociety.net/pubs/ia/Discriminating_Tastes_Customer_Ratings_as_Vehicles_for_Bias.pdf and Mateescu, A., & Nguyen, A. (2019). Explainer: Algorithmic Management in the Workplace. *Data & Society Institute*, (February), 1–15. Retrieved from https://datasociety.net/library/explainer-algorithmic-management-in-the-workplace/.

[44] See Iansiti, M., & Lakhani, K. R. (2014, November). Digital ubiquity: How connections, sensors, and data are revolutionizing business. *Harvard Business Review*, 37–39. Retrieved from https://hbr.org/2014/11/digital-ubiquity-how-connections-sensors-and-data-are-revolutionizing-business and Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B., & Sethupathy, G. (2016). *The Age of Analytics: Competing in a Data-Driven World*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-age-of-analytics-competing-in-a-data-driven-world; and McCollum, C. (2019). *Intelligent sensing: The impact of AI on sensor capabilities*. Retrieved from https://web.luxresearchinc.com/hubfs/Press Release Assets/Lux Research - Intelligent Sensing - Executive Summary.pdf?utm_campaign=2019.05 Sensors Press Release&utm_source=email&utm_content=2019.05.16 Sensors Press Release – English. Also, for a brief overview of IoT technologies and data monetization strategies see Opher, A., Chou, A., Onda, A., & Sounderrajan, K. (2016). *The Rise of the Data Economy: Driving Value through Internet of Things Data Monetization*. *IBM Corporation*. Retrieved from https://www.ibm.com/downloads/cas/4JROLDQ7.

[45] See Macharla, M. (n.d.). *List of Commonly used Sensors in the Internet of Things (IoT) Devices you need to know*. Retrieved from https://iot4beginners.com/commonly-used-sensors-in-the-internet-of-things-iot-devices-and-their-application/ and Sharma, R. (2020). Top 15 sensor types being used most by IoT application development companies. Retrieved from https://www.finoit.com/blog/top-15-sensor-types-used-iot/.

[46] For a comprehensive overview of the 'Internet of Things', see Ranger, S. (2018, February 3). What is the IoT? Everything you need to know about the Internet of Things right now. *ZDNet*, pp. 1–25. Retrieved from https://www.zdnet.com/article/what-is-the-internet-of-things-everything-you-need-to-know-about-the-iot-right-now/; Braun, A. (2019, January 25). History of IoT: A Timeline of Development. *IoT Tech Trends*. Retrieved from https://www.iottechtrends.com/history-of-iot/; Whitmore, A., Agarwal, A., & Da Xu, L. (2015). The Internet of Things—A survey of topics and trends. *Information Systems Frontiers*, *17*(2), 261–274. https://doi.org/10.1007/s10796-014-9489-2; Khodadadi, F., Dastjerdi, A. V., & Buyya, R. (2020). *Internet of Things: An Overview*. *Advances in Intelligent Systems and Computing* (Vol. 1118). https://doi.org/10.1007/978-981-15-2475-2_8; and Martin, C., & Leurent, H. (2017). *Technology and innovation for the future of production: Accelerating value creation*. *World Economic Forum*. https://doi.org/10.1074/jbc.M003388200. For a discussion about IoT technology in the workplace, see Bersin, J., Mariani, J., & Monahan, K. (2016). *Will IoT technology bring us the quantified employee? The Internet of Things in human resources*. Retrieved from http://www2.deloitte.com/us/en/pages/tech-nology-media-and-telecommunications/topics/the-internet-of-things.html.

[47] Beam Technologies, https://beam.dental/.

[48] See Wiggers, K. (2019, May). Beam raises $55 million for a connected toothbrush that lowers dental premiums. *Venture Beat*. Retrieved from https://venturebeat.com/2019/05/29/beam-raises-50-million-for-a-connected-toothbrush-that-lowers-dental-premiums/; Barlyn, S. (2017, January 19). Bluetooth toothbrushes, telematics, Fitbits and data tracking acceptance. *Insurance Journal*. Retrieved from https://www.insurancejournal.com/news/national/2017/01/19/438925.htm; and Mayer, N. (2018, April 25). Smart Toothbrush Sparks Concern for Data Security Smart Toothbrush Sparks Concern for Data Security. Retrieved from https://bloggingrepublic.com/smart-toothbrush-sparks-concern-for-data-security/.

[49] For examples, see Wollenhaupt, G. (2017, June 23). Warehouse operations go hands-free with wearable tech. *Samsung Insights*. Retrieved from https://insights.samsung.com/2017/06/23/warehouse-operations-go-hands-free-with-wearable-tech/; Hitachi. (2017). *DFKI and Hitachi jointly develop AI technology for human activity recognition of workers using wearable devices* (Vol. 0). Retrieved from https://www.hitachi.com/New/cnews/month/2019/03/190320.html; ABI Research. (2016, September 14). Wearable scanners aid work automation and mobility to boost business efficiency. Retrieved from https://www.abiresearch.com/press/wearable-scanners-aid-work-automation-and-mobility/; and Venook, J. (2017, April 10). The Upcoming Privacy Battle Over Wearables in the NBA. *The Atlantic*. Retrieved from https://www.theatlantic.com/business/archive/2017/04/biometric-tracking-sports/522222/.

[50] Humanyze, https://www.humanyze.com/. Also see Olguin, D. O., Jaanu, T., Heyman, D., & Waber, B. (2014). *US 2014/0249891 A1*. United States. Retrieved from https://www.freepatentsonline.com/20140249891.pdf; Chan, R. (2018, June 6). The high-tech office of the future will spy on you. *The Week*. Retrieved from https://theweek.com/articles/760582/hightech-office-future-spy; and Lindsay, G. (2015, September 21). HR Meets Data: How your boss will monitor you to create the quantified workplace. *Fast Company*. Retrieved from https://www.fastcompany.com/3051275/hr-meets-data-how-your-boss-will-monitor-you-to-create-the-quantified-workplace.

[51] For example, see Boyle, A. (2018, January 30). Amazon wins a pair of patents for wireless wristbands that track warehouse workers. *Geekwire*. Retrieved from https://www.geekwire.com/2018/amazon-wins-patents-wireless-wristbands-track-warehouse-workers/ and Murphy, C. (2020). How wearable devices are changing the future of workplace safety. Retrieved from https://www.nationwide.com/cps/cic/industries/wearable-devices-are-changing-workplace-safety.html.

[52] See Schatsky, D., & Kumar, N. (2018). Workforce superpowers: Wearables are augmenting employees' abilities. *Deloitte Insights*, 1–8. Retrieved from https://www2.deloitte.com/content/dam/insights/us/articles/4599_Superhuman-workforce/DI_Workforce-superpowers.pdf and Nicastro, D. (2018, August 27). Examining the role of wearables technology in the workplace. *CMS Wire*. Retrieved from https://www.cmswire.com/digital-workplace/examining-the-role-of-wearables-technology-in-the-workplace/.

[53] See Rowland, C. (2019, February 17). Your Next Fitness Coach Is... Your Boss? *The Washington Post*. Retrieved from https://mrtechnews.com/your-next-fitness-coach-is-your-boss/; Corporate Wellness Magazine. (n.d.). The elephant in the room - just how big will wearables get? Retrieved from https://www.corporatewellnessmagazine.com/article/the-elephant-in-the-room-just-how-big-will-wearables-get; Ajunwa, I., Crawford, K., & Schultz, J. (2017). Limitless worker surveillance. *California Law Review*, *105*(3), 735–776. https://doi.org/10.15779/Z38BR8MF94; and Ajunwa, I. (2018). Algorithms at work: Productivity monitoring platforms and wearable technology as the new data-Centric research agenda for employment and labor law. *Saint Luis University Law Journal*, *63*(21), 21–54. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3247286.

[54] Wailgum, T. (2008, May). UPS's New Telematics System Cuts Fuel Costs and Makes Drivers More Efficient. *CIO*. Retrieved from https://www.cio.com/article/2436358/ups-s-new-telematics-system-cuts-fuel-costs-and-makes-drivers-more-efficient.html.

[55] See Nield, D. (2020, June 29). All the sensors in your smartphone, and how they work. *Gizmodo*. Retrieved from https://gizmodo.com/all-the-sensors-in-your-smartphone-and-how-they-work-1797121002 and Priyadarshini, M. (2018, September 25). Which sensors do I have in my smartphone? How do they work? *Fossbytes*, pp. 1–20. Retrieved from https://fossbytes.com/which-smartphone-sensors-how-work/. For an example of Smartphone apps that collect data, see Harwell, D. (2014, April 10). Is your pregnancy app sharing your intimate data with your boss? *The Washington Post*, pp. 1–12. Retrieved from https://www.washingtonpost.com/technology/2019/04/10/tracking-your-pregnancy-an-app-may-be-more-public-than-you-think/?arc404=true and Castlight Health. (2020). Activision Blizzard Increases Participation in Pregnancy Program with Castlight. Retrieved from https://www.castlighthealth.com/resources/thought-leadership/activision-blizzard-increases-participation-pregnancy-program-ovia-jiff/.

[56] See Spiceworks. (2018, March 12). Spiceworks study reveals nearly 90 percent of businesses will use biometric authentication technology by 2020. Retrieved from https://www.spiceworks.com/press/releases/spiceworks-study-reveals-nearly-90-percent-businesses-will-use-biometric-authentication-technology-2020/.

Stupp, C. (2020, January 6). The humble office ID badge is about to be unrecognizable. *Wall Street Journal (Online)*. Retrieved from https://www.wsj.com/articles/the-humble-office-id-badge-is-about-to-be-unrecognizable-11578333651; and Metcalf, J. (2018, February). When verification is also surveillance: EVV devices could intrusively track Medicaid recipients. *Data & Society Points*, 1–14. Retrieved from https://points.datasociety.net/when-verification-is-also-surveillance-21edb6c12cc9.

[57] Prolacs, https://www.prolacs.com/.

[58] See Arellano, C., DiLeonardo, A., & Felix, I. (2017). *Using people analytics to drive business performance: A case study*. *McKinsey Quarterly*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/using-people-analytics-to-drive-business-performance-a-case-study; and Adler-Bell, S., & Miller, M. (2018). *The Datafication of Employment*. *The Century Foundation*. Retrieved from https://tcf.org/content/report/datafication-employment-surveillance-capitalism-shaping-workers-futures-without-knowledge/

[59] For an overview of the different types of third-party vendors that provide products and services related to workers, see Norton, M., & Nurthen, J. (2018). *Workforce solutions ecosystem: Defining the staffing industry and other workforce solutions*. Retrieved from https://www2.staffingindustry.com/content/download/247534/9158885/Workforce_Solutions_Ecosystem__2017_Update_20170928.pdf.

[60] For a discussion on the rise of data ecosystems, see Henke, N., & Kaka, N. (2018). *Analytics comes of age*. *McKinsey Analytics*. Retrieved from https://www.mckinsey.com/~/media/McKinsey/Business Functions/McKinsey Analytics/Our Insights/Analytics comes of age/Analytics-comes-of-age.ashx and Schatsky, D., Camhi, J., & Muraskin, C. (2019). *Data ecosystems: How third-party information can enhance data analytics*. *Deloitte Insights*. Retrieved from https://www2.deloitte.com/content/dam/insights/us/articles/4603_Data-ecosystems/DI_Data-ecosystems.pdf. Also see Opher, A., Chou, A., Onda, A., & Sounderrajan, K. (2016). *The Rise of the Data Economy: Driving Value through Internet of Things Data Monetization*. *IBM Corporation*. Retrieved from https://www.ibm.com/downloads/cas/4JROLDQ7 for an overview of the different roles companies play in the data economy.

[61] See Winston, J. (2017, November). Facebook and America's largest companies quietly give worker data to Equifax. *Fast Company*. Retrieved from https://www.fastcompany.com/40485634/equifax-salary-data-and-the-work-number-database and Sullivan, B. (2013, January 30). Exclusive: Your employer may share your salary, and Equifax might sell that data. *NBC News*. Retrieved from https://www.nbcnews.com/technolog/exclusive-your-employer-may-share-your-salary-equifax-might-sell-1B8173066. For a description of Equifax's service products, see Equifax Unemployment Cost Management services, https://workforce.equifax.com/solutions/unemployment-cost-management; Equifax Work Number verification services, https://theworknumber.com/how-it-works//

[62] Winston, J. (2017, November). Facebook and America's largest companies quietly give worker data to Equifax. *Fast Company*. Retrieved from https://www.fastcompany.com/40485634/equifax-salary-data-and-the-work-number-database.

[63] For a general overview of the retail databases and the various lawsuits and FTC actions, see Clifford, S., & Silver-Greenberg, J. (2013, April 2). Retailers Track Employee Thefts in Vast Databases. The New York Times. Retrieved from https://www.nytimes.com/2013/04/03/business/retailers-use-databases-to-track-worker-thefts.html and Kramer, R. (2011, May 6). Database Calls Innocent Workers "Thieves," | Retail Employees Say in Class Action. Courthouse News Service. Retrieved from https://www.courthousenews.com/database-calls-innocent-workers-thievesretail-employees-say-in-class-action/. For information about the specific cases against LexisNexis and HireRight, see Bucher, A. (2014, August 4). LexisNexis Settles Esteem Retail Theft Database Class Action Lawsuit. Retrieved from https://topclassactions.com/lawsuit-settlements/lawsuit-news/36229-lexisnexis-settles-esteem-retail-theft-database-class-action-lawsuit/ and Federal Trade Commission (FTC). (2012). Employment Background Screening Company to Pay $2.6 Million Penalty for Multiple Violations of the Fair Credit Reporting Act. Retrieved

from https://www.ftc.gov/news-events/press-releases/2012/08/employment-background-screening-company-pay-26-million-penalty.

[64] GIS HireRight. (2018). *NRMA: The retail theft database (full overview)*. Retrieved from http://www.geninfo.com/EXTRAS/industry-specific-solutions/retail/retail-industry-whitepapers/NRMA_Overview.pdf?v=00000091. Also see GIS HireRight. (2018). *NRMA: The Retail Theft Database (brief)*. Retrieved from http://www.geninfo.com/EXTRAS/industry-specific-solutions/retail/retail-industry-whitepapers/NRMA_The-Retail-Theft-Database.pdf?v=00000093 and HireRight, https://www.hireright.com/retail.

[65] See HireVue's privacy disclosure notice, https://www.hirevue.com/company/privacy

[66] See Humanyze privacy disclosure notice, https://www.humanyze.com/data-privacy/

[67] See sources listed in note 45. Also, for a description of the different types of vendors in the AI technology ecosystem, see Cognilytica. (2019). Cognilytica's Classification of the AI Vendor Ecosystem: Part I. Retrieved from https://www.cognilytica.com/2019/01/16/cognilyticas-classification-of-the-ai-vendor-ecosystem-overview-and-bottom-3-layers/ and Cognilytica. (2019). Cognilytica's Classification of the AI Vendor Ecosystem: Part II. Retrieved from https://www.cognilytica.com/2019/01/21/cognilyticas-classification-of-the-ai-vendor-ecosystem-part-ii/.Also see this comprehensive analysis of the business relationships involved in cloud computing services: Floerecke, S., Lehner, F., & Schweikl, S. (2020). Cloud computing ecosystem model: evaluation and role clusters. *Electronic Markets*. https://doi.org/10.1007/s12525-020-00419-2.

[68] For example, see this IBM case study of a Spanish HR technology vendor that develops their products on IBM's Watson platform: IBM. (2018). Vidahora: Cultivating happy, healthy and productive workplaces with AI-driven support. Retrieved from https://www.ibm.com/case-studies/vidahora-watson-employee-engagement.

[69] See IBM. (2020). IBM Data Responsibility Perspective for Watson Data and AI. Retrieved from https://www.ibm.com/watson/data-privacy/.

[70] For information about mergers and acquisitions among data and technology companies, see: Verdict. (2019, June). Salesforce's $ 15.7bn Tableau acquisition heralds new wave of AI and big data M & A. Retrieved from https://www.verdict.co.uk/big-data-acquisitions-2019/; Li, W. C. Y., Nirei, M., & Yamana, K. (2019). *Value of Data: There's No Such Thing as a Free Lunch in the Digital Economy* (No. 19- E- 022). *RIETI Discussion Paper Series*. Retrieved from https://www.rieti.go.jp/jp/publications/dp/19e022.pdf.; World Intellectual Property Organization (WIPO). (2019). *WIPO Technology Trends 2019: Artificial Intelligence*. Geneva.

[71] For a very brief description of the difference between basic algorithms and machine learning algorithms, see Ismail, K. (2018, October 26). AI vs. Algorithms: What's the Difference? *CMS Wire*. Retrieved from https://www.cmswire.com/information-management/ai-vs-algorithms-whats-the-difference/. For a discussion of the initial stages of algorithms in the business context, see Harris, J. G., & Davenport, T. H. (2005). *Automated decision making comes of age*. *MIT Sloan Management Review*. Retrieved from https://sloanreview.mit.edu/article/automated-decision-making-comes-of-age/. For a more comprehensive comparison of different types of business analytics and algorithms, see Davenport, T. H. (2018). From analytics to artificial intelligence. *Journal of Business Analytics*, *1*(2), 73–80. https://doi.org/10.1080/2573234x.2018.1543535.

[72] For a general description of machine learning and recent technological innovations enabled by machine learning, see The Royal Society. (2017). *Machine learning: the power and promise of computers that learn by example*. Retrieved from https://royalsociety.org/~/media/policy/projects/machine-learning/publications/machine-learning-report.pdf ; National Academies of Sciences Engineering and Medicine. (2017). *Information technology and the U.S. workforce: Where are we and where do we go from here?* Washington, DC: The National Academies Press. Retrieved from https://www.nap.edu/catalog/24649/information-technology-and-the-us-workforce-where-are-we-and; Hao, K. (2018, November). What is the definition of machine learning? *MIT Technology Review*. Retrieved from https://www.technologyreview.com/2018/11/17/103781/what-is-machine-learning-we-drew-you-another-flowchart/; and Martin, C., & Leurent, H. (2017). *Technology and innovation for the future of production: Accelerating value creation*. *World Economic Forum*.https://doi.org/10.1074/jbc.M003388200.

[73] Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Society*, *3*(1), 205395171562251. https://doi.org/10.1177/2053951715622512.

[74] AI researchers sometimes refer to AI capabilities as "weak versus strong" AI. For a short description of the different types of AI, see Grossman, G. (2020, September). We're entering the AI twilight zone between narrow and general AI. *Venture Beat*, 1–6. Retrieved from https://venturebeat.com/2020/09/03/were-entering-the-ai-twilight-zone-between-narrow-and-general-ai/ and Vorhies, W. (2016, February 23). Artificial General Intelligence – The Holy Grail of AI. Retrieved from https://www.datasciencecentral.com/profiles/blogs/artificial-general-intelligence-the-holy-grail-of-ai.

[75] Algorithms are at the heart of artificial intelligence systems. For a basic description of an AI system, see: Expert Group on Artificial Intelligence at the OECD (AIGO). (2019). *Scoping the OECD AI Principles: Deliberations of the expert group on artificial intelligence at the OECD (AIGO)* (OECD Digital Economy Papers) (Vol. No 291). Retrieved from https://www.oecd-ilibrary.org/science-and-technology/scoping-the-oecd-ai-principles_d62f618a-en. This description of an AI system is drawn from one of the primary textbooks on AI: Russell, S. J., & Norvig, P. (2010). *Artificial Intelligence: A Modern Approach* (Third). Prentice Hall. https://doi.org/10.1017/CBO9781107415324.004.

[76] For a description of the different capabilities of AI technologies and related subfields see National Academies of Sciences Engineering and Medicine. (2017). *Information technology and the U.S. workforce: Where are we and where do we go from here?* Washington, DC: The National Academies Press. Retrieved from https://www.nap.edu/catalog/24649/information-technology-and-the-us-workforce-where-are-we-and; and Russell, S. J., & Norvig, P. (2010). *Artificial Intelligence: A Modern Approach* (Third). Prentice Hall. https://doi.org/10.1017/CBO9781107415324.004. For discussions on the relationship between machine learning, statistics, data science, robotics, and AI see The Royal Society. (2017). *Machine learning: the power and promise of computers that learn by example*. Retrieved from https://royalsociety.org/~/media/policy/projects/machine-learning/publications/machine-learning-report.pdf; Hao, K. (2018, November). What is AI? We drew you a flowchart to work it out. *MIT Technology Review*. Retrieved from https://www.technologyreview.com/2018/11/10/139137/is-this-ai-we-drew-you-a-flowchart-to-work-it-out/; and Raj, M., & Seamans, R. (2019). Primer on artificial intelligence and robotics. *Journal of Organization Design*, *8*(1), 1–14.

[77] See Kim, P. T. (2019). Big Data and Artificial Intelligence: New Challenges for Workplace Equity. *University of Louisville Law Review*, *57*. Retrieved from https://ssrn.com/abstract=3296521. For more about using prediction to aid in decision-making in the context of uncertainty, see Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. *Journal of Economic Perspectives*, *33*(2), 31–50. Retrieved from https://www.aeaweb.org/articles?id=10.1257/jep.33.2.31 and Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007.

[78] Levy, K., & Barocas, S. (2018). Refractive surveillance: Monitoring customers to manage workers. *International Journal of Communication*, *12*, 1166–1188. Retrieved from https://ijoc.org/index.php/ijoc/article/viewFile/7041/2302.

[79] For more information about the role of humans in technology design decisions, see Waschull, S., Bokhorst, J. A. C., Molleman, E., & Wortmann, J. C. (2019). Work design in future industrial production: Transforming towards cyber-physical systems. *Computers and Industrial Engineering*, (xxxx), 1–11. https://doi.org/10.1016/j.cie.2019.01.053; Gabriel, I. (2020). Artificial intelligence, values, and alignment. *Minds and Machines*, *30*(3), 411–437. https://deepmind.com/research/publications/Artificial-Intelligence-Values-and-Alignment; Winner, L. (1980). Do Artifacts Have Politics? *Daedalus*, *109*(1), 121–136. https://doi.org/10.4324/9781315259697-21; Guszcza, James; Lee, Michelle; Ammanath, Beena; Kuder, D. (2020). *Human values in the loop: Design principles for ethical AI (Deloitte Insights)*. *Deloitte Review: Technology and Ethics*; Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society*, *July-Decem*, 1–21. https://doi.org/10.1177/2053951716679679; and Kraemer, F., van Overveld, K., & Peterson, M. (2011). Is there an ethics of algorithms? *Ethics and Information Technology*, *13*(3), 251–260. https://doi.org/10.1007/s10676-010-9233-7.

[80] See Rebele, R. (2019, February 12). Can we really test people for potential? *MIT Sloan Management Review*. https://doi.org/10.7551/mitpress/13661.003.0008. For a discussion about the use of personality tests for hiring, see Meinert, D. (2015, June). What do personality tests really reveal? *HR Magazine*. Retrieved from https://www.shrm.org/hr-today/news/hr-magazine/pages/0615-personality-tests.aspx; and Martin, W. (2014,

August 27). The problem with using personality tests for hiring. *Harvard Business Review*, pp. 1–5. Retrieved from https://hbr.org/2014/08/the-problem-with-using-personality-tests-for-hiring?autocomplete=true.

[81] Luca, B. Y. M., Kleinberg, J. O. N., & Mullainathan, S. (2016). Algorithms need managers, too: Know how to get the most out of your predictive tools. *Harvard Business Review*, *January-Fe*, 97–101. Retrieved from https://hbr.org/2016/01/algorithms-need-managers-too.

[82] See Harris, M. (2019, November 7). NTSB investigation into deadly Uber self- driving car crash reveals lax attitude toward safety: New documents suggest that neither Uber, the state of Arizona, nor the car's operator were vigilant. *IEEE Spectrum*, (March). Retrieved from https://spectrum.ieee.org/cars-that-think/transportation/self-driving/ntsb-investigation-into-deadly-uber-selfdriving-car-crash-reveals-lax-attitude-toward-safety and Jones, R. (2018, May 7). Report: Uber's self-driving car sensors ignored cyclist in fatal accident. *Gizmodo*. Retrieved from https://gizmodo.com/report-ubers-self-driving-car-sensors-ignored-cyclist-1825832504.

[83] Loggins, K. (2020, February 24). Here's what happens when an algorithm determines your work schedule. *Vice*. Retrieved from https://www.vice.com/en/article/g5xwby/heres-what-happens-when-an-algorithm-determines-your-work-schedule.

[84] Bernstein, E., Kesavan, S., & Staats, B. (2014). How to manage scheduling software fairly. *Harvard Business Review*, (December). Retrieved from https://hbr.org/2014/09/how-to-manage-scheduling-software-fairly.

[85] Luce, S., Hammad, S., & Sipe, D. (2014). *Short Shifted*. Retrieved from http://retailactionproject.org/wp-content/uploads/2014/09/ShortShifted_report_FINAL.pdf.

[86] Kantor, J. (2014, August 13). Working anything but 9 to 5: Scheduling technology leaves low-income parents with hours of chaos. *The New York Times*. Retrieved from https://www.nytimes.com/interactive/2014/08/13/us/starbucks-workers-scheduling-hours.html.

[87] Cormen, T. H., Leiserson, C. E., Rivest, R. L., & Stein, C. (2009). The Role of Algorithms in Computing. In *Introduction to Algorithms* (Third, pp. 6–15). MIT Press. Retrieved from https://mitpress.mit.edu/books/introduction-algorithms-third-edition; Algorithms are at the heart of AI systems, for a more conceptual model of how data inputs (sensor data) relate to technological outputs that lead to machine or human actions (actuators), see the basic description of an AI system in Expert Group on Artificial Intelligence at the OECD (AIGO). (2019). *Scoping the OECD AI Principles: Deliberations of the expert group on artificial intelligence at the OECD (AIGO)* (OECD Digital Economy Papers) (Vol. No 291). Retrieved from https://www.oecd-ilibrary.org/science-and-technology/scoping-the-oecd-ai-principles_d62f618a-en.

[88] For a discussion about levels of automation in systems involving human and machine interaction, see Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans.*, *30*(3), 286–297. https://doi.org/10.1109/3468.844354.

[89] See Expert Group on Artificial Intelligence at the OECD (AIGO). (2019). *Scoping the OECD AI Principles: Deliberations of the expert group on artificial intelligence at the OECD (AIGO)* (OECD Digital Economy Papers) (Vol. No 291). Retrieved from https://www.oecd-ilibrary.org/science-and-technology/scoping-the-oecd-ai-principles_d62f618a-en.

[90] The Royal Society. (2017). *Machine learning: the power and promise of computers that learn by example*. Retrieved from https://royalsociety.org/~/media/policy/projects/machine-learning/publications/machine-learning-report.pdf. A computer learns through examples when a human programmer trains the algorithm with labeled examples, based on expert knowledge or historical awareness, to help the computer system develop an understanding of the relationships in the data. A computer learns by experience when the algorithms are designed to explore a dataset in order to identify patterns in the data. In a third learning strategy, the algorithm uses trial and error to learn which behaviors will achieve the desired output. The human programmer sets the objective and the machine will continue to adjust the algorithm to arrive at a decision that is closer to the desired objective. For a very brief (visual) description of these learning strategies, see Hao, K. (2018, November). What is the definition of machine learning? *MIT Technology Review*. Retrieved from https://www.technologyreview.com/2018/11/17/103781/what-is-machine-learning-we-drew-you-another-flowchart/.

[91] The computer algorithm can provide this recommendation for future action to a human as options for the human to evaluate and then select which course of action to take or the computer system can take the decision one step further and restrict the information provided to the human to a single course of action for the human to implement. See Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. *Journal of Economic Perspectives*, *33*(2), 31–50. Retrieved from https://www.aeaweb.org/articles?id=10.1257/jep.33.2.31 and Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans.*, *30*(3), 286–297. https://doi.org/10.1109/3468.844354.

[92] For a description of the different capabilities of machine learning and the different types of problems technologists attempt to solve with machine learning, see Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B., & Sethupathy, G. (2016). *The Age of Analytics: Competing in a Data-Driven World*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-age-of-analytics-competing-in-a-data-driven-world; and The Royal Society. (2017). *Machine learning: the power and promise of computers that learn by example*. Retrieved from https://royalsociety.org/~/media/policy/projects/machine-learning/publications/machine-learning-report.pdf.

[93] For a brief description of some of these technologies, see Walch, K. (2019, September). The Seven Patterns Of AI. *Forbes*. Retrieved from https://www.forbes.com/sites/cognitiveworld/2019/09/17/the-seven-patterns-of-ai/#330d7c1a12d0. For a more comprehensive discussion of these different technologies along with examples of the technologies applied in the context of everyday life and business, see Talwar, R., & Koury, A. (2017). Artificial intelligence: The next digital frontier. Retrieved from https://www.mckinsey.com/~/media/mckinsey/industries/advanced electronics/our insights/how artificial intelligence can deliver real value to companies/mgi-artificial-intelligence-discussion-paper.ashx; National Academies of Sciences Engineering and Medicine. (2017). *Information technology and the U.S. workforce: Where are we and where do we go from here?* Washington, DC: The National Academies Press. Retrieved from https://www.nap.edu/catalog/24649/information-technology-and-the-us-workforce-where-are-we-and; Martin, C., & Leurent, H. (2017). *Technology and innovation for the future of production: Accelerating value creation*. *World Economic Forum*.; and The Royal Society. (2017). *Machine learning: the power and promise of computers that learn by example*. Retrieved from https://royalsociety.org/~/media/policy/projects/machine-learning/publications/machine-learning-report.pdf; Heires, K. (2015, December 1). Management Are You Feeling Risky? – Risk Management. *Risk Management*. Retrieved from http://www.rmmagazine.com/2015/12/01/sentiment-analysis-are-you-feeling-risky/. Waddell, K. (2016, September 29). The Algorithms That Tell Bosses How Employees Are Feeling. *The Atlantic*, pp. 1–5. Retrieved from https://www.theatlantic.com/technology/archive/2016/09/the-algorithms-that-tell-bosses-how-employees-feel/502064/.

[94] For categorizations of the different types of algorithmic systems in the workplace, see Davenport, T. H. (2018). From analytics to artificial intelligence. *Journal of Business Analytics*, *1*(2), 73–80. https://doi.org/10.1080/2573234x.2018.1543535 and Moore, P. V. (2020). Artificial intelligence in the workplace: What is at stake for workers? In *Work in the Age of Data* (pp. 1–14). Madrid: BBVA. Retrieved from https://www.bbvaopenmind.com/wp-content/uploads/2020/02/BBVA-OpenMind-Phoebe-V-Moore-Artificial-Intelligence-in-workplace-what-is-at-stake-for-workers.pdf.

[95] See Russell, S. J., & Norvig, P. (2010). *Artificial Intelligence: A Modern Approach* (Third). Prentice Hall. https://doi.org/10.1017/CBO9781107415324.004; Expert Group on Artificial Intelligence at the OECD (AIGO). (2019). *Scoping the OECD AI Principles: Deliberations of the expert group on artificial intelligence at the OECD (AIGO)* (OECD Digital Economy Papers) (Vol. No 291). Retrieved from https://www.oecd-ilibrary.org/science-and-technology/scoping-the-oecd-ai-principles_d62f618a-en; and Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. *Journal of Economic Perspectives*, *33*(2), 31–50. Retrieved from https://www.aeaweb.org/articles?id=10.1257/jep.33.2.31.

[96] Other terms that could describe this category of applications include data analytics, predictive analytics, people analytics. For an overview of the trajectory of business analytics from basic data analytics to artificial intelligence, see Davenport, T. H. (2018). From analytics to artificial intelligence. *Journal of Business Analytics*, *1*(2), 73–80. https://doi.org/10.1080/2573234x.2018.1543535. For a business perspective on business insights derived from

data analytics, statistics and more advanced machine learning algorithms, see Gottlieb, J., & Rifai, K. (2017). *Fueling growth through data monetization*. *McKinsey & Company*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/fueling-growth-through-data-monetization and Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B., & Sethupathy, G. (2016). *The Age of Analytics: Competing in a Data-Driven World*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-age-of-analytics-competing-in-a-data-driven-world. For a description of the relationship between data science, statistics, and machine learning, see The Royal Society. (2017). *Machine learning: the power and promise of computers that learn by example*. Retrieved from https://royalsociety.org/~/media/policy/projects/machine-learning/publications/machine-learning-report.pdf.

[97] For a discussion of the role of prediction in decision-making, see Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. *Journal of Economic Perspectives*, *33*(2), 31–50. Retrieved from https://www.aeaweb.org/articles?id=10.1257/jep.33.2.31.

[98] For a comprehensive overview of predictive analytics, see Siegel, E. (2016). *Predictive Analytics: The power to predict who will click, buy, lie, or die*. Hoboken, NJ: John Wiley & Sons, Ltd. Retrieved from https://www.wiley.com/en-us/Predictive+Analytics%3A+The+Power+to+Predict+Who+Will+Click%2C+Buy%2C+Lie%2C+or+Die%2C+Revised+and+Updated-p-9781119145677. For a discussion of more advanced forms of prediction enabled and automated by machine learning algorithms, see Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. *Journal of Economic Perspectives*, *33*(2), 31–50. Retrieved from https://www.aeaweb.org/articles?id=10.1257/jep.33.2.31.

[99] For example, see Siegal, E. (2013). Predictive analytics: The privacy pickle – Hewlett-Packard's prediction of employee behavior. *Analytics Magazine*, (November/December). Retrieved from http://analytics-magazine.org/predictive-analytics-the-privacy-pickle-hewlett-packards-prediction-of-employee-behavior/.

[100] For a basic description of a machine learning algorithm used for fraud detection, see The Royal Society. (2017). *Machine learning: the power and promise of computers that learn by example*. Retrieved from https://royalsociety.org/~/media/policy/projects/machine-learning/publications/machine-learning-report.pdf. Also see, Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B., & Sethupathy, G. (2016). *The Age of Analytics: Competing in a Data-Driven World*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-age-of-analytics-competing-in-a-data-driven-world and Davenport, T. H. (2018). From analytics to artificial intelligence. *Journal of Business Analytics*, *1*(2), 73–80. https://doi.org/10.1080/2573234x.2018.1543535.

[101] For examples of predictive insights provided to managers, see Mateescu, A., & Nguyen, A. (2019). *Explainer: Workplace Monitoring & Surveillance*. *Data & Society Research Institute*. Retrieved from https://datasociety.net/library/explainer-workplace-monitoring-surveillance/. For examples of managerial dashboards, see Puckett, J. (2019, August 22). HR Dashboards: Examples, Metrics, and Workforce Analytics. Retrieved from https://technologyadvice.com/blog/human-resources/hr-dashboards-examples-metrics-workforce-analytics/.

[102] For a discussion about the relationship between prediction and decision-making, see Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. *Journal of Economic Perspectives*, *33*(2), 31–50. Retrieved from https://www.aeaweb.org/articles?id=10.1257/jep.33.2.31. Also see Harris, J. G., & Davenport, T. H. (2005). *Automated decision making comes of age*. *MIT Sloan Management Review*. Retrieved from https://sloanreview.mit.edu/article/automated-decision-making-comes-of-age/.

[103] See Anadiotis, G. (2019, June 3). A guide for prescriptive analytics: The art and science of choosing and applying the right techniques. *ZDNet*. Retrieved from https://www.zdnet.com/article/a-guide-for-prescriptive-analytics-the-art-and-science-of-choosing-and-applying-the-right-techniques/; Vigliarolo, B. B. (2019). *Prescriptive analytics: An insider's guide*. Retrieved from https://www.techrepublic.com/resource-library/whitepapers/prescriptive-analytics-an-insider-s-guide-free-pdf/; Kart, L. (2015). How to Get Started with Prescriptive Analytics. *Gartner, Inc.*, (May). Retrieved from https://www.gartner.com/document/3044418; and Lepenioti, K., Bousdekis, A., Apostolou, D., & Mentzas, G. (2020). Prescriptive analytics: Literature review and research challenges. *International Journal of Information Management*, *50*(April 2019), 57–70. https://doi.org/10.1016/j.ijinfomgt.2019.04.003.

[104] Lalwani, P. (2019, August 29). What is workforce scheduling? Definition, features, benefits, and optimization tips. *HR Technologist*. Retrieved from https://www.hrtechnologist.com/articles/workforce-scheduling/what-is-workforce-scheduling/.

[105] See Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, *14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174. For a discussion on the use of technology to structure the work context and limit worker discretion, see Edwards, R. C. (1978). The social relations of production at the point of production. *Critical Sociology*, *8*(42403), 109–125. https://doi.org/10.1177/089692057800800213 and Callaghan, G., & Thompson, P. (2001). Edwards revisited: Technical control and call centers. *Economic and Industrial Democracy*, *22*, 13–37. Retrieved from https://doi.org/10.1177/0143831X01221002.

[106] See Scheiber, N. (2017, April 2). How Uber uses psychological tricks to push its drivers' buttons. *New York Times*. Retrieved from https://www.nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html?smid=fb-nytscience&smtyp=cur&_r=0; Yeung, K. (2017). 'Hypernudge'': Big Data as a mode of regulation by design.' *Information Communication and Society*, *20*(1), 118–136. https://doi.org/10.1080/1369118X.2016.1186713; Deterding, S. (2019). Gamification in Management: Between Choice Architecture and Humanistic Design. *Journal of Management Inquiry*, *28*(2), 131–136. https://doi.org/10.1177/1056492618790912; Schweyer, A. (2017). *Using behavioral economics insights in incentives, rewards, and recognition: A nudge guide*. Retrieved from https://theirf.org/am-site/media/behavioral-economics-nudge-guide.pdf; and Guszcza, J. (2015). The last-mile problem: How data science and behavioral science can work together. *Deloitte Review*, 63–79. Retrieved from https://www2.deloitte.com/us/en/insights/deloitte-review/issue-16/behavioral-economics-predictive-analytics.html.

[107] See Dzieza, J. (2020, February 27). Robots aren't taking our jobs — they're becoming our bosses. *The Verge*. Retrieved from https://www.theverge.com/2020/2/27/21155254/automation-robots-unemployment-jobs-vs-human-google-amazon and Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). Working with Machines: The impact of algorithmic and data-driven management on human workers. In *CHI '15 Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (pp. 1603–1612). https://doi.org/10.4324/9780429272806.

[108] See Sarah O'Connor. (2016, September 7). When your boss is an algorithm. *Financial Times*, pp. 1–7. Retrieved from https://www.ft.com/content/88fdc58e-754f-11e6-b60a-de4532d5ea35 and Mateescu, A., & Nguyen, A. (2019). Explainer: Algorithmic Management in the Workplace. *Data & Society Institute*, (February), 1–15. Retrieved from https://datasociety.net/library/explainer-algorithmic-management-in-the-workplace/; and Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). Working with Machines: The impact of algorithmic and data-driven management on human workers. In *CHI '15 Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (pp. 1603–1612). https://doi.org/10.4324/9780429272806.

[109] See Russell, S. J., & Norvig, P. (2010). *Artificial Intelligence: A Modern Approach* (Third). Prentice Hall. https://doi.org/10.1017/CBO9781107415324.004 and Expert Group on Artificial Intelligence at the OECD (AIGO). (2019). *Scoping the OECD AI Principles: Deliberations of the expert group on artificial intelligence at the OECD (AIGO)* (OECD Digital Economy Papers) (Vol. No 291). Retrieved from https://www.oecd-ilibrary.org/science-and-technology/scoping-the-oecd-ai-principles_d62f618a-en.

[110] See Cognilytica. (2019, January 16). Cognilytica's Classification of the AI Vendor Ecosystem: Part I. Retrieved from https://www.cognilytica.com/2019/01/16/cognilyticas-classification-of-the-ai-vendor-ecosystem-overview-and-bottom-3-layers/.

[111] The Royal Society. (2017). *Machine learning: the power and promise of computers that learn by example*. Retrieved from https://royalsociety.org/~/media/policy/projects/machine-learning/publications/machine-learning-report.pdf and Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., … Trench, M. (2017). *Artificial intelligence: The next digital frontier* (Vol. June). Retrieved from https://www.mckinsey.com/~/media/mckinsey/industries/advanced electronics/our insights/how artificial intelligence can deliver real value to companies/mgi-artificial-intelligence-discussion-paper.ashx.

[112] See Kaufman, B. E. (2004). Employment relations and the employment relations system: A guide to theorizing. In B. E. Kaufman (Ed.), *Theoretical Perspectives on Work and the Employment Relationship* (First Edit, pp. 41–76). Champaign, IL: Industrial Relations Research Association for a framework for understanding the different dimensions and functional areas in the employment relations system. For other papers analyzing the different ways firms use algorithms in the workplace, see Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, *14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174; Moore, P. V. (2020). Artificial intelligence in the workplace: What is at stake for workers? In *Work in the Age of Data* (pp. 1–14). Madrid: BBVA. Retrieved from https://www.bbvaopenmind.com/wp-content/uploads/2020/02/BBVA-OpenMind-Phoebe-V-Moore-Artificial-Intelligence-in-workplace-what-is-at-stake-for-workers.pdf; Mateescu, A., & Nguyen, A. (2019). Explainer: Algorithmic Management in the Workplace. *Data & Society Institute*, February, 1–15. Retrieved from https://doi.org/10.1145/2702123.2702548; Mateescu, A., & Nguyen, A. (2019). *Explainer: Workplace Monitoring & Surveillance*. *Data & Society Research Institute*. Retrieved from www.datasociety.net; and Sánchez-monedero, J., & Dencik, L. (2019). The datafication of the workplace. *Data Justice Project, Cardiff University*, 1–46. Retrieved from https://datajusticeproject.net/wp-content/uploads/sites/30/2019/05/Report-The-datafication-of-the-workplace.pdf.

[113] For an overview of the history and current trend toward "people analytics", see: Peck, D. (2013, December). They're Watching You at Work. *The Atlantic*, 72–84. Retrieved from http://www.theatlantic.com/magazine/archive/2013/12/theyre-watching-you-at-work/354681/. For an HR practitioners guide to "people analytics", see Isson, J. P., & Harriott, J. I. (2016). *People Analytics in the Era of Big Data: Changing the way you attract, acquire, develop, and retain talent*. Hoboken: Wiley. https://www.wiley.com/en-us/People+Analytics+in+the+Era+of+Big+Data%3A+Changing+the+Way+You+Attract%2C+Acquire%2C+Develop%2C+and+Retain+Talent+-p-9781119050780. For an academic review of HR analytics literature, see: Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR Analytics. *International Journal of Human Resource Management*, *28*(1), 3–26. https://doi.org/10.1080/09585192.2016.1244699. For a description of "people analytics" and discussion of the legal implications, see Bodie, M. T., Cherry, M. A., McCormick, Marcia, L., & Tang, J. (2017). The Law and Policy of People Analytics. *University of Colorado Law Review*, *88*, 961–1042.

[114] For a general description of predictive analytics, see Siegel, E. (2016). *Predictive Analytics: The power to predict who will click, buy, lie, or die*. Hoboken, NJ: John Wiley & Sons, Ltd. Retrieved from https://www.wiley.com/en-us/Predictive+Analytics%3A+The+Power+to+Predict+Who+Will+Click%2C+Buy%2C+Lie%2C+or+Die%2C+Revised+and+Updated-p-9781119145677. In some cases, predictive algorithms focus on workers indirectly – e.g., tools aimed to predict recruiter preferences in order to match workers to those preferences, see Bogen, M., & Rieke, A. (2018). *Help wanted: An examination of hiring algorithms, equity, and bias*. Washington, D.C. Retrieved from https://www.upturn.org/reports/2018/hiring-algorithms/.

[115] For a full review of the landscape of HR technologies see: Bersin, J. (2019). *HR Technology Market 2019: Disruption Ahead*. Retrieved from https://oliver-dev.s3.amazonaws.com/2019/01/27/12/54/25/916/Tech_Disruptions.pdf

[116] Bersin, J. (2018). AI comes to recruiting: Will interviews go the way of the dinosaur? Retrieved from https://joshbersin.com/2018/11/ai-comes-to-recruiting-will-interviews-go-the-way-of-the-dinosaur/

[117] See Bogen, M., & Rieke, A. (2018). *Help wanted: An examination of hiring algorithms, equity, and bias*. Washington, D.C. Retrieved from https://www.upturn.org/reports/2018/hiring-algorithms/; Sánchez-monedero, J., & Dencik, L. (2019). *The datafication of the workplace*. Retrieved from https://datajusticeproject.net/wp-content/uploads/sites/30/2019/05/Report-The-datafication-of-the-workplace.pdf; Ajunwa, I. (2019). Algorithms at Work: Productivity Monitoring Platforms and Wearable Technology as the New Data-Centric Research Agenda for Employment and Labor Law. *St. Louis Law Journal*, (63), 42. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3247286; also, see Bersin, J. (2019). *HR Technology Market 2019: Disruption Ahead*. Retrieved from https://oliver-dev.s3.amazonaws.com/2019/01/27/12/54/25/916/Tech_Disruptions.pdf.

[118] See: Society for Human Resource Management (SHRM). (2016). Average Cost-per-Hire for Companies Is $4,129, SHRM Survey Finds. Retrieved from https://www.shrm.org/about-shrm/press-room/press-releases/pages/human-

capital-benchmarking-report.aspx; Peterson, A. (2018, October). Consider these costs before hiring a new employee. *Fast Company*. Retrieved from https://www.fastcompany.com/90250227/consider-these-costs-before-hiring-a-new-employee

[119] See Bogen, M., & Rieke, A. (2018). *Help wanted: An examination of hiring algorithms, equity, and bias*. Washington, D.C. Retrieved from https://www.upturn.org/reports/2018/hiring-algorithms/. Bogen and Reike (2018) group the hiring technologies into the four categories listed in this section.

[120] For a discussion about motivations that drive the adoption of hiring technologies, see Bogen, M., & Rieke, A. (2018). *Help wanted: An examination of hiring algorithms, equity, and bias*. Washington, D.C. Retrieved from https://www.upturn.org/reports/2018/hiring-algorithms/.

[121] For a review of the different types of technologies designed to increase diversity and inclusion in the workplace, see Garr, S. S., & Jackson, C. (2019). *Diversity & Inclusion Technology: The Rise of a Transformative Market*. Retrieved from https://info.mercer.com/rs/521-DEV-513/images/Mercer_DI_Report_Digital.pdf and Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2019). Mitigating Bias in Algorithmic Employment Screening: Evaluating Claims and Practices. *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, (January), 469–481. Retrieved from https://dl.acm.org/doi/pdf/10.1145/3351095.3372828?casa_token=4edYqAX4PBcAAAAA%3AchrmNO2pBntpERHx2d_XrVqIrX4I_1IhBXJTFolOTzngO5_UgfW43mMPdptL5zsczMUW9kq0A2AOLQ.

[122] Bersin, J. (2017). HR Technology in 2018: Ten Disruptions Ahead. Retrieved from https://joshbersin.com/2017/11/hr-technology-in-2018-ten-disruptions-ahead/.

[123] Bogen, M., & Rieke, A. (2018). *Help wanted: An examination of hiring algorithms, equity, and bias*. Washington, D.C. Retrieved from https://www.upturn.org/reports/2018/hiring-algorithms/.

[124] HireVue, Inc., https://www.hirevue.com/. Also see Mondragon, N., Aichholzer, C., & Leutner, K. (2019). *HireVue White Paper: The next generation of assessments*. Retrieved from https://www.hirevue.com/resources/the-next-generation-of-assessments. Also, see Bogen, M., & Rieke, A. (2018). *Help wanted: An examination of hiring algorithms, equity, and bias*. Washington, D.C. Retrieved from https://www.upturn.org/reports/2018/hiring-algorithms/. To get an idea about the extent to which employers have adopted the HireVue technologies, see HireVue to receive growth investment from new majority investor The Carlyle Group. (2019). Retrieved from https://markets.businessinsider.com/news/stocks/hirevue-to-receive-growth-investment-from-new-majority-investor-the-carlyle-group-1028494459 andHireVue. (2020). Retrieved from https://www.crunchbase.com/organization/hirevue#section-overview.

[125] For a description of the interview process from the perspective of a job candidate, see Feloni, R. (2017, August 23). I tried the software that uses AI to scan job applicants for companies like Goldman Sachs and Unilever before meeting them — and it's not as creepy as it sounds. *Business Insider*. Retrieved from https://www.businessinsider.com/hirevue-ai-powered-job-interview-platform-2017-8#applicants-can-choose-to-take-the-application-on-their-desktop-or-laptop-and-use-a-webcam-or-use-their-smartphone-or-tablet-i-downloaded-the-hirevue-app-to-my-iphone-7-plus-which-has-a-large-sharp-screen-1.

[126] Mondragon, N., Aichholzer, C., & Leutner, K. (2019). *HireVue White Paper: The next generation of assessments*. Retrieved from https://www.hirevue.com/resources/the-next-generation-of-assessments.

[127] See Larsen, L., & Taylor, B. (2015). *US Patent 9,009,045 B1:* Model-driven candidate sorting. United States. Retrieved from https://www.freepatentsonline.com/9009045.html and Mondragon, N., Aichholzer, C., & Leutner, K. (2019). *HireVue White Paper: The next generation of assessments*. Retrieved from https://www.hirevue.com/resources/the-next-generation-of-assessments.

[128] Specific insights HireVue purports can be derived from video-based assessments include ability to work in team, problem solving skills, communication skills, adaptability, willingness to learn, conscientiousness, responsibility, drive for results & initiative-taking, personal stability/stress tolerance, and more. See Mondragon, N., Aichholzer, C., & Leutner, K. (2019). *HireVue White Paper: The next generation of assessments*. Retrieved from https://www.hirevue.com/resources/the-next-generation-of-assessments.

[129] HireVue. (2017, November 2). RecTechFest - Hire Vue "Reimagining Hiring”. Retrieved from https://youtu.be/dflPqaJFEy4.

[130] Bogen, M., & Rieke, A. (2018). *Help wanted: An examination of hiring algorithms, equity, and bias*. Washington, D.C. Retrieved from https://www.upturn.org/reports/2018/hiring-algorithms/.

[131] For some examples of fraud detection technologies, see Seidler, K. (2018, November). Does AI hold the secret to stopping employee theft? *Loss Prevention Magazine*. Retrieved from https://losspreventionmedia.com/case-study-using-ai-to-detect-fraudulent-and-abusive-employees/; Ryerson, M. (2017). Machine learning and the evolution of employee fraud detection. *Appriss Retail*, (May). Retrieved from https://www.retailexcellence.ie/wp-content/uploads/pdfs/presentations/David Speights (Appriss) - Evolution of Fraud Detection.pdf; and Metcalf, J. (2018, February). When verification is also surveillance: EVV devices could intrusively track Medicaid recipients. *Data & Society Points*, 1–14. Retrieved from https://points.datasociety.net/when-verification-is-also-surveillance-21edb6c12cc9.

[132] See Waddell, K. (2016, September 29). The Algorithms That Tell Bosses How Employees Are Feeling. *The Atlantic*, pp. 1–5. Retrieved from https://www.theatlantic.com/technology/archive/2016/09/the-algorithms-that-tell-bosses-how-employees-feel/502064/; Heires, K. (2015, December 1). Management Are You Feeling Risky? – Risk Management. *Risk Management*. Retrieved from http://www.rmmagazine.com/2015/12/01/sentiment-analysis-are-you-feeling-risky/; and Charney, M. (2017, July 7). That Would Be Great: Sentiment Analysis for HR and Recruiting. *Recruiting Daily*. Retrieved from https://recruitingdaily.com/sentiment-analysis-hr-recruiting/.

[133] See Rosenbaum, E. (2019, April 3). IBM artificial intelligence can predict with 95% accuracy which workers are about to quit their jobs. *CNBC*. Retrieved from https://www.cnbc.com/2019/04/03/ibm-ai-can-predict-with-95-percent-accuracy-which-employees-will-quit.html; Siegal, E. (2013). Predictive analytics: The privacy pickle – Hewlett-Packard’s prediction of employee behavior. *Analytics Magazine*, (November/December). Retrieved from http://analytics-magazine.org/predictive-analytics-the-privacy-pickle-hewlett-packards-prediction-of-employee-behavior/; and Isson, J. P., & Harriott, J. I. (2016). *People Analytics in the Era of Big Data: Changing the way you attract, acquire, develop, and retain talent*. Hoboken: Wiley.

[134] Maurer, R. (2019, May 14). How to Identify Your Company’s Flight Risks. Retrieved from https://www.shrm.org/resourcesandtools/hr-topics/technology/pages/how-to-identify-your-companys-flight-risks.aspx.

[135] Fang, L. (2020, June 11). Facebook Pitched New Tool Allowing Employers to Suppress Words Like “Unionize” in Workplace Chat Product. *The Intercept*. Retrieved from https://theintercept.com/2020/06/11/facebook-workplace-unionize/?utm_campaign=theintercept&utm_source=twitter&utm_medium=social. Also, for a discussion and examples of algorithms designed to detect potential risk of unionization, see Peters, J. (2020, April 20). Whole Foods is reportedly using a heat map to track stores at risk of unionization. *The Verge*. Retrieved from https://www.theverge.com/2020/4/20/21228324/amazon-whole-foods-unionization-heat-map-union and Newman, N. (2017). Reengineering Workplace Bargaining: How Big Data Drives Lower Wages and How Reframing Labor Law Can Restore Information Equality in the Workplace. *University of Cincinnati Law Review*, *85*, 693–760. https://doi.org/10.2139/ssrn.2819142.

[136] See Ajunwa, I., Crawford, K., & Schultz, J. (2017). Limitless worker surveillance. *California Law Review*, *105*(3), 735–776. https://doi.org/10.15779/Z38BR8MF94.

[137] See Rowland, C. (2019). Your Next Fitness Coach Is... Your Boss? *The Washington Post*, pp. A1, A10. Retrieved from https://mrtechnews.com/your-next-fitness-coach-is-your-boss/.

[138] See Olson, P. (2014, July 19). Wearable Tech is Plugging into Health Insurance - Forbes. *Forbes*. Retrieved from http://www.forbes.com/sites/parmyolson/2014/06/19/wearable-tech-health-insurance/ and Shemkus, S. (2015, April 17) and Fitness trackers are popular among insurers and employers – but is your data safe? *The Guardian*. Retrieved from https://www.theguardian.com/lifeandstyle/2015/apr/17/fitness-trackers-wearables-insurance-employees-jobs-health-data.

[139] Bersin, J. (2018, November 24). The Learning Experience Platform (LXP) Market Expands. Retrieved from https://joshbersin.com/2018/09/the-learning-experience-platform-lxp-market-expands/.

[140] See Gasparevic, D. (2018, August 14). Why Virtual-Reality Training for Employees is Catching On. Retrieved from https://www.shrm.org/resourcesandtools/hr-topics/technology/pages/why-virtual-reality-training-for-employees-is-catching-on.aspx.

[141] Bersin, J. (2019, March 9). VR Enters Corporate Learning with a Vengeance: And The Results are Amazing. *Josh Bersin: Insights on Corporate Talent, Learning, and HR Technology*. Retrieved from https://joshbersin.com/2019/01/vr-enters-corporate-learning-with-a-vengeance-and-the-results-are-amazing/ and Bodley, M. (2018, November 5). Walmart is using virtual reality to train more than 1 million in-store employees. *Digiday*. Retrieved from https://digiday.com/retail/walmart-using-virtual-reality-train-1-million-store-employees/. Also see Strivr Labs, Inc., https://www.strivr.com/.

[142] Nassauer, S. (2019, June 30). Walmart Turns to VR to Pick Middle Managers; Retailer using virtual reality headsets to gauge workers' potential and skill level, help determine promotions and pay cuts. *Wall Street Journal (Online)*. Retrieved from https://www.wsj.com/articles/walmart-turns-to-vr-to-pick-middle-managers-11561887001.

[143] See Rockwood, K. (2017, May). A Personalized Approach to Corporate Learning A Personalized Approach to Corporate Learning. *HR Magazine*. Retrieved from https://www.shrm.org/hr-today/news/hr-magazine/0517/pages/a-personalized-approach-to-corporate-learning.aspx and Stanton, M. (2020, January 30). How Technology Enables Personalized Learning. *HR Technologist*. Retrieved from https://www.hrtechnologist.com/articles/learning-development/how-technology-enables-personalized-learning/.

[144] Filtered, https://learn.filtered.com/magpie; Littlewood, B. C. (n.d.). Language processing, AI, and L&D. Retrieved from https://learn.filtered.com/thoughts/language-processing-ai.

[145] See Talespin Reality Labs, Inc., https://www.talespin.company/copilot-virtual-human-training/.

[146] Horwitz, J. (2019, February 28). Talespin' s virtual human platform uses VR and AI to teach employees soft skills. *Venture Beat*. Retrieved from https://venturebeat.com/2019/02/28/talespins-virtual-human-platform-uses-vr-and-ai-to-teach-employees-soft-skills/.

[147] Dean, S. (2019, August 27). Barry sobbed as he begged me not to fire him. I canned him anyway, over and over. *Los Angeles Times*. Retrieved from https://www.latimes.com/business/story/2019-08-26/virtual-reality-vr-technology-fire-simulator-future.

[148] See Talespin. (2019, February 28). New Virtual Human Technology from Talespin Leverages VR and AI for Teaching "Soft Skills." Retrieved from https://www.talespin.com/news/new-virtual-human-technology-from-talespin-leverages-vr-and-ai-for-teaching-soft-skills.

[149] Strongarm Technologies, Inc., https://www.strongarmtech.com/fuse.

[150] Enseo MadeSafe, https://enseo.com/madesafe/. Also see Kudialis, C. (2018, July 19). Panic button maker displays devices that protect hotel workers. *Las Vegas Sun*. Retrieved from https://vegasinc.lasvegassun.com/business/2018/jul/19/panic-button-maker-displays-devices-that-protect-h/.

[151] See Woyke, E. (2018, June 12). AI could help the construction industry work faster—and keep its workforce accident-free. *MIT Technology Review*. Retrieved from https://www.technologyreview.com/s/611141/ai-could-help-the-construction-industry-work-faster-and-keep-its-workforce-accident-free/.

[152] Presien Toolbox Spotter, https://www.presien.com/. Also, see Australian Industry Group (Ai Group). (2019). *Fourth Industrial Revolution: Australian Businesses in Transition*. Retrieved from https://cdn.aigroup.com.au/Reports/2019/AiGroup_Fourth_Industrial_Revolution_Report.pdf.

[153] Quarry Magazine. (2018, September 6). Shaping tomorrow: Robots, digital and virtual reality. Retrieved from https://www.quarrymagazine.com/2018/06/09/shaping-tomorrow-robots-digital-and-virtual-reality/.

[154] See Mateescu, A., & Nguyen, A. (2019). *Explainer: Workplace Monitoring & Surveillance*. *Data & Society Research Institute*. Retrieved from https://datasociety.net/library/explainer-workplace-monitoring-surveillance/; Peck, D. (2013, December). They're watching you at work. *The Atlantic*, 72–84. Retrieved from https://www.theatlantic.com/magazine/archive/2013/12/theyre-watching-you-at-work/354681/; Kaplan, E. (2015). The spy who fired Me: The human costs of workplace monitoring. *Harper's Magazine*, 31–40. Retrieved

from https://harpers.org/archive/2015/03/the-spy-who-fired-me/6/; Ajunwa, I. (2018). Algorithms at work: Productivity Monitoring Platforms and Wearable Technology as the New Data-Centric Research Agenda for Employment and Labor Law. *Saint Luis University Law Journal*, *63*(21), 21–54. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3247286; and Peppet, S. R. (2014). Regulating the internet of things: First steps toward managing discrimination, Privacy, Security, And consent. *Texas Law Review*, *93*(1), 85–179.

[155] Isson, J. P., & Harriott, J. I. (2016). *People Analytics in the Era of Big Data: Changing the way you attract, acquire, develop, and retain talent*. Hoboken: Wiley.

[156] Lecher, C. (2019, August 25). How Amazon automatically tracks and fires warehouse workers for 'productivity. *The Verge*. Retrieved from https://www.theverge.com/2019/4/25/18516004/amazon-warehouse-fulfillment-centers-productivity-firing-terminations.

[157] Enaible, https://www.enaible.io/.

[158]Heaven, W. D. (2020, June 4). This startup is using AI to give workers a "productivity score" | MIT Technology Review. *MIT Technology Review*. Retrieved from https://www.technologyreview.com/2020/06/04/1002671/startup-ai-workers-productivity-score-bias-machine-learning-business-covid/?mod=djemAIPro.

[159] PR Newswire. (2020, January 28). enaible Launches to Bring AI-Powered Leadership to the Enterprise. *Business Insider*. Retrieved from https://markets.businessinsider.com/news/stocks/enaible-launches-to-bring-ai-powered-leadership-to-the-enterprise-1028850929# and enaible. (2020, June 16). enaible unveils remote work management and productivity capabilities. *Businesswire*. Retrieved from https://www.businesswire.com/news/home/20200616005262/en/enaible-Unveils-Remote-Work-Management-Productivity-Capabilities.

[160] Humanyze, https://www.humanyze.com/. For information about organizational network analysis, see Borowska, K. (2019, June 21). Data-Minded or Data-Blinded? *Forbes*. Retrieved from https://www.forbes.com/sites/kasiaborowska/2019/06/21/data-minded-or-data-blinded-2/#4482ef027e8c.

[161] Chan, R. (2018, June 6). The high-tech o ffi ce of the future will spy on you. *The Week*. Retrieved from https://theweek.com/articles/760582/hightech-office-future-spy.

[162] Olguin, D. O., Jaanu, T., Heyman, D., & Waber, B. (2014). *US 2014/0249891 A1*. United States. Retrieved from https://www.freepatentsonline.com/20140249891.pdf.

[163] Isson, J. P., & Harriott, J. I. (2016). *People Analytics in the Era of Big Data: Changing the way you attract, acquire, develop, and retain talent*. Hoboken: Wiley.

[164] Olguin, D. O., Jaanu, T., Heyman, D., & Waber, B. (2014). *US 2014/0249891 A1*. United States. Retrieved from https://www.freepatentsonline.com/20140249891.pdf.

[165] Olguin, D. O., Jaanu, T., Heyman, D., & Waber, B. (2014). *US 2014/0249891 A1*. United States. Retrieved from https://www.freepatentsonline.com/20140249891.pdf.

[166] See Lindsay, G. (2015, September 21). HR Meets Data: How your boss will monitor you to create the quantified workplace. *Fast Company*. Retrieved from https://www.fastcompany.com/3051275/hr-meets-data-how-your-boss-will-monitor-you-to-create-the-quantified-workplace and The Economist. (2018, March 28). There will be little privacy in the workplace of the future. *The Economist*. Retrieved from https://www.economist.com/special-report/2018/03/28/there-will-be-little-privacy-in-the-workplace-of-the-future.

[167] See Kart, L., & Zaidi, E. (2015). *Market guide for optimization solutions*. *Gartner, Inc.* Retrieved from http://cdn2.hubspot.net/hubfs/484375/Content/Gartner/Gartner_Market_Guide_for_Optimization_Solutions_2015.pdf and Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B., & Sethupathy, G. (2016). *The Age of Analytics: Competing in a Data-Driven World*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-age-of-analytics-competing-in-a-data-driven-world.

[168] Levy, K., & Barocas, S. (2018). Refractive surveillance: Monitoring customers to manage workers. *International Journal of Communication*, *12*, 1166–1188. Retrieved from https://ijoc.org/index.php/ijoc/article/viewFile/7041/2302.

[169] Loggins, K. (2020, February 24). Here's what happens when an algorithm determines your work schedule. *Vice*. Retrieved from https://www.vice.com/en/article/g5xwby/heres-what-happens-when-an-algorithm-determines-your-work-schedule.

[170] See Percolata, https://www.percolata.com/; Tanaka, G., Liu, Z., Wong, G., Gao, Z., Ming, L., Cho, P. C. T., & Benjamin, S. K. (2016). *US 2016/0342929 A1*. United States. Retrieved from https://www.freepatentsonline.com/y2016/0342929.html; and Sarah O'Connor. (2016, September 7). When your boss is an algorithm. *Financial Times*, pp. 1–7. Retrieved from https://www.ft.com/content/88fdc58e-754f-11e6-b60a-de4532d5ea35.

[171] Uber. (2019). How does Uber match riders with drivers? Retrieved from https://marketplace.uber.com/matching. Nguyen, T. (2014). ETA phone home: How Uber engineers an efficient route ETA phone home. Retrieved from https://eng.uber.com/engineering-routing-engine/

[172] *How Uber makes — and loses — money*. (2019). *CB Insights Research*. Retrieved from https://www.cbinsights.com/research/report/how-uber-makes-money/%0Ahttp://files/2793/how-uber-makes-money.html and Belanger, L. (2016, December 30). How Uber and Lyft get drivers on the road on busy nights like New Year's. *Entrepreneur*. Retrieved from https://www.entrepreneur.com/article/284288.

[173] See UPS Staff Writer. (2016). ORION: The algorithm proving that left isn't right. Retrieved from https://www.ups.com/us/en/services/knowledge-center/article.page?kid=aa3710c2; Holland, C., Levis, J., Nuggehalli, R., Santilli, B., & Winters, J. (2017). UPS Optimizes Delivery Routes. *Journal on Applied Analytics*, *47*(1), 7–23. Retrieved from https://pdfs.semanticscholar.org/c09d/de9eedd6073944a5576d5ba61799aae924f9.pdf; and Analytics Magazine. (2018). ORION optimizes deliveries at UPS. Retrieved from http://analytics-magazine.org/orion-optimizes-deliveries-at-ups/.

[174] See Kaplan, E. (2015). The spy who fired Me: The human costs of workplace monitoring. *Harper's Magazine*, 31–40. Retrieved from https://harpers.org/archive/2015/03/the-spy-who-fired-me/6/ and Wailgum, T. (2008, May). UPS's New Telematics System Cuts Fuel Costs and Makes Drivers More Efficient. *CIO*. Retrieved from https://www.cio.com/article/2436358/ups-s-new-telematics-system-cuts-fuel-costs-and-makes-drivers-more-efficient.html.

[175] Rosenbush, S., & Stevens, L. (2015, February 17). At UPS, the Algorithm is the Driver: Turn right, turn left, turn right: Inside Orion, the 10-year effort to squeeze every penny from delivery routes. *Wall Street Journal*. Retrieved from https://www.wsj.com/articles/at-ups-the-algorithm-is-the-driver-1424136536.

[176] Afiniti, https://www.afiniti.com/; Afiniti. (2020). How it works: What we do. Retrieved from https://www.afiniti.com/what-we-do/how-it-works; Sturdivant-Sani, C. (2019). Why this DC artificial intelligence company is worth more than $1 Billion: You might have used Afiniti's tech without even knowing it. *Washingtonian*. Retrieved from https://www.washingtonian.com/2019/05/06/why-dc-artificial-intelligence-company-afiniti-worth-more-than-1-billion/; and Afiniti. (2017, December 18). Afiniti taps AI to optimize customer-agent Pairing. Retrieved from https://www.afiniti.com/news/detail/afiniti-taps-ai-to-optimize-customer-agent-pairing.

[177] See Lindsay, G. (2015, September 21). HR Meets Data: How your boss will monitor you to create the quantified workplace. *Fast Company*. Retrieved from https://www.fastcompany.com/3051275/hr-meets-data-how-your-boss-will-monitor-you-to-create-the-quantified-workplace; Digital Taylorism; Schumpeter. (2015, September 12). *The Economist*, 7–8. Retrieved from https://www.economist.com/business/2015/09/10/digital-taylorism; Sarah O'Connor. (2016, September 7). When your boss is an algorithm. *Financial Times*, pp. 1–7. Retrieved from https://www.ft.com/content/88fdc58e-754f-11e6-b60a-de4532d5ea35; and Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, *14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174.

[178] Friedman, A. (1977). Responsible Autonomy Versus Direct Control Over the Labour Process. *Capital & Class*, *1*(1), 43–57. https://doi.org/10.1177/030981687700100104 and Burawoy, M. (1983). Between the Labor Process

and the State: The Changing Face of Factory Regimes Under Advanced Capitalism. *American Sociological Review*, *48*(5), 587–605. Retrieved from https://www.jstor.org/stable/pdf/2094921.pdf.

[179] Strategies that attempt to influence or motivate workers' decisions and behaviors using psychological strategies developed out the human relations perspective of management often attributed to Elton Mayo. For a juxtaposition of the two strategies of labor management, see Friedman, A. (1977). Responsible Autonomy Versus Direct Control Over the Labour Process. *Capital & Class*, *1*(1), 43–57. https://doi.org/10.1177/030981687700100104 and Burawoy, M. (1983). Between the Labor Process and the State: The Changing Face of Factory Regimes Under Advanced Capitalism. *American Sociological Review*, *48*(5), 587–605. Retrieved from https://www.jstor.org/stable/pdf/2094921.pdf.

[180] For a discussion about technologies as a means to control workers to do specific tasks in a particular order and at a particular time, see Edwards, R. C. (1978). The social relations of production at the point of production. *Critical Sociology*, *8*(42403), 109–125. https://doi.org/10.1177/089692057800800213.

[181] See Zain. (2016, December 15). Instacart Spotlight: Shopper Engineering. Retrieved from https://medium.com/@zainali/instacart-spotlight-shopper-engineering-2c00223fb8a3 and Kolodny, L. (2016, August 31). Instacart's app has changed grocery stores for good. *TechCrunch*. Retrieved from https://techcrunch.com/2016/08/31/instacarts-app-has-changed-grocery-stores-for-good/.

[182]See Metcalf, J. (2018, February). When verification is also surveillance: EVV devices could intrusively track Medicaid recipients. *Data & Society Points*, 1–14. Retrieved from https://points.datasociety.net/when-verification-is-also-surveillance-21edb6c12cc9.

[183] See Cohn, J. E. (2018). *9,881,276 B2*. United States. Retrieved from http://pdfpiw.uspto.gov/.piw?PageNum=0&docid=09881276&IDKey=4B77C237270E%250D%250A&HomeUrl=http%253A%252F%252Fpatft.uspto.gov%252Fnetacgi%252Fnph-Parser%253FSect2%253DPTO1%252526Sect2%253DHITOFF%252526p%253D1%252526u%253D%252Fnetahtml%252FPTO%252Fsearch-b and Boyle, A. (2018, January 30). Amazon wins a pair of patents for wireless wristbands that track warehouse workers. *Geekwire*. Retrieved from https://www.geekwire.com/2018/amazon-wins-patents-wireless-wristbands-track-warehouse-workers/.

[184] See Del Rey, J. (2019, December 11). How robots are transforming Amazon warehouse jobs — for better and worse. *Vox*. Retrieved from https://www.vox.com/recode/2019/12/11/20982652/robots-amazon-warehouse-jobs-automation and Dzieza, J. (2020, February 27). Robots aren't taking our jobs — they're becoming our bosses. *The Verge*. Retrieved from https://www.theverge.com/2020/2/27/21155254/automation-robots-unemployment-jobs-vs-human-google-amazon.

[185] See Cogito Corporation, https://www.cogitocorp.com/. Also, see Cogito Corporation. (n.d.). Enhance the emotional intelligence of phone professionals. Retrieved from https://www.cogitocorp.com/wp-content/uploads/2017/02/Cogito-Dialog-Brochure.pdf; Cognito Corporation. (n.d.). The Cognito guide to emotional intelligence. Retrieved from https://www.cogitocorp.com/wp-content/uploads/2018/05/cogito-emotional-intelligence-guide.pdf; Cogito Corporation. (2019, September 5). Cogito receives $20 million in funding to extend market leadership. *Businesswire*. Retrieved from https://www.businesswire.com/news/home/20190905005209/en/Cogito-Receives-20-Million-in-Funding-to-Extend-Market-Leadership; and Simonite, T. (2018, March 19). This Call May Be Monitored for Tone and Emotion. *Wired*. Retrieved from https://www.wired.com/story/this-call-may-be-monitored-for-tone-and-emotion/.

[186] For information on behavioral modification through data analytics combined with behavioral economics and cognitive science, see Guszcza, J. (2015). The last-mile problem: How data science and behavioral science can work together. *Deloitte Review*, 63–79. Retrieved from https://www2.deloitte.com/us/en/insights/deloitte-review/issue-16/behavioral-economics-predictive-analytics.html and Yeung, K. (2017). 'Hypernudge'': Big Data as a mode of regulation by design.' *Information Communication and Society*, *20*(1), 118–136. https://doi.org/10.1080/1369118X.2016.1186713; and Schweyer, A. (2017). *Using behavioral economics insights in incentives, rewards, and recognition: A nudge guide*. Retrieved from https://theirf.org/am-site/media/behavioral-economics-nudge-guide.pdf. For information on the use of nudges and gamification in the workplace, see Deterding, S. (2019). Gamification in Management: Between Choice Architecture and Humanistic Design. *Journal of Management Inquiry*, *28*(2), 131–136. https://doi.org/10.1177/1056492618790912; and Kellogg, K. C., Valentine,

M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, *14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174.

[187] Anderson, J. Q., & Rainie, L. (2012). *Gamification: Experts expect 'game layers' to expand in the future, with positive and negative results*. *Pew Internet & American Life Project*. Retrieved from https://www.pewresearch.org/internet/wp-content/uploads/sites/9/media/Files/Reports/2012/PIP_Future_of_Internet_2012_Gamification.pdf. Also see Koivisto, J., & Hamari, J. (2019). The rise of motivational information systems: A review of gamification research. *International Journal of Information Management*, *45*(June 2017), 191–210. https://doi.org/10.1016/j.ijinfomgt.2018.10.013.

[188] See Palmer, D., Lunceford, S., & Patton, A. J. (2012). The engagement economy: How gamification is reshaping businesses. *Deloitte Review*, (11), 52–69. Retrieved from http://dupress.com/articles/the-engagement-economy-how-gamification-is-reshaping-businesses/.

[189] For example, see Lopez, S. (2011, October 19). Disney's "electronic whip": Anaheim laundry workers monitored by giant screens aim to keep productivity high as they worry about paying more for healthcare. *Los Angeles Times*. Retrieved from https://www.latimes.com/health/la-xpm-2011-oct-19-la-me-1019-lopez-disney-20111018-story.html.

[190] Bogost, I. (2011, May 3). Persuasive Games: Exploitationware. *Gamastura*. Retrieved from https://www.gamasutra.com/view/feature/134735/persuasive_games_exploitationware.php. Also see Gabrielle, V. (2019). The dark side of gamifying work. *Fast Company*, 1–10. Retrieved from https://www.fastcompany.com/90260703/the-dark-side-of-gamifying-work; Kim, T. W., & Werbach, K. (2016). More than just a game: ethical issues in gamification. *Ethics and Information Technology*, *18*(2), 157–173. https://doi.org/10.1007/s10676-016-9401-5 and Deterding, S. (2019). Gamification in Management: Between Choice Architecture and Humanistic Design. *Journal of Management Inquiry*, *28*(2), 131–136. https://doi.org/10.1177/1056492618790912.

[191] See Anadea. (2018). How Gamification in the Workplace Impacts Employee Productivity. *The Startup*. Retrieved from https://medium.com/swlh/how-gamification-in-the-workplace-impacts-employee-productivity-a4e8add048e6 and Warmelink, H., Koivisto, J., Mayer, I., Vesa, M., & Hamari, J. (2020). Gamification of production and logistics operations: Status quo and future directions. *Journal of Business Research*, *106*(September), 1–10. https://doi.org/10.1016/j.jbusres.2018.09.011.

[192] Scheiber, N. (2017, April 2). How Uber uses psychological tricks to push its drivers' buttons. *New York Times*. Retrieved from https://www.nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html?smid=fb-nytscience&smtyp=cur&_r=0.

[193] Rosenblat, A., & Stark, L. (2015). Algorithmic Labor and Information Asymmetries: A Case Study of Uber's Drivers. *International Journal of Communication*, *10*, 3758–3784. https://doi.org/10.2139/ssrn.2686227; Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). Working with Machines: The impact of algorithmic and data-driven management on human workers. In *CHI '15 Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (pp. 1603–1612). https://doi.org/10.4324/9780429272806; Rosenblat, A. (2016, April 6). The truth about how Uber's app manages drivers. *Harvard Business Review*, 1–7. Retrieved from https://hbr.org/2016/04/the-truth-about-how-ubers-app-manages-drivers.

[194] Mateescu, A., & Nguyen, A. (2019). Explainer: Algorithmic Management in the Workplace. *Data & Society Institute*, (February), 1–15. Retrieved from https://datasociety.net/library/explainer-algorithmic-management-in-the-workplace/.

[195] Sarah O'Connor. (2016, September 7). When your boss is an algorithm. *Financial Times*, pp. 1–7. Retrieved from https://www.ft.com/content/88fdc58e-754f-11e6-b60a-de4532d5ea35.

[196] NCR Corporation. (2014). The power of cashier training: Scanning best practices and techniques. Retrieved from https://www.ncr.com/content/dam/ncrcom/content-type/white_papers/RET_Cashier-Training_wp.pdf.

[197] See Lopez, S. (2011, October 19). Disney's "electronic whip": Anaheim laundry workers monitored by giant screens aim to keep productivity high as they worry about paying more for healthcare. *Los Angeles Times*.

Retrieved from https://www.latimes.com/health/la-xpm-2011-oct-19-la-me-1019-lopez-disney-20111018-story.html.

[198] Bensinger, G. (2019, May 21). 'MissionRacer ': How Amazon turned the tedium of warehouse work into a game. *The Washington Post* and Brodkin, J. (2019, May 22). Amazon made video games for its workers to reduce tedium of warehouse jobs. *Ars Technica*. Retrieved from https://arstechnica.com/information-technology/2019/05/amazon-gamifies-its-warehouse-work-like-tetris-but-with-real-boxes/.

[199] Vincent, J. (2019, May 22). Amazon turns warehouse tasks into video games to make work 'fun.' *The Verge*. Retrieved from https://www.theverge.com/2019/5/22/18635272/amazon-warehouse-working-conditions-gamification-video-games.

[200] See Parasuraman, R., & Wickens, C. D. (2008). Humans: Still vital after all these years of automation. *Human Factors*, *50*(3), 511–520. https://doi.org/10.1518/001872008X312198. Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans.*, *30*(3), 286–297. https://doi.org/10.1109/3468.844354.

[201] For example, see Wilson, H. J., & Daugherty, P. R. (2018). Humans and AI Are Joining Forces. *Harvard Business Review*, *96*(4), 114–123 and Moore, P. V. (2020). Artificial intelligence in the workplace: What is at stake for workers? In *Work in the Age of Data* (pp. 1–14). Madrid: BBVA. Retrieved from https://www.bbvaopenmind.com/wp-content/uploads/2020/02/BBVA-OpenMind-Phoebe-V-Moore-Artificial-Intelligence-in-workplace-what-is-at-stake-for-workers.pdf.

[202] See Dzieza, J. (2020, February 27). Robots aren't taking our jobs — they're becoming our bosses. *The Verge*. Retrieved from https://www.theverge.com/2020/2/27/21155254/automation-robots-unemployment-jobs-vs-human-google-amazon; Del Rey, J. (2019, December 11). How robots are transforming Amazon warehouse jobs — for better and worse. *Vox*. Retrieved from https://www.vox.com/recode/2019/12/11/20982652/robots-amazon-warehouse-jobs-automation; and Simon, M. (2019, June 5). Inside the Amazon Warehouse Where Humans and Machines Become One. *Wired*. Retrieved from https://www.wired.com/story/amazon-warehouse-robots/.

[203] Walmart Staff. (2018, October 4). You'll Never Believe Who's Scrubbing the Floors at Walmart. Retrieved from https://corporate.walmart.com/newsroom/innovation/20181004/youll-never-believe-whos-scrubbing-the-floors-at-walmart; Brain Corporation, https://www.braincorp.com/applications/floor-care/; Pasick, A., & Karen, H. (2017, November 22). Walmart's relentless march to automation is coming for the late-night cleaning crew. *Quartz*. Retrieved from https://qz.com/1136473/walmart-is-testing-self-driving-mechanical-floor-scrubbers-to-clean-store-aisles/; and Huddleston Jr., T. (2019, December 5). Walmart will soon use hundreds of A.I. robot janitors to scrub the floors of US stores. *CNBC*, pp. 1–2. Retrieved from https://www.cnbc.com/2018/12/05/walmart-will-use-hundreds-of-ai-robot-janitors-to-scrub-store-floors.html.

[204] For example, see National Highway Traffic Safety Administration. (2018). *Automated vehicles for safety: The evolution of automated safety technologies*. Retrieved from https://www.nhtsa.gov/technology-innovation/automated-vehicles. Also see Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans.*, *30*(3), 286–297. https://doi.org/10.1109/3468.844354 and Sheridan, T. B., & Parasuraman, R. (2005). Human-Automation interaction. *Reviews of Human Factors and Ergonomics*, 89–129. https://doi.org/https://doi.org/10.1518/155723405783703082.

[205] See Gray, M. L., & Suri, S. (2019). *Ghost work: How to stop Silicon Valley from building a new global underclass*. New York, NY: Houghton Mifflin Harcourt. Retrieved from https://ghostwork.info/ and Chen, A. (2019). How Silicon Valley's successes are fueled by an underclass of 'ghost workers.' *The Verge*. Retrieved from https://www.theverge.com/2019/5/13/18563284/mary-gray-ghost-work-microwork-labor-silicon-valley-automation-employment-interview.

[206] See Elish, M. C. (2015, July 25). Moral crumple zones: When your self-driving car crashes, you could still be the one who gets sued. *Quartz*, 1–9. Retrieved from https://qz.com/461905/when-your-self-driving-car-crashes-you-could-still-be-the-one-who-gets-sued/ and Elish, M. C. (2019). Moral Crumple Zones: Cautionary Tales in Human-Robot Interaction. *Engaging Science, Technology, and Society*, *5*, 40. https://doi.org/10.17351/ests2019.260.

[207] See Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, *14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174; Moore, P. V. (2020). Artificial intelligence in the workplace: What is at stake for workers? In *Work in the Age of Data* (pp. 1–14). Madrid: BBVA. Retrieved from https://www.bbvaopenmind.com/wp-content/uploads/2020/02/BBVA-OpenMind-Phoebe-V-Moore-Artificial-Intelligence-in-workplace-what-is-at-stake-for-workers.pdf; Mateescu, A., & Nguyen, A. (2019). Explainer: Algorithmic Management in the Workplace. *Data & Society Institute*, February 1–15. Retrieved from https://doi.org/10.1145/2702123.2702548; Mateescu, A., & Nguyen, A. (2019). *Explainer: Workplace Monitoring & Surveillance*. *Data & Society Research Institute*. Retrieved from www.datasociety.net; and Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society*, *July-Decem*, 1–21. https://doi.org/10.1177/2053951716679679, and Bogen, M., & Rieke, A. (2018). *Help wanted: An examination of hiring algorithms, equity, and bias*. Washington, D.C. Retrieved from https://www.upturn.org/reports/2018/hiring-algorithms/. Kim, P. T. (2017). Data-Driven Discrimination at Work. *William & Mary Law Review*, *58*(3), 857–936.

[208] For example, see Nonnecke, B., Gummi, M., Crittenden, C., Lindeman, D., & Gillette, D. (2018). *Putting AI to work: Technology and policy for enabling the workforceofthe future* (Vol. September). Retrieved from https://citrispolicylab.org/wp-content/uploads/2018/11/Putting-AI-To-Work_CITRIS_Sept-2018.pdf and Logg, J. M. (2019, August 9). Using Algorithms to Understand the Biases in Your Organization. *Harvard Business Review*, 1–2. Retrieved from https://hbr.org/2019/08/using-algorithms-to-understand-the-biases-in-your-organization.