A Systematic Review of Biometric Monitoring in the Workplace: Analyzing Socio-technical Harms in Development, Deployment and Use

Ezra Awumey
eawumey@andrew.cmu.edu
Human-Computer Interaction Institute, Carnegie Mellon University
Pittsburgh, Pennsylvania, USA

Sauvik Das
sauvik@cmu.edu
Human-Computer Interaction Institute, Carnegie Mellon University
Pittsburgh, Pennsylvania, USA

Jodi Forlizzi
forlizzi@cs.cmu.edu
Human-Computer Interaction Institute, Carnegie Mellon University
Pittsburgh, Pennsylvania, USA

ABSTRACT

Modern advances in AI have increased employer interest in tracking workers' biometric signals — e.g., their brainwaves and facial expressions — to evaluate and make predictions about their performance and productivity. These technologies afford managers information about internal emotional and physiological states that were previously accessible only to individual workers, raising new concerns around worker privacy and autonomy. Yet, the research literature on the impact of AI-powered biometric work monitoring (AI-BWM) technologies on workers remains fragmented across disciplines and industry sectors, limiting our understanding of its impacts on workers at large. In this paper, we sytematically review 129 papers, spanning varied disciplines and industry sectors, that discuss and analyze the impact of AI-powered biometric monitoring technologies in occupational settings. We situate this literature across a process model that spans the development, deployment, and usage phases of these technologies. We further draw on Shelby et al.'s Taxonomy of Socio-technical Harms in AI systems to systematize the harms experienced by workers across the three phases of our process model. We find that the development, deployment, and sustained use of AI-powered biometric work monitoring technologies put workers at risk of a number of the socio-technical harms specified by Shelby et al.: e.g., by forcing workers to exert additional emotional labor to avoid flagging unreliable affect monitoring systems, or through the use of these data to make inferences about productivity. Our research contributes to the field of critical AI studies by highlighting the potential for a cascade of harms to occur when the impact of these technologies on workers is not considered at all phases of our process model.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**; • **Social and professional topics → Surveillance**.

ACM Reference Format:
Ezra Awumey, Sauvik Das, and Jodi Forlizzi. 2024. A Systematic Review of Biometric Monitoring in the Workplace: Analyzing Socio-technical Harms in Development, Deployment and Use. In *The 2024 ACM Conference on Fairness, Accountability, and Transparency (FAccT '24), June 03–06, 2024, Rio de Janeiro, Brazil.* ACM, New York, NY, USA, 13 pages. https://doi.org/10.1145/3630106.3658945

FAccT '24, June 03–06, 2024, Rio de Janeiro, Brazil

ACM ISBN 979-8-4007-0450-5/24/06
https://doi.org/10.1145/3630106.3658945

1 INTRODUCTION

As technology has advanced, so have the implements used to monitor workers — from manual and crude to automated and granular. However, while monitoring technologies have historically sought to measure work-specific behaviors and indicators such as "time on task," a new class of AI-powered biometric work monitoring (AI-BWM)technology aims to measure not just work-specific behaviors but also to apply machine learning techniques to infer workers' cognitive and physical states like mood, attentiveness, and stress (thought to be antecedents of work-specific behaviors) [34, 44, 123]. As firms across several industry sectors now seek to use these technologies to collect information on the internal states of their employees, the boundaries between work and personal life become less well-defined [70, 102, 130]. As a result, AI-BWM technologies not only further concentrate power in the workplace towards managers but also expand the potential scope of workplace harm by allowing employers to harvest personal information about workers that was previously inaccessible. Ostensibly, organizations justify their use of these technologies for reasons ranging from improving worker well-being to providing managers with more objective means for evaluating employee performance [28, 34, 102, 106]. However, the affordances of these systems also satisfy long-held managerial visions like reducing cost inefficiencies and worker absenteeism — ambitions fueled by the savvy marketing of the companies selling these technologies[49, 114, 117].

Critical scholarship and journalism have shed light on the negative social consequences of biometric monitoring technology. News headlines demonstrate concern about employers using workers' biometric data to renegotiate the workplace social contract. For example, Canon Information Technology deployed "AI cameras" to "ensure that only happy employees are allowed into its offices"[137]. Another piece discusses the tensions surrounding the use of emotion recognition technology to screen job candidates[71]. Prior academic work on the continuous real-time monitoring of workers has contributed to a clearer understanding of how the adoption of this technology may lead to harmful labor conditions, exacerbate power asymmetries between workers and management, and raise new questions about bias, discrimination, and the right to privacy in the workplace [11]. Case studies offer details about workers' experiences subject to these AI systems and highlight the mechanisms through which unlawful surveillance, data coercion, and the intensification of labor might occur [58, 89, 118]. Given sparse worker privacy protections and the lack of enforceable AI regulations, some scholars have argued that the limits to intrusive and exploitative labor practices under biometric surveillance are yet to be seen [2, 11].

This prior work has advanced our understanding of the problems of using these technologies as isolated cases within specific workplace contexts. However, we lack a comprehensive understanding of the risks associated with biometric monitoring technologies across their many forms and use contexts. Additionally, we do not yet have a clear picture of how decisions made in designing and implementing these systems harm workers who are subject to them.

A systemic view of what is currently known about AI-BWM technologies is necessary to anticipate and attenuate this technology's adverse effects on the future of work. Furthermore, cultivating a better understanding of how design decisions made early on can result in post-deployment harms might help construct resources that help "high-road" managers make decisions that improve working conditions[14]. Similarly, technologists and policy makers can use this review to understand the range of threats posed by these systems as they devise harm-mitigating interventions. Our research aims to fill these gaps by systematically reviewing the literature on various AI-BWM technologies used across different occupational settings. We explore the following research questions to achieve this aim:

RQ1 How do decisions made in the development, deployment, and sustained use of AI-powered biometric work monitoring technologies in workplace create the potential for harms to workers?

RQ2 What harms do workers experience and anticipate in response to the managerial deployment of AI-powered biometric work monitoring technologies?

We organize our findings on how these technologies impact workers into a process model building on Shelby et al. spanning the development, deployment, and use of AI-powered biometric work monitoring technologies[122]. This approach provides a descriptive means to systemically examine these technologies' development, deployment, and impact on workers as illustrated in Figure 2. In summary, our review of the broad but disparate literature on AI-powered biometric work monitoring technologies suggests that workers are exposed to a wide range of socio-technical harms based on, for example, the faulty assumptions underlying the development of these technologies, the further shifting of workplace power towards employers in affording them access to workers' internal cognitive and physiological states in deployment; and the increased emotional labor required of workers in their use.

2 METHODS

We conducted a systematic literature review of articles on biometric work monitoring to answer our two research questions. Our literature review was guided by the standards of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines[110].

We began our literature review by examining 65 preliminary sources on workplace surveillance collected through Google searches and suggestions from field experts. This collection of sources included academic journal articles, policy briefs, industry reports, and popular news media. We used these documents to identify significant themes within academic research related to the topic.

To broaden our collection of academic research articles on the research topic, we queried different permutations of the search terms "Employee," "Worker," "Surveillance," and "Monitoring" in the Scopus database, retrieving a total of 41,160 papers. We determined that many of these papers were unrelated to workplace surveillance and instead discussed topics like astronomy but were retrieved because they contained words like surveillance and monitoring in their abstracts.

To avoid noise in our results from non-archival papers and papers in ancillary fields, we conducted a second round of searches using the built-in pre-filtering function in Scopus only to include archival research papers in social science, computer science, business, engineering, business, and decision science. We limited our search to these fields because other search filters did not retrieve relevant articles. This second round of searches returned 9,598 papers.

To retrieve papers on AI-powered biometric work monitoring, specifically, we derived a set of keywords based on related words frequently appearing in article abstracts such as "EEG," "Wearable," "Emotion Recognition" and "Internet of things." We then constructed different pairings of these keywords in relation to the different ways biometric monitoring interacts with work-related concepts. The rationale for this decision was to retrieve a more balanced mixture of sources ranging from descriptions of technical applications to worker case studies and analyses of the broader implications of the technology's development and adoption. To that end, we constructed four types of searches:

(1) Biometric sensing modality *AND* workplace setting (e.g., heart rate monitoring *AND* warehouse) This search query was constructed to retrieve papers discussing the occupational settings where biometric technology is used.
(2) Biometric sensing modality *AND* worker job classification (e.g., affective monitoring *AND* customer service representative) This search query was constructed to retrieve papers on the different job classifications subject to biometric monitoring.
(3) Biometric sensing modality *AND* metric targeted by monitoring (e.g., brainwave monitoring *AND* productivity) This search query was constructed to retrieve papers on metrics of performance and productivity assessed by biometric technologies.
(4) Biometric sensing modality *AND* technological concept/paradigm (e.g., gait tracking *AND* internet of things *OR* Industry 4.0) This search query was constructed to retrieve sources describing how biometric monitoring maps onto broader trends in technology and labor.

We then queried these searches within the Scopus database, which indexes some but not all of the proceedings listed in IEEE Xplore and the ACM Digital Library. To ensure that coverage of relevant research articles was comprehensive, we later queried these two databases independently to locate articles possibly missed in our initial searches. Following this procedure, we retrieved a total of 1,151 articles.

Over six months, we reviewed abstracts and excluded any papers unrelated to workplace biometric performance monitoring, including papers on biometric authentication and security, legal scholarship on surveillance-related topics peripheral to our organizing framework, papers describing non-biometric electronic performance monitoring technologies, and papers developing techniques building on established biometric monitoring practices. Although we did not include these papers in the final collection of articles, they helped contextualize our research findings.

After applying these exclusion criteria and removing duplicates, we arrived at a final corpus of 129 articles, spanning journals such as Applied Bionics and Biomechanics, Accident Analysis and Prevention, The Journal of Computer-Mediated Communication, ILR Review, Digital Business, Conference on Human Factors and Computing, and Journal of Organizational Behavior.

3 FINDINGS

Shelby et al.'s taxonomy of Socio-Technical Harms in Algorithmic Systems provides a starting point for understanding how AI-BWM technologies effect labor processes. This taxonomy provides a general overview of how deployed algorithmic systems can negatively impact individuals, communities, and social systems[122].

However, because the framework is descriptive, it does not offer prescriptive information to address the harms caused by these technologies. In order to devise actionable solutions to the lived and anticipated harms experienced by workers subject to these systems, the research community needs to *i*) surface the decisions and limitations of technologists as they develop AI-BWM systems, *ii*) understand the considerations and constraints on employers as they adopt and deploy them and *iii*) share the experiences and attitudes of workers as they anticipate and interact with the technology.

Since these issues represent distinct problem areas addressable through different interventions, we devise a process model which highlights harms unique to the development, deployment and use of AI-BWM technologies. This framework extends Shelby et al.'s taxonomy to better highlight and differentiate between harms attributable to the different practices, beliefs, and goals of stakeholders at each phase. We surface these issues through an analysis done at two different apertures. First, by examining findings pertinent to each phase of the process model, and second, through reviewing biometric performance monitoring through case studies in three occupations, specifically athletes, construction & mining workers, and office workers. This approach allows us to cover a range of related topics spanning different industries, while also demonstrating how harms may occur uniquely across diverse settings supporting analysis along the lines of technical, design, management, labor and policy considerations. For example, we find that while athletes might be more accustomed to having their performance monitored and scrutinized, they face new concerns in how this information is distributed to the public after these technologies are deployed[57]. In contrast, office workers might be less accustomed to constant performance monitoring and may benefit more greatly from having their concerns represented earlier in the design and development life-cycle of these technologies[34, 70, 111]. Since cases may differ both in how harms manifest and what actions can be taken to mitigate them, we organize our findings such that that readers spanning disciplines might more easily identify problems addressable through their specific domain expertise and approaches. In figure 2, we present our application of the socio-technical harms taxonomy to our process model.

3.1 Shelby et al.'s Taxonomy of Harms Applied to AI-BWM

3.1.1 Harms in the Development Phase of AI-BWM Technologies. The 95 research papers that spoke to the development phase include 1) technical descriptions of applications of AI-BWM technologies found in technical research papers (57/95), 2) papers describing the development of models used to develop these systems (14/95), 3) review papers discussing state of the art (12/95); 3) analyses of the methodologies and datasets (5/95) used in development; and 4) papers examining the premises and development practices underlying the development of AI-BWM systems (7/95).

We included papers in the development phase if they described applications of AI-powered biometrics currently in use or presented a form of biometric monitoring that marked a significant leap from earlier monitoring practice, as determined by the data it collected. For example, Michelin et al. describe FaceGuard, a deep-learning system for predicting when workers are likely to touch their faces to reduce the spread of COVID-19 [103].

Interpersonal Harms in Development. Decisions made during the development phase may lead to interpersonal harm when technology is designed to collect information about workers' private lives. This information may be used to 1) support managerial practices that may diminish worker privacy and agency (26/95), 2) reduce the impact of emotions on job performance (4/95), and 3) direct and manage attention during work (13/95).

Developers of affect monitoring technologies may frame their considerations as reducing the impact of emotions on worker job performance. Girardi et al.,[55] describe the development and testing of an algorithm for detecting workers' emotional triggers during programming tasks, as emotions have been shown to affect cognitive skills. Another paper similarly focuses on the high volatility of service-industry employees' emotions during the service delivery process, claiming that it is essential to "effectively judge the emotional states of customer service staff" to justify the development of a multi-modal emotion recognition database[92].

Nižetić et al.[108] discuss the results of a field study where wearable devices are used to develop an AI model for tracking worker metabolic rate as a proxy for worker comfort. Caporale et al.[22] similarly discuss the development of an analytical model for estimating metabolic rate to improve the work performance of aging workers. The authors describe how their model can also be used estimate workers' age, gender, and physical fitness level. This function (or "mission") creep occurs when AI-BWM technology is used to infer things about workers beyond what they are originally intended to use [130]. Despite developers' attempts to introduce privacy protections in the development phase, the potential for privacy infringements remains through side-channels. For example, [64, 84, 95] discuss how biometric sensing modalities such as electroencephalogram (EEG) and accelerometer-based movement tracking might leak sensitive private information about workers'

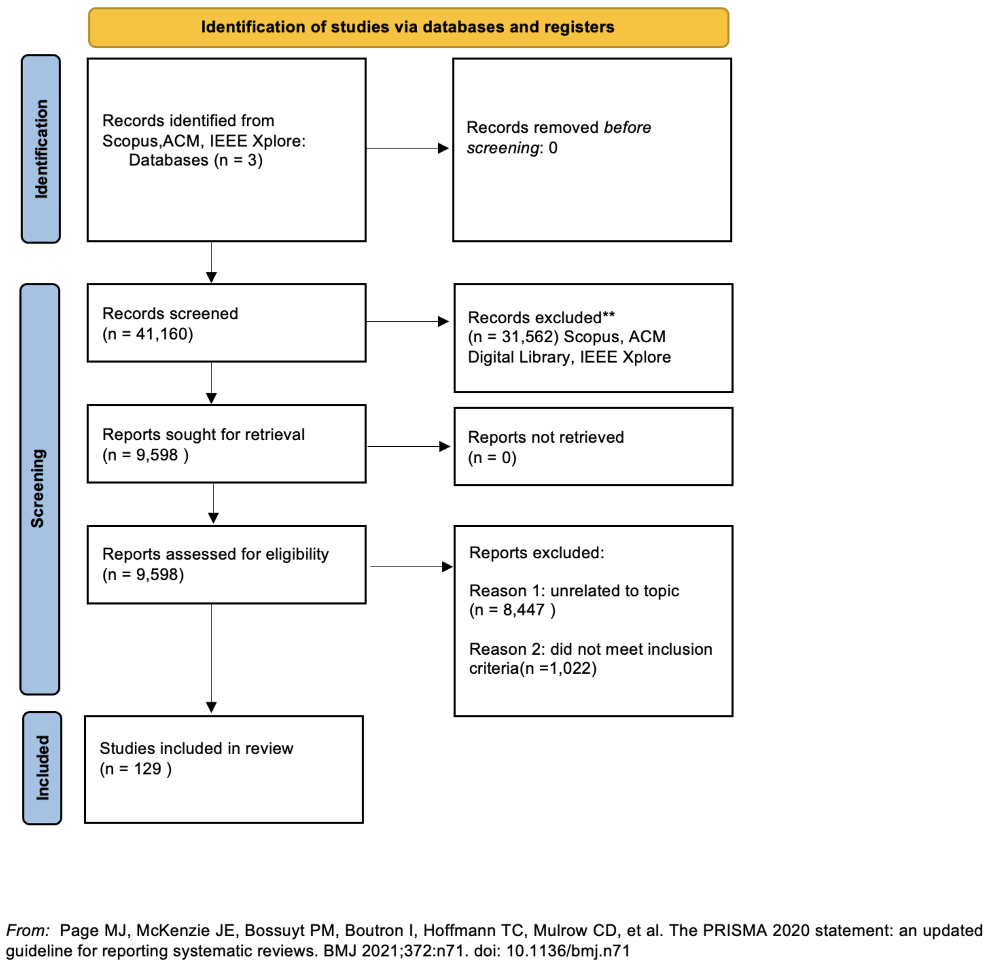

Figure 1: PRISMA Flow Diagram

mental health and physical well-being, such as the presence of mental illness or musculoskeletal disorders.

Representation and Allocation (Bias Harms) in Development. Representation harms occur in the development stage when AI-BWM monitoring technologies 1) determine worker performance and productivity based on insufficient or unrepresentative data or 2) categorize workers in ways that unfairly advantage and disproportionately allocate resources to specific groups.

A study analyzing 86 patents for Automatic Emotion Recognition (AER) technologies used to monitor the emotions of workers found that they described applications of technologies to help managers optimize their workforce, lay off under-performing employees, and promote employees who display a positive attitude toward customers [16]. However, the literature also describes how AER technologies often fail to accurately represent human emotion due to several faulty assumptions and well-documented methodological shortcomings — for example, the idea that humans share a set of universally expressed human emotions [9, 100]. These approaches fail to account for cultural and neurological differences among individuals [75, 79], potentially exacerbating inequities. Furthermore, the datasets used for training these deep learning models may rely on a single classification label based on simulated emotions from actors instead of genuinely expressed emotion [9, 16]. Errors in emotion perception may lead to representative harm to workers whose unique physical features and means of expression are not well captured in the training data [75, 77, 132]. When the metrics these systems target are limited or fail to include critical aspects of workers' job performance (i.e., creative and affective labor) and are used to justify punitive measures or promotions, allocative harms can occur[102, 118]. Further complicating the situation is that AI-BWM technologies are trained on datasets that might be designed specifically for clinical applications or are not robust enough to support the inferences they make. For these reasons, the research literature describes how datasets used to develop AI-powered work monitoring technologies may be unsuitable for use in occupational settings, potentially resulting in unrepresentative categorizations of workers' internal physical states [12, 101].

Socio-Technical Harms	Development	Deployment	Use
Interpersonal Harms	**Privacy:** when sensors used in the development of AI-BWM systems leak private information about workers [Höller, 2018; Kröger, 2019; Mandal, 2022].	**Loss of Agency:** when Al-BWM systems collect sensitive information about workers to support patriarchal managerial practices [Grandinetti, 2019; Naous, 2022; Chowdhary, 2023].	**Privacy:** when workers fear that Al-BWM may disclose private information about them or be used to infer things beyond its intended purpose [Stark, 2020; Richter, 2020; Fugate, 2023].
Representative Harms	**Reifying Essentialist Categories:** when datasets are unsuitable for creating deployable Al-BWM technologies used on diverse populations [Merone, 2017; Bisogni, 2022; Kang 2023].	**Stereotyping:** when Al-BWM is used to categorize workers into ideal and underperforming groups (e.g. healthy or unhealthy) [Esmonde, 2021; Mettler 2022; Roemmich, 2023a].	**Alienation:** when workers report low alignment of reported internal states, and the assessments of Al-BWM systems [Kaur, 2022].
Allocative Harms	**Economic and Opportunity Loss:** when Al-BWM systems are designed without consideration of how they might be used to disadvantage or deny resources to certain groups [Kaur, 2022; Boyd, 2023].	**Economic and Opportunity Loss:** when managers deny workers opportunities for failing to meet requirements set by Al-BWM systems [Ajunwa, 2019; Watkins, 2020].	**Alienation:** when workers are denied opportunities given to other workers based on the evaluations and predictions of Al-BWM technology [Mantello, 2021].
Quality of Service Harms	**Labor Intensification:** when Al-BWM systems are designed to narrowly target certain worker behaviors and metrics indicative of their performance [Boyd, 2023; Bowell, 2023].	**Alienation:** when managers use Al-BWM systems to demand additional labor or challenge workers' accounts of their own work [Levy, 2015; Roemmich, 2023b].	**Labor Intensification:** when workers feel compelled to modify their behavior to avoid unfavorable evaluations from Al-BWM systems [Bowell, 2023; Roemmich, 2023b.]
Social System Harms	**Information Asymmetry:** when Al-BWM systems are not designed to provide equal benefit (information) to both employers and workers [Vatcha, 2020].	**Information Asymmetry:** when management does not share or clearly communicate the information generated by Al-BWM systems with workers [Greene, 2023].	**Erroneous Information:** when workers develop dysfunctional mental-models regarding the purposes of Al-BWM use [Carpenter, 2016; Fugate, 2023].

Figure 2: Socio-technical Harms Taxonomy Applied to AI-BWM Process Model

Quality of Service and Social System Harms in Development. Quality of service harms occur when AI-BWM technologies are developed to enforce worker compliance towards a narrow set of behaviors and performance metrics and result in an intensification of workers' labor towards fulfillment of the indicative of having met those metrics[16, 79, 118]. Applications of AI-BWM may stereotype and raise suspicions about certain groups of workers, creating a burden of negative evaluation and alienation that may be greater than others. For example, Joshi et al., [72] describe machine learning approaches for predicting worker attrition based on data related to their behavior, job classification, and even marital status. Similarly, Zaman et al.,[135] propose an algorithm for determining worker satisfaction based on real-time emotion recognition.Workers' economic well-being is threatened when AI-BWM technologies are used to predict the likelihood they will leave their jobs. These harms may be amplified by the challenges developers face in designing AI-BWM systems for use within real-world contexts. Raghavan et al.,[116] describe how the lack of conceptual clarity in hiring assessment metrics such as "cultural fit" and retention likelihood, for example, can result in developers making incorrect or biased decisions about which data best support these predictions. In many cases, workers are left often unaware of what these systems measure and infer about them. Social system harms arise when biometric monitoring technologies are designed without providing equitable benefits (typically in the form of information) to both management and workers, informational asymmetries may result. For example, electronic logging devices designed to collect data and track the driving behaviors and whereabouts of truckers inform new metrics which and challenge their own accounts of their labor [89].

3.1.2 Harms in the Deployment Phase of AI-BWM Technologies.

The deployment phase is related to how managers implement these technologies within their operations. We find 34 articles discussing managerial deployment of AI-power biometric monitoring systems. These include papers that 1) discuss the motivations for the managerial deployment of AI-BWM technologies (22/34) and 2) examine how the technology is used to support or replace Human Resource Management (HRM) and other managerial decision functions(24/34).

The miniaturization of electronic devices, in tandem with advancements in data storage and networking, has lowered the costs of implementation, making the technology more accessible for organizations to deploy than ever before [2]. Some firms justify their increased adoption of biometric monitoring technologies with considerations of worker safety and wellness [120]. Other employers may view the collection of worker biometric data as an opportunity to exercise tighter control over workers to mitigate risk and reduce inefficiencies (i.e., via worker attrition and absenteeism)in their workforce[6, 115].

Offices represent the fastest growing work contexts deploying AI-BWM technologies for worker performance and productivity monitoring, such as Automatic Emotion Recognition [79, 98]. Other forms of biometric monitoring technologies, like smart wearables, have seen more widespread usage in higher-risk industries like construction and manufacturing [5, 18, 59, 74, 111]. Several other applications for wearable biometric monitoring technologies have emerged in recent years including human activity recognition for adaptive manufacturing, worker fatigue management, and environmental stress detection[27, 113, 121]. However, the deployment of these systems may also cause harm when they create or exacerbate extant informational and power asymmetries between managers and workers, assume the functions of human resource management (i.e., job candidate screening), and replace formal and informal controls, creating more rigid and depersonalized work interactions.[3, 70, 102].

Interpersonal Harms in Deployment. Interpersonal harms in deployment relate to the collection of workers' biometric data and its nefarious use. 1) The sharing of worker data with third parties and 2) reliance on the data collected by these systems to make decisions for workers that they might otherwise make for themselves.

Managers in office settings deploy a variety of passive sensing devices, wearable devices, and camera-based emotion recognition systems[34, 132]. Well-being sensing technologies can suggest when workers should take a break or, in more extreme cases, determine when they may be suffering from mental health crises[93, 106]. These applications cause interpersonal harm to workers when they impinge on workers' agency, for example, in determining the appropriate time to take a break, or when they private information about a worker's mental health in ways that could disadvantage them[28, 30] The research literature demonstrates that some managers also recognize the potential for well-being sensing technologies to cause interpersonal harm as they consider deployment. For example, a survey study of managers in Western Europe found that while they generally viewed IoT well-being sensing technologies as beneficial, they also had reservations about its capacity to impinge on worker privacy and sovereignty [115].

Representation and Allocation Harms in Deployment. Representation harms in deployment arise when managers adopt AI-BWM technologies to identify a subset of desirable task-specific attributes, though they may not accurately represent workers' performance and or productivity[16, 118]. Managers across a wide variety of occupational settings may use technologies which monitor workers' physical condition to make determinations about their performance, which may deprive them of certain opportunities and benefits given to workers deemed healthier [7, 43].

Quality of Service and Social System Harms in Deployment. Quality of Service, Harms in Deployment, may arise when AI-BWM technologies are used to replace the formal controls in workplaces (i.e., periodic evaluations conducted by human managers) and cause workers to adapt their behaviors to continuous monitoring, which may result in intensified work[3, 11, 118] A study of 2500 found that managers are more likely than workers to consider the benefits of workplace monitoring technologies, even though the implementation of Information and Communications (ICT) technologies is positively correlated with technology-related stress for *both* workers and management as it may increase the demands of their work [20]. Another survey of 192 practitioners from different manufacturing firms adopting Industry 4.0 technologies suggests that misalignments between the outputs of sensing-communication technologies and organizational practices may negatively impact workers' health, performance quality, and productivity[128]

Societal harms in deployment arise when insights about the biometric information collected on workers are not shared with them but instead used to exert more control over them.

Given the opaque nature of the deep learning models typically at the heart of these technologies, developers of these systems are unable to communicate their capabilities and limitations to the managers using them clearly. [78, 116]. Similarly, workers frequently do not know what personal data are being collected about them and to what end[23, 24, 31]. These working conditions lead to information asymmetries and may lead workers to form suspicious mental models of how these systems operate and are used [31, 51]. The lack of transparency in how these systems operate poses barriers to managerial understanding of the exact means by which workers are being evaluated. For example, managers may rely on AER technologies to evaluate workers even though these systems often suffer from bias and the technical limitations described in the development phase [1, 75, 98].

3.1.3 Harms in the Use Phase of AI-BWM technologies. The use phase encompasses workers' initial reactions to AI-BWM, its effect on their labor, and the strategies they employ to adapt to it. We find 28 articles describing worker experience and attitudes towards the deployment of these technologies. The papers included 1) field and case studies (23/28) and 3) papers analyzing surveys of workers (5/28). We included articles that highlight worker experiences with AI-powered AI-BWM in different occupational settings, in addition to papers describing their concerns about its current and potential use.

Interpersonal Harms Experienced and Anticipated in Use. One central theme uncovered in our findings is that workers are concerned that using biometric monitoring technology will result in interpersonal harms like unjust performance evaluations and unlawful surveillance. Workers may view the inferences made by monitoring techniques like Automatic Emotion Recognition (AER) as deep privacy violations as they consider its potential to reveal things about their intimate private lives which may be used against them in punitive or exclusionary ways[106, 118]. Worker agency may be diminished when workers are unable to consent to the collection of their biometric data and challenge the determinations made about them [34, 58, 89].

A variety of demographic factors mediates attitudes toward biometric monitoring. Prior work [39] also observes differences in public and private sector office workers' perception of facial-recognition-based monitoring technologies (FRT), finding that older public sector workers were less likely than other groups, particularly younger private sector workers, to tolerate monitoring due to concerns about transparency, agency and excessive managerial control stemming from authoritarian practices. Another study reviewing employee responses to a national survey on the implementation of FRT in workplaces found that women were less likely than men to accept the technology and consider the differential impact of workplace surveillance technologies on women, which may moderate their perception of privacy risk in the face of workplace surveillance [124]. These results are echoed by a third study identifying differences between how minority and majority group workers frame privacy concerns related to employer use of biometric technology. This study found that while perceived distrust and vulnerability were reduced through continued use of biometric technologies in minority and majority groups, perception of vulnerability was consistently lower for individuals belonging to the majority group [23].

Representation and Allocation (Bias Harms) Experienced and Anticipated in Use. AI-BWM technologies may fail to accurately represent workers' emotions and behaviors linked to performance and productivity. Workers express fears about how these systems may disadvantage them[15, 51]. Like interpersonal harms, worker experiences and perception of risk related to bias harms may vary significantly across demographic groups and are influenced by the purpose for which AI-BWM technologies are employed[23, 30, 39, 98, 124]. Kaur et al.,[78] report low alignment between the inferences made by affect monitoring technologies and self-reported emotions in office settings. These accuracy challenges are further complicated by the technology's comparatively poor ability to accurately detect the facial expressions of marginalized groups like racial minorities, disabled, and neuro-divergent populations [75, 98]. Unsurprisingly, then, the use of AER technologies for hiring and other HR functions was associated with increased anxiety in minorities, women, and lower-income individuals in a study of job seekers across 48 countries [98]. The same study found that higher-income men were less likely to have a worried outlook toward AER technologies used for hiring and other HR functions.[ibid]A study analyzing 395 survey responses on worker perception of AI emotion monitoring technologies used in workplaces finds that workers are concerned about how these systems may amplify biases and stigmas, specifically along the axes of race, gender, disability, and mental health[30]. In this study, almost one-third of the respondents did not view AI-emotion recognition technology as offering any benefits when presented with a series of vignettes related to its deployment. More generally, participants' conceptions of the technology's potential risks led them to consider avoiding or mitigating harms either through engaging in additional emotional labor or even quitting [ibid].

Quality of Service Harms and Societal Harms Experienced and Anticipated in Use. The literature discusses how AI-BWM technologies may require workers to engage in additional labor to meet job demands. In a scenario-based interview study, Roemmich et al.,[118] found that automatic emotion recognition (AER) technologies may cause workers to take on additional emotional labor and go to great lengths to keep their emotions hidden. In a study consisting of eleven qualitative interviews of employers and workers, Bowell et al., [15] found that workers internalized workplace monitoring and described the process of embodiment as "the tangible coalescence of being monitored within themselves – in their interactions with workplace tracking." These harms are exacerbated by worker uncertainty about how these systems hold them accountable for certain behaviors. One worker described the experience of being monitored as " walking on eggshells just waiting, you know, to stand on an egg that just was not a shell!"[15]. When workers are unable to make sense of how the data collected about them is used, they may reject the technology [51].

4 DISCUSSION

Our first research question sought to determine how the decisions made in developing and deploying AI-powered biometric work monitoring technologies create the potential for worker harm. We found that during development, human emotions may be framed as obstacles to job performance and build technologies that target a limited set of features to make inferences about workers potentially leading to interpersonal harms [55, 92]. These technologies are often trained on datasets which are unsuitable for deployment in occupational settings[9, 12, 16, 101]. Developers may also create technologies that collect sensitive private information about workers but, given the inherent vulnerabilities of specific sensing modalities, are unable to prevent data leakages and function creep[46, 64, 95]. Moreover, in deployment, these technologies — while generally unreliable — work especially poorly for some groups of workers (e.g., those with disabilities [75, 98]), leading to representation and allocation harms[1, 3, 132] When these technologies are designed to provide management with information about workers but fail to provide workers with the means to access their own data or challenge the inaccurate determinations made by these systems, workers are at risk of facing social system harms associated with asymmetric power relations[69, 89]. When managers deploy these systems to promote worker well-being but deny workers opportunities to opt out of these programs, workers face interpersonal harms[28]. Similarly, AER technologies, which replace functions that were traditionally the responsibility of human management, like performance evaluations, may lead to alienation and intensification of workers' labor[16, 107, 118].

Our second research question concerned the harms workers experience and anticipate due to managerial use of AI-powered biometric work monitoring technologies. We found that worker experience of these technology in the use phase is mediated by their perceived vulnerability (e.g. as a member of a disenfranchised group) as well as their understanding of the reasons motivating managerial deployment of AI-powered biometric work monitoring technologies[23, 39, 98, 124]. Workers required to use these systems consider how their data might be used in ways which reveal private information, and potentially used to disadvantage them[30, 51]. For example, workers subject to AER technologies may go to great lengths to keep their emotions hidden and may engage in additional labor to avoid unfavorable evaluations from these systems[15]. In some cases, workers may internalize monitoring and engage in self-regulating behaviors even when they are not explicitly monitored [15, 40, 118].

4.1 Application of Taxonomy to Case Studies

Through the lens of three case studies, we show how the potential for harm manifests at each stage of our process model. This approach illustrates that problems often overlap and that a holistic understanding of the development and adoption process is needed to fully understand the harm these systems pose to workers if left unchecked.

Professional Sports Industry. The professional sports industry presents a mature, large-scale, and highly visible example of deploying AI-BWM technologies. We draw on this example to highlight that while these systems can be used to benefit athletes, they may also facilitate exploitative practices when worker agency and privacy are not considered. When deployed in ways that do not allow workers to understand or challenge what is being sensed and inferred about them, they may exacerbate power asymmetries and alienate workers, resulting in harm.

AI-BWM technologies are developed to track athletes' vital signs, and computer vision technology can analyze their behaviors and movements. For example, Burke [17] proposes an application of deep neural networks to estimate quarterback decision-making, describing the proposed model as a mechanism to assess and understand quarterback decision-making quantitatively–information they claim provides value to teams, the media, and fans alike. Another paper elicits one sports scientist's justification for the need for AI-powered biometric monitoring technology, describing it as critical for asset management[58]. Other applications of AI-BWM technologies include fitness and injury tracking, which can be used to inform coaching strategies such as the appropriate duration of practice sessions in order to prevent injuries related to overtraining, which could potentially be career extending[53]. Karkazis and Fishman [76] describe how Professional sports organizations may use AI-BWM as motivational tools to modify athletes' behavior, detect laziness, or deter complacency, which may result in an intensification of their labor. When these technologies are deployed in ways that constrain players' autonomy related to behaviors both on and off-the-field [38, 112], or in ways that collect private information about them and share with third parties, athletes are at risk of interpersonal harms like privacy violations and diminished agency.

In 2020, the U.S. National Football League (NFL) partnered with Amazon Web Services (AWS) to collect players' biometric data for the purposes of generating player statistics [119]. The Next-Gen Stats program uses machine learning algorithms to analyze player data in the cloud to compare players and generate statistics like what player has the fastest sprint in the league [ibid]. Deploying these systems may result in alienation when the classification labels used to determine an athlete's performance either distort or fail to capture the entirety of that athlete's performance[58]. Allocation harms may arise when incomplete representations of athletes' performance (based on prior performance or target a limited set of metrics) are used as a replacement for coaches' experience and judgment when deciding to field certain players over others [58, 112].

Additionally, predictive analytics may be used to predict the likelihood that a player will be able to complete a play based on past performance and give coaches suggestions on what decision they should make regarding the team's next action[17, 112]. One paper describes worker confusion about the meaning of metrics used to evaluate their performance, which the authors argue is one indication of how workers are managed through power asymmetries, whereby managers possess information about athletes' performance which they do not have access to[57]. For example, Greene et al., [58] describe how a softball coach directed their team to be "92% routine on defense" and how one player felt compelled to satisfy this demand without actually knowing what it meant.

Construction Industry. The construction industry provides an example of a high-danger setting where the use of AI-BWM technologies may in some cases provide life-saving benefits.

For example, devices that monitor skin conductance might be used to measure heat exhaustion and physical strain [121]. Guo et al.[59] develop a computer vision system designed to detect violations ranging from unsafe behaviors to potential catastrophic actions that might lead to a severe accident involving many casualties and property loss. One paper proposes the use of brainwave and pulse data as a means for identifying cumulative fatigue, physical vitality, and autonomic nerve health in construction workers to evaluate them for risk factors related to safety consciousness and safety commitment. The authors describe how this approach can be implemented using big data, artificial intelligence, and sensed bio-signals in real-time [111]. Cai et al. describe an algorithm designed to estimate construction workers' visual focus of attention to interpret their intentions and predict their movements[18]. Each of these examples demonstrates how AI-BWM can be used to protect workers from dangerous environments and situations. However, when workers are not made aware of what data is collected or given guarantees about how their data is being used, they may reject these technologies. For example, a study analyzing surveys from construction workers across 15 independent contracting firms in California found that nearly half of the workers were unwilling to adopt safety wearables, such as attention-tracking smart helmets [51]. Their rejection of these tools — marketed as potentially "life-saving" — was rooted in concerns that the technology might reveal private information about their physical well-being and or possibly be used to measure their productivity instead of protecting them from safety risks [ibid]. In other words, despite the fact that construction work is hazardous (accounting for nearly one-fifth of all workplace deaths in the U.S. in 2021 [109]), workers weighed concerns over facing harms like privacy violations, alienation and the intensification of their labor over the potential safety benefits provided by these devices.

The research literature suggests that different outcomes are possible when these technologies are implemented with consideration for worker rights and dignity and guarantees about how the technology will be used fairly [67]. For example, Killoran et al., [81]describe how BHP Group Limited — the largest mining company in the world — utilizes smart helmets that use electroencephalogram (EEG) brainwave monitoring technology to track worker fatigue and drowsiness to monitor their safety. They explain how the company was able to deploy the AI-BWM in a way that was transparent, respectful, and understanding of worker concerns and their role in the decision-making process. Ostensibly, this case provides an example of AI-BWM providing value to both workers and their employers.

Office Work. Offices represent the fastest-growing applications for AI-BWM technologies for purposes such as candidate screening, worker performance monitoring, and well-being sensing[28, 79, 116] This case provides an example of biometric data collection to extend managerial control and enforce worker compliance to rigid standards and behaviors for cost-savings and reducing labor inefficiencies[49, 102].

Office workers may receive fitness wearables as part of corporate wellness initiatives designed to encourage the adoption of healthier lifestyles. Employers implement these programs for the purposes of lowering costs associated with medical insurance and extension illness-related absenteeism[43, 94, 102]. However, when managers collect information for purposes beyond what workers consent to or in ways that disadvantage them, they are put at risk of harms[28, 106, 107, 114].

For example, In 2019, the AARP sued Yale University for requiring workers to share their personal health data with the school or pay a $1300 yearly fee as part of its Health Expectations initiative. This program gave third parties access to information related to workers' health insurance claims, which used to discriminate against elderly, disabled, and chronically ill workers. One worker was forced to disclose private information about a mastectomy operation to multiple people in order to avoid the program's penalties[129]. As a result, these workers were pressured to disclose their private information and were victims of privacy violations. Additionally, their dignity and agency regarding the ownership of their data was compromised [47]. Ultimately, the controversy resulted in a class action lawsuit against the school. This case demonstrates that neither side benefits when managers collect sensitive information without regard for workers.

In examining the impacts of AI-powered biometric work monitoring technologies in the workplace, our research focused on two primary questions: first, the potential harms to workers stemming from decisions made during the development and deployment of these technologies, and second, the outcomes experienced by workers interacting with these systems. Based on our literature review, we synthesize broad responses to these questions below.

4.2 Opportunities for Future Work

When used responsibly, AI-BWM technologies can contribute to worker health and safety. However, our findings suggest that in many current applications of these technologies, the limited benefits skew towards employers, and put workers at risk of harms that threaten their privacy, well-being, and access to fair and unbiased employment. This is largely attributable to the fact that the majority of workers subject to AI-BWM do not have mechanisms or legal protections to make sense of how their data is collected and used [11]. Based on our review of literature, we identify a number of opportunities for future research in this area. These ideas center around worker agency and understanding in relation to AI-BWM technologies.

Workers should be informed about when AI-BWM technologies are being used in the workplace. They should also be able to consent or refuse the use of AI-BWM technologies which make critical determinations tied to their physical and mental condition, performance, and productivity. For example, workers should have the option to refuse technologies that make inferences about their private inner emotional lives, especially in light of the fact that these systems are often inaccurate and may not provide information related to the demands of a particular job [28, 34, 79, 118]. More research is needed to understand how workers can be supported to make informed decisions when determining whether the conditions of employment under these systems is in alignment with their values, personal comfort levels, and privacy expectations.

Workers' voices should be heard in the design, development and training of these systems. This inclusion of worker voices will contribute to positive and equitable outcomes for both workers and employers[67, 81]. Our literature review identifies several harms experienced by workers ranging from alienation and the denial of opportunity to the intensification of their labor as they attempt to avoid negative evaluations. Awareness of these harms and how they interact can be used by design and development teams to anticipate the effects of these technologies during development and prior to adoption.

Our process model provides a map for stakeholders to anticipate the tensions surrounding the use of these technologies and how harms caused by their use might manifest across occupational contexts and phases of development. For example, when anticipating the impact of brainwave monitoring systems on office workers, our process model could be used to understand the technical factors which contribute to worker alienation — e.g., the surveillance, aggregation, and physiognomic privacy risks inherent to many AI technologies [33, 86]. The model could then be used to assess how social factors such as opaque managerial practices surrounding the technology's use might exacerbate worker's negative experiences rooted in their concerns about privacy. Finally, after devising strategies for redress, the process model can be used plan how the technology will be monitored in the future, for example by highlighting its differential impact on specific demographic groups.

We hope that the research community can provide viable case studies of how a number of stakeholders — including technology developers, managers, workers, policy advocates, and the public — ground their product and policy initiatives on the acceptable development, deployment, and uses of AI-BWM technology. We find that in particular, more work is needed to understand how the design of AI-powered biometric work monitoring technologies shapes managerial perceptions of its affordances and workers' mental models about its purpose and potential to harm them. More research is also needed to determine whether the introduction of these systems has a lasting effect on organizational behavior and worker psychology. For example, in what contexts might managers attempt to exert more control over workers' personal lives? Or if accustomed to continuous monitoring, do workers alter their behavior due to a lingering sense of surveillance outside of the workplace? Shared understandings about the purposes and limitations the systems then creates a basis for negotiation and broader discussions on AI-BWM.

5 CONCLUSION

In analyzing the research literature on AI-powered biometric monitoring through the well-defined lens of socio-technical harm, further stratified across the deployment life-cycle of these technologies, we established a novel taxonomy of workplace BPM harms. We find that developer decisions in creating AI-BWM technologies put workers at risk of several socio-technical harms, which managerial decisions in deploying these technologies across industries may compound. Our research contributes to the field of critical AI studies by highlighting the potential for harm to occur when the impact of these technologies on workers is not considered during the development and deployment of these technologies. Our approach highlights critical issues in the development and deployment of these technologies. It demonstrates a need for more research examining the cascading effects of these technologies throughout the process model and to better understand the differential impact of these technologies across different demographic groups, job classifications, and occupational settings.

ACKNOWLEDGMENTS

This work was generously funded, in part, by the National Science Foundation Secure and Trustworthy Cyberspace Program through grants #2126066 and #2316768. We thank William Agnew and Anna Fang for the feedback they provided on drafts of this paper, as well as our anonymous reviewers for being generous with their time.

REFERENCES

[1] M. Abbasi, S.A. Friedler, C. Scheidegger, and S. Venkatasubramanian. 2019. Fairness in representation: Quantifying stereotyping as a representational harm. *SIAM International Conference on Data Mining, SDM 2019* (2019), 801–809. https://doi.org/10.1137/1.9781611975673.90 cited By 27.

[2] I. Ajunwa, K. Crawford, and J. Schultz. 2017. Limitless worker surveillance. *California Law Review* 105, 3 (2017), 735–776. https://doi.org/10.15779/Z38BR8MF94 cited By 139.

[3] I. Ajunwa and D. Greene. 2019. Platforms at work: Automated hiring platforms and other new intermediaries in the organization of work. *Research in the Sociology of Work* 33 (2019), 61–91. https://doi.org/10.1108/S0277-283320190000033005 cited By 42.

[4] M. Al-Hitmi and K. Sherif. 2018. Employee perceptions of fairness toward IoT monitoring. *VINE Journal of Information and Knowledge Management Systems* 48, 4 (2018), 504–516. https://doi.org/10.1108/VJIKMS-01-2018-0007 cited By 9.

[5] R.E. Angelia, R.S. Pangantihon, and J.F. Villaverde. 2021. Wireless Sensor Network for Safety Tracking of Construction Workers through Hard Hat. *ACM International Conference Proceeding Series* (2021), 412–417. https://doi.org/10.1145/3467707.3467769 cited By 8.

[6] M. Anteby and C.K. Chan. 2018. A self-fulfilling cycle of coercive surveillance: Workers' invisibility practices and managerial justification. *Organization Science* 29, 2 (2018), 247–263. https://doi.org/10.1287/orsc.2017.1175 cited By 81.

[7] J. Aroles, N. Mitev, and F.-X. de Vaujany. 2019. Mapping themes in the study of new work practices. *New Technology, Work and Employment* 34, 3 (2019), 285–299. https://doi.org/10.1111/ntwe.12146 cited By 92.

[8] S. Bankins, A.C. Ocampo, M. Marrone, S.L.D. Restubog, and S.E. Woo. 2024. A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior* 45, 2 (2024), 159–182. https://doi.org/10.1002/job.2735 cited By 29.

[9] L.F. Barrett, R. Adolphs, S. Marsella, A.M. Martinez, and S.D. Pollak. 2019. Emotional Expressions Reconsidered: Challenges to Inferring Emotion From Human Facial Movements. *Psychological Science in the Public Interest* 20, 1 (2019), 1–68. https://doi.org/10.1177/1529100619832930 cited By 830.

[10] R. Bavaresco, H. Arruda, E. Rocha, J. Barbosa, and G.-P. Li. 2021. Internet of Things and occupational well-being in industry 4.0: A systematic mapping study and taxonomy. *Computers and Industrial Engineering* 161 (2021). https://doi.org/10.1016/j.cie.2021.107670 cited By 17.

[11] A. Bernhardt, L. Kresge, and R. Suleiman. 2023. The Data-Driven Workplace and the Case for Worker Technology Rights. *ILR Review* 76, 1 (2023), 3–29. https://doi.org/10.1177/00197939221131558 cited By 6.

[12] C. Bisogni, F. Hao, V. Loia, and F. Narducci. 2022. Drowsiness Detection in the Era of Industry 4.0: Are We Ready? *IEEE Transactions on Industrial Informatics* 18, 12 (2022), 9083–9091. https://doi.org/10.1109/TII.2022.3173004 cited By 4.

[13] J. Blasco, T.M. Chen, J. Tapiador, and P. Peris-Lopez. 2016. A survey of wearable biometric recognition systems. *Comput. Surveys* 49, 3 (2016). https://doi.org/10.1145/2968215 cited By 110.

[14] Heather Boushey and Kevin Rinz. 2022. Blocking the Low Road and Paving the High Road: Management Practices to Improve Productivity. https://www.whitehouse.gov/cea/written-materials/2022/04/06/blocking-the-low-road-and-paving-the-high-road-management-practices-to-improve-productivity/. Accessed: 2023-05-01.

[15] P. Bowell, G.J.D. Smith, E. Pechenkina, and P. Scifleet. 2023. 'You're walking on eggshells': exploring subjective experiences of workplace tracking. *Culture and Organization* 29, 6 (2023), 471–490. https://doi.org/10.1080/14759551.2023.2198717 cited By 0.

[16] K.L. Boyd and N. Andalibi. 2023. Automated Emotion Recognition in the Workplace: How Proposed Technologies Reveal Potential Futures of Work. *Proceedings of the ACM on Human-Computer Interaction* 7, 1 CSCW (2023). https://doi.org/10.1145/3579528 cited By 8.

[17] Brian C. Burke and Espn Analytics. 2019. DeepQB: Deep Learning with Player Tracking to Quantify Quarterback Decision-Making & Performance. (2019). https://api.semanticscholar.org/CorpusID:212412002

[18] J. Cai, L. Yang, Y. Zhang, S. Li, and H. Cai. 2021. Multitask Learning Method for Detecting the Visual Focus of Attention of Construction Workers. *Journal of Construction Engineering and Management* 147, 7 (2021). https://doi.org/10.1061/(ASCE)CO.1943-7862.0002071 cited By 8.

[19] T. Calvard. 2019. Integrating social scientific perspectives on the quantified employee self. *Social Sciences* 8, 9 (2019). https://doi.org/10.3390/socsci8090262 cited By 9.

[20] L. Camarena and F. Fusi. 2022. Always Connected: Technology Use Increases Technostress Among Public Managers. *American Review of Public Administration* 52, 2 (2022), 154–168. https://doi.org/10.1177/02750740211050387 cited By 22.

[21] L. Cameron, A. Christin, M. Ann Devito, T.R. Dillahunt, M. Elish, M. Gray, R. Qadri, N. Raval, M. Valentine, and E. Anne Watkins. 2021. This Seems toWork: Designing Technological Systems with the Algorithmic Imaginations of Those Who Labor. *Conference on Human Factors in Computing Systems - Proceedings* (2021). https://doi.org/10.1145/3411763.3441331 cited By 10.

[22] Alice Caporale, Francesco Gabriele Galizia, Lucia Botti, Cristina Mora, et al. 2022. Thermal comfort prediction of aged industrial workers based on occupants' basal metabolic rate. 65 (2022), 120–129. https://doi.org/10.54941/AHFE1002666

[23] D. Carpenter, M. Maasberg, C. Hicks, and X. Chen. 2016. A multicultural study of biometric privacy concerns in a fire ground accountability crisis response system. *International Journal of Information Management* 36, 5 (2016), 735–747. https://doi.org/10.1016/j.ijinfomgt.2016.02.013 cited By 9.

[24] D. Carpenter, A. McLeod, C. Hicks, and M. Maasberg. 2018. Privacy and biometrics: An empirical examination of employee concerns. *Information Systems Frontiers* 20, 1 (2018), 91–110. https://doi.org/10.1007/s10796-016-9667-5 cited By 33.

[25] A. Channa, N. Popescu, J. Skibinska, and R. Burget. 2021. The rise of wearable devices during the COVID-19 pandemic: A systematic review. *Sensors* 21, 17 (2021). https://doi.org/10.3390/s21175787 cited By 90.

[26] É. Charbonneau and C. Doberstein. 2020. An Empirical Assessment of the Intrusiveness and Reasonableness of Emerging Work Surveillance Technologies in the Public Sector. *Public Administration Review* 80, 5 (2020), 780–791. https://doi.org/10.1111/puar.13278 cited By 40.

[27] Y. Cheng, H. Meng, and Y. Tan. 2022. Research on fatigue detection System based on Facial Feature Recognition in big Data environment. *Proceedings of SPIE - The International Society for Optical Engineering* 12348 (2022). https://doi.org/10.1117/12.2641454 cited By 1.

[28] S. Chowdhary, A. Kawakami, M.L. Gray, J. Suh, A. Olteanu, and K. Saha. 2023. Can Workers Meaningfully Consent to Workplace Wellbeing Technologies? *ACM International Conference Proceeding Series* (2023), 569–582. https://doi.org/10.1145/3593013.3594023 cited By 4.

[29] H. Claure, S. Kim, R.F. Kizilcec, and M. Jung. 2023. The social consequences of Machine Allocation Behavior: Fairness, interpersonal perceptions and performance. *Computers in Human Behavior* 146 (2023). https://doi.org/10.1016/j.chb.2022.107628 cited By 3.

[30] S. Corvite, K. Roemmich, T.I. Rosenberg, and N. Andalibi. 2023. Data Subjects' Perspectives on Emotion Artificial Intelligence Use in the Workplace: A Relational Ethics Lens. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW1 (2023). https://doi.org/10.1145/3579600 cited By 0.

[31] W.A. Cram, M. Wiener, M. Tarafdar, and A. Benlian. 2022. Examining the Impact of Algorithmic Control on Uber Drivers' Technostress. *Journal of Management Information Systems* 39, 2 (2022), 426–453. https://doi.org/10.1080/07421222.

2022.2063556 cited By 35.

[32] S. Das, H.-P.H. Lee, and J. Forlizzi. 2023. Privacy in the Age of AI. *Commun. ACM* 66, 11 (2023), 29–31. https://doi.org/10.1145/3625254 cited By 0.

[33] Sauvik Das, Hao-Ping (Hank) Lee, and Jodi Forlizzi. 2023. Privacy in the Age of AI. *Commun. ACM* 66, 11 (oct 2023), 29–31. https://doi.org/10.1145/3625254

[34] V. Das Swain, L. Gao, W.A. Wood, S.C. Matli, G.D. Abowd, and M. De Choudhury. 2023. Algorithmic Power or Punishment: Information Worker Perspectives on Passive Sensing Enabled AI Phenotyping of Performance and Wellbeing. *Conference on Human Factors in Computing Systems - Proceedings* (2023). https://doi.org/10.1145/3544548.3581376 cited By 9.

[35] A. De Keyser, Y. Bart, X. Gu, S.Q. Liu, S.G. Robinson, and P.K. Kannan. 2021. Opportunities and challenges of using biometrics for business: Developing a research agenda. *Journal of Business Research* 136 (2021), 52–62. https://doi.org/10.1016/j.jbusres.2021.07.028 cited By 22.

[36] G. Deshmukh, A. Khuspe, R. Kadam, A. Kamble, and A. Phalke. 2023. Survey on Driver Fatigue Detection Using Sensors, Big Data Analytics and Machine Learning Techniques. *Smart Innovation, Systems and Technologies* 311 (2023), 81–90. https://doi.org/10.1007/978-981-19-3571-8_10 cited By 1.

[37] S.K. Deshpande and K. Evans. 2020. Expected hypothetical completion probability. *Journal of Quantitative Analysis in Sports* 16, 2 (2020), 85–94. https://doi.org/10.1515/jqas-2019-0050 cited By 8.

[38] Tristan A Dietrick. 2020. Biometric Monitoring Devices: Modern Solutions to Protecting Athletes' Data Privacy. *Pitt. J. Tech. L. & Pol'y* 21 (2020), 61. https://doi.org/10.5195/TLP.2021.245

[39] C. Doberstein, É. Charbonneau, G. Morin, and S. Despatie. 2022. Measuring the Acceptability of Facial Recognition-Enabled Work Surveillance Cameras in the Public and Private Sector. *Public Performance and Management Review* 45, 1 (2022), 198–227. https://doi.org/10.1080/15309576.2021.1931374 cited By 10.

[40] Upol Ehsan, Ranjit Singh, Jacob Metcalf, Mark O. Riedl, Upol Ehsan, Ranjit Singh, Jacob Metcalf, and Mark O. Riedl. 2022. The Algorithmic Imprint. (2022). https://doi.org/10.1145/3531146.3533186

[41] A. El Ali, R. Zwitser, L. Ashby, P. Cesar, and A.M. Webb. 2019. Uncovering perceived identification accuracy of in-vehicle biometric sensing. *Adjunct Proceedings - 11th International ACM Conference on Automotive User Interfaces and Interactive Vehicular Applications, AutomotiveUI 2019* (2019), 327–334. https://doi.org/10.1145/3349263.3351506 cited By 2.

[42] H.A. Elfenbein and N. Ambady. 2002. Predicting workplace outcomes from the ability to eavesdrop on feelings. *Journal of Applied Psychology* 87, 5 (2002), 963–971. https://doi.org/10.1037/0021-9010.87.5.963 cited By 135.

[43] K. Esmonde. 2021. 'From fat and frazzled to fit and happy': governing the unhealthy employee through quantification and wearable technologies. *Qualitative Research in Sport, Exercise and Health* 13, 1 (2021), 113–127. https://doi.org/10.1080/2159676X.2020.1836510 cited By 5.

[44] A. Esposito, E. Braccili, F. Sgro, E. Chiarantano, M. D'Ippolito, I. Pisotta, A. Bigioni, A. Guerrieri, D. Mattia, and F. Cincotti. 2022. Attention, Boredom and Mind Wandering during a Vigilance Task: EEG and Ocular Markers. *2022 IEEE International Workshop on Metrology for Extended Reality, Artificial Intelligence and Neural Engineering, MetroXRAINE 2022 - Proceedings* (2022), 477–482. https://doi.org/10.1109/MetroXRAINE54828.2022.9967678 cited By 1.

[45] F. Feldmann, R. Seitz, V. Kretschmer, N. Bednorz, and M. Ten Hompel. 2019. Ergonomic Evaluation of Body Postures in Order Picking Systems Using Motion Capturing. *Proceedings - 2019 Prognostics and System Health Management Conference, PHM-Paris 2019* (2019), 204–209. https://doi.org/10.1109/PHM-Paris.2019.00041 cited By 3.

[46] C.O. Fernandes, S.D.J. Barbosa, F.B. Moreira, and C.J.P. De Lucena. 2017. What your EEG wearable sensors can tell about you? *ACM International Conference Proceeding Series* (2017). https://doi.org/10.1145/3109761.3158389 cited By 0.

[47] AARP FOUNDATION. 2019. AARP Foundation Files Class Action Against Yale University Challenging Workplace Wellness Penalties. https://press.aarp.org/2019-07-16-AARP-Foundation-Files-Class-Action-Against-Yale-University-Challenging-Workplace-Wellness-Penalties. (2019).

[48] S.E. Fox, V. Khovanskaya, C. Crivellaro, N. Salehi, L. Dombrowski, C. Kulkarni, L. Irani, and J. Forlizzi. 2020. Worker-centered design: Expanding HCI methods for supporting labor. *Conference on Human Factors in Computing Systems - Proceedings* (2020). https://doi.org/10.1145/3334480.3375157 cited By 34.

[49] S.E. Fox, K. Sobel, and D.K. Rosner. 2019. Managerial visions stories of upgrading and maintaining the public restroom with IoT. *Conference on Human Factors in Computing Systems - Proceedings* (2019). https://doi.org/10.1145/3290605.3300723 cited By 21.

[50] P.L. Fu, K.L. Bradley, S. Viswanathan, J.M. Chan, and M. Stampfer. 2016. Trends in Biometric Health Indices Within an Employer-Sponsored Wellness Program with Outcome-Based Incentives. *American Journal of Health Promotion* 30, 6 (2016), 453–457. https://doi.org/10.1177/0890117116658241 cited By 10.

[51] H. Fugate and H. Alzraiee. 2023. Quantitative analysis of construction labor acceptance of wearable sensing devices to enhance workers' safety. *Results in Engineering* 17 (2023). https://doi.org/10.1016/j.rineng.2022.100841 cited By 5.

[52] S. Gangadharan K and A.P. Vinod. 2022. Drowsiness detection using portable wireless EEG. *Computer Methods and Programs in Biomedicine* 214 (2022). https://doi.org/10.1016/j.cmpb.2021.106535 cited By 12.

[53] W. Ghasem, J. Valenzuela, and L.A. Saxon. 2021. Player Tracking Technology and Data for Injury Prevention in the National Football League. *Current Sports Medicine Reports* 20, 9 (2021), 436–439. https://doi.org/10.1249/JSR.0000000000000873 cited By 1.

[54] D. Giakoumis, S. Segkouli, K. Votis, I. Paliokas, E. Altsitsiadis, and D. Tzovaras. 2019. Smart, personalized and adaptive ICT solutions for active, healthy and productive ageing with enhanced workability. *ACM International Conference Proceeding Series* (2019), 442–447. https://doi.org/10.1145/3316782.3322767 cited By 15.

[55] D. Girardi, F. Lanubile, N. Novielli, and A. Serebrenik. 2022. Emotions and Perceived Productivity of Software Developers at the Workplace. *IEEE Transactions on Software Engineering* 48, 9 (2022), 3326–3341. https://doi.org/10.1109/TSE.2021.3087906 cited By 14.

[56] L. Goncales, K. Farias, B. Da Silva, and J. Fessler. 2019. Measuring the cognitive load of software developers: A systematic mapping study. *IEEE International Conference on Program Comprehension* 2019-May (2019), 42–52. https://doi.org/10.1109/ICPC.2019.00018 cited By 31.

[57] J. Grandinetti. 2019. Welcome to a new generation of entertainment: Amazon web services and the normalization of big data analytics and RFID tracking. *Surveillance and Society* 17, 1-2 (2019), 169–175. https://doi.org/10.24908/ss.v17i1/2.12919 cited By 1.

[58] D. Greene, N. Beard, T. Clegg, and E. Weight. 2023. The visible body and the invisible organization: Information asymmetry and college athletics data. *Big Data and Society* 10, 1 (2023). https://doi.org/10.1177/20539517231179197 cited By 1.

[59] S. Guo, C. Xiong, and P. Gong. 2018. A real-time control approach based on intelligent video surveillance for violations by construction workers. *Journal of Civil Engineering and Management* 24, 1 (2018), 67–78. https://doi.org/10.3846/jcem.2018.301 cited By 19.

[60] E. Hafermalz. 2021. Out of the Panopticon and into Exile: Visibility and control in distributed new culture organizations. *Organization Studies* 42, 5 (2021), 697–717. https://doi.org/10.1177/0170840620909962 cited By 52.

[61] P. Heikkilä, A. Honka, and E. Kaasinen. 2018. Quantified factory worker: Designing a worker feedback dashboard. *ACM International Conference Proceeding Series* (2018), 515–523. https://doi.org/10.1145/3240167.3240187 cited By 14.

[62] M.-T. Ho, P. Mantello, N. Ghotbi, M.-H. Nguyen, H.-K.T. Nguyen, and Q.-H. Vuong. 2022. Rethinking technological acceptance in the age of emotional AI: Surveying Gen Z (Zoomer) attitudes toward non-conscious data collection. *Technology in Society* 70 (2022). https://doi.org/10.1016/j.techsoc.2022.102011 cited By 28.

[63] J. Huber, M. Haslgrübler, M. Schobesberger, A. Ferscha, V. Malisa, and G. Effenberger. 2021. Addressing Worker Safety and Accident Prevention with AI. *ACM International Conference Proceeding Series* (2021), 150–157. https://doi.org/10.1145/3494322.3494342 cited By 1.

[64] Y. Höller and A. Uhl. 2018. Do EEG-biometric templates threaten user privacy? *IH and MMSec 2018 - Proceedings of the 6th ACM Workshop on Information Hiding and Multimedia Security* (2018), 31–42. https://doi.org/10.1145/3206004.3206006 cited By 12.

[65] N.N. Islam, N.I. Khan, M.A. Razzak, and M.N. Islam. 2021. Design, Development, and Evaluation of a Physical Exercise Monitoring and Managing System for Athletes. *ACM International Conference Proceeding Series* (2021), 443–451. https://doi.org/10.1145/3487664.3487725 cited By 0.

[66] J.V. Jacobs, L.J. Hettinger, Y.-H. Huang, S. Jeffries, M.F. Lesch, L.A. Simmons, S.K. Verma, and J.L. Willetts. 2019. Employee acceptance of wearable technology in the workplace. *Applied Ergonomics* 78 (2019), 148–156. https://doi.org/10.1016/j.apergo.2019.03.003 cited By 91.

[67] C. Jandl, S. Zafari, F. Taurer, M. Hartner-Tiefenthaler, and S. Schlund. 2023. Location-based monitoring in production environments: does transparency help to increase the acceptance of monitoring? *Production and Manufacturing Research* 11, 1 (2023). https://doi.org/10.1080/21693277.2022.2160387 cited By 4.

[68] M.H. Jarrahi, D.L. Blyth, and C. Goray. 2023. Mindful work and mindful technology: Redressing digital distraction in knowledge work. *Digital Business* 3, 1 (2023). https://doi.org/10.1016/j.digbus.2022.100051 cited By 3.

[69] M.H. Jarrahi, G. Newlands, M.K. Lee, C.T. Wolf, E. Kinder, and W. Sutherland. 2021. Algorithmic management in a work context. *Big Data and Society* 8, 2 (2021). https://doi.org/10.1177/20539517211020332 cited By 104.

[70] D. Jeske. 2022. Remote workers' experiences with electronic monitoring during Covid-19: implications and recommendations. *International Journal of Workplace Health Management* 15, 3 (2022), 393–409. https://doi.org/10.1108/IJWHM-02-2021-0042 cited By 21.

[71] Katie Johnson. 2023. A Milton resident's lawsuit against CVS raises questions about the use of AI lie detectors in hiring. https://www.boston.com/news/the-boston-globe/2023/05/22/milton-residents-lawsuit-cvs-ai-lie-detectors/. (2023).

[72] D. Joshi, G. Sharma, A. Nainwal, and V. Tripathi. 2023. An AI-Based Scientific Approach to Analyze and Predict Attritions in an Organization. *Lecture Notes*

in Networks and Systems 520 (2023), 565–573. https://doi.org/10.1007/978-981-19-5331-6_58 cited By 0.

[73] E. Kaasinen, M. Liinasuo, F. Schmalfuß, H. Koskinen, S. Aromaa, P. Heikkilä, A. Honka, S. Mach, and T. Malm. 2019. A worker-centric design and evaluation framework for operator 4.0 solutions that support work well-being. *IFIP Advances in Information and Communication Technology* 544 (2019), 263–282. https://doi.org/10.1007/978-3-030-05297-3_18 cited By 22.

[74] R. Kamal, A.J. Chemmanam, B.A. Jose, S. Mathews, and E. Varghese. 2020. Construction safety surveillance using machine learning. *2020 International Symposium on Networks, Computers and Communications, ISNCC 2020* (2020). https://doi.org/10.1109/ISNCC49221.2020.9297198 cited By 8.

[75] E.B. Kang. 2023. On the Praxes and Politics of AI Speech Emotion Recognition. *ACM International Conference Proceeding Series* (2023), 455–466. https://doi.org/10.1145/3593013.3594011 cited By 0.

[76] K. Karkazis and J.R. Fishman. 2017. Tracking U.S. Professional Athletes: The Ethics of Biometric Technologies. *American Journal of Bioethics* 17, 1 (2017), 45–60. https://doi.org/10.1080/15265161.2016.1251633 cited By 39.

[77] J. Katzman, A. Wang, M. Scheuerman, S.L. Blodgett, K. Laird, H. Wallach, and S. Barocas. 2023. Taxonomizing and Measuring Representational Harms: A Look at Image Tagging. *Proceedings of the 37th AAAI Conference on Artificial Intelligence, AAAI 2023* 37 (2023), 14277–14285. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85167994715&partnerID=40&md5=344df53573379b3fc6240ffbc1d0f6ec cited By 0.

[78] H. Kaur, D. McDuff, A.C. Williams, J. Teevan, and S.T. Iqbal. 2022. "I Didn't Know I Looked Angry": Characterizing Observed Emotion and Reported Affect at Work. *Conference on Human Factors in Computing Systems - Proceedings* (2022). https://doi.org/10.1145/3491102.3517453 cited By 22.

[79] H. Kaur, A.C. Williams, D. McDuff, M. Czerwinski, J. Teevan, and S.T. Iqbal. 2020. Optimizing for Happiness and Productivity: Modeling Opportune Moments for Transitions and Breaks at Work. *Conference on Human Factors in Computing Systems - Proceedings* (2020). https://doi.org/10.1145/3313831.3376817 cited By 37.

[80] K.C. Kellogg, M.A. Valentine, and A. Christin. 2020. Algorithms at work: The new contested terrain of control. *Academy of Management Annals* 14, 1 (2020), 366–410. https://doi.org/10.5465/annals.2018.0174 cited By 634.

[81] J. Killoran, Y.G. Cui, A. Park, P.V. Esch, A. Dabirian, and J. Kietzmann. 2023. Implementing Behavioral Biometrics With TRUST. *IT Professional* 25, 1 (2023), 13–16. https://doi.org/10.1109/MITP.2023.3236532 cited By 3.

[82] N. Kosmyna and P. Maes. 2019. AttentivU: A Biofeedback Device to Monitor and Improve Engagement in the Workplace. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* (2019), 1702–1708. https://doi.org/10.1109/EMBC.2019.8857177 cited By 0.

[83] N. Kosmyna and P. Maes. 2019. Attentivu: An EEG-based closed-loop biofeedback system for real-time monitoring and improvement of engagement for personalized learning. *Sensors (Switzerland)* 19, 23 (2019). https://doi.org/10.3390/s19235200 cited By 35.

[84] J.L. Kröger, P. Raschke, and T.R. Bhuiyan. 2019. Privacy implications of accelerometer data: A review of possible inferences. *ACM International Conference Proceeding Series* (2019), 81–87. https://doi.org/10.1145/3309074.3309076 cited By 34.

[85] S. Kurundkar, K.M. Bhure, A.D. Kamath, A.J. Tyagi, A. Barde, and A.A. Pimpalgaonkar. 2023. Smart Mining Helmet with Body Vitals and Location Tracking. *Proceedings of the International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics, ICIITCEE 2023* (2023), 30–33. https://doi.org/10.1109/IITCEE57236.2023.10090871 cited By 0.

[86] Hao-Ping Lee, Yu-Ju Yang, Thomas Serban von Davier, Jodi Forlizzi, and Sauvik Das. 2023. Deepfakes, Phrenology, Surveillance, and More! A Taxonomy of AI Privacy Risks. *arXiv preprint arXiv:2310.07879* (2023).

[87] M.K. Lee. 2018. Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data and Society* 5, 1 (2018). https://doi.org/10.1177/2053951718756684 cited By 513.

[88] M.K. Lee, D. Kusbit, E. Metsky, and L. Dabbish. 2015. Working with machines: The impact of algorithmic and data-driven management on human workers. *Conference on Human Factors in Computing Systems - Proceedings* 2015-April (2015), 1603–1612. https://doi.org/10.1145/2702123.2702548 cited By 473.

[89] K.E.C. Levy. 2015. The Contexts of Control: Information, Power, and Truck-Driving Work. *Information Society* 31, 2 (2015), 160–174. https://doi.org/10.1080/01972243.2015.998105 cited By 122.

[90] Q. Li, K.K.H. Ng, S.C.M. Yu, C.Y. Yiu, and M. Lyu. 2023. Recognising situation awareness associated with different workloads using EEG and eye-tracking features in air traffic control tasks. *Knowledge-Based Systems* 260 (2023). https://doi.org/10.1016/j.knosys.2022.110179 cited By 10.

[91] C.-W. Lien and S. Vhaduri. 2023. Challenges and Opportunities of Biometric User Authentication in the Age of IoT: A Survey. *Comput. Surveys* 56, 1 (2023). https://doi.org/10.1145/3603705 cited By 6.

[92] P. Liu, Y. Zhang, Z. Xiong, Y. Wang, and L. Qing. 2022. Judging the emotional states of customer service staff in the workplace: A multimodal dataset analysis. *Frontiers in Psychology* 13 (2022). https://doi.org/10.3389/fpsyg.2022.1001885 cited By 7.

[93] C. Lucia, G. Zhiwei, and N. Michele. 2023. Biometrics for Industry 4.0: a survey of recent applications. *Journal of Ambient Intelligence and Humanized Computing* 14, 8 (2023), 11239–11261. https://doi.org/10.1007/s12652-023-04632-7 cited By 4.

[94] K. Maltseva. 2020. Wearables in the workplace: The brave new world of employee engagement. *Business Horizons* 63, 4 (2020), 493–505. https://doi.org/10.1016/j.bushor.2020.03.007 cited By 43.

[95] A. Mandal and N. Saxena. 2022. SoK: Your Mind Tells a Lot About You: On the Privacy Leakage via Brainwave Devices. *WiSec 2022 - Proceedings of the 15th ACM Conference on Security and Privacy in Wireless and Mobile Networks* (2022), 175–187. https://doi.org/10.1145/3507657.3528541 cited By 3.

[96] V.M. Manghisi, M. Fiorentino, A. Boccaccio, M. Gattullo, G.L. Cascella, N. Toschi, A. Pietroiusti, and A.E. Uva. 2020. A body tracking-based low-cost solution for monitoring workers' hygiene best practices during pandemics. *Sensors (Switzerland)* 20, 21 (2020), 1–17. https://doi.org/10.3390/s20216149 cited By 11.

[97] I. Manokha. 2020. The implications of digital employee monitoring and people analytics for power relations in the workplace. *Surveillance and Society* 18, 4 (2020), 540–554. https://doi.org/10.24908/ss.v18i4.13776 cited By 24.

[98] P. Mantello, M.-T. Ho, M.-H. Nguyen, and Q.-H. Vuong. 2023. Bosses without a heart: socio-demographic and cross-cultural determinants of attitude toward Emotional AI in the workplace. *AI and Society* 38, 1 (2023), 97–119. https://doi.org/10.1007/s00146-021-01290-1 cited By 34.

[99] A. Martin and J. Voix. 2018. In-ear audio wearable: Measurement of heart and breathing rates for health and safety monitoring. *IEEE Transactions on Biomedical Engineering* 65, 6 (2018), 1256–1263. https://doi.org/10.1109/TBME.2017.2720463 cited By 60.

[100] A. McStay. 2020. Emotional AI, soft biometrics and the surveillance of emotional life: An unusual consensus on privacy. *Big Data and Society* 7, 1 (2020). https://doi.org/10.1177/2053951720904386 cited By 63.

[101] M. Merone, P. Soda, M. Sansone, and C. Sansone. 2017. ECG databases for biometric systems: A systematic review. *Expert Systems with Applications* 67 (2017), 189–202. https://doi.org/10.1016/j.eswa.2016.09.030 cited By 97.

[102] T. Mettler. 2023. The connected workplace: Characteristics and social consequences of work surveillance in the age of datification, sensorization, and artificial intelligence. *Journal of Information Technology* (2023). https://doi.org/10.1177/02683962231202535 cited By 0.

[103] A.M. Michelin, G. Korres, S. Ba'ara, H. Assadi, H. Alsuradi, R.R. Sayegh, A. Argyros, and M. Eid. 2021. FaceGuard: A Wearable System To Avoid Face Touching. *Frontiers in Robotics and AI* 8 (2021). https://doi.org/10.3389/frobt.2021.612392 cited By 19.

[104] S. Monteith, T. Glenn, J. Geddes, P.C. Whybrow, and M. Bauer. 2022. Commercial Use of Emotion Artificial Intelligence (AI): Implications for Psychiatry. *Current Psychiatry Reports* 24, 3 (2022), 203–211. https://doi.org/10.1007/s11920-022-01330-7 cited By 13.

[105] P.V. Moore. 2018. Tracking Affective Labour for Agility in the Quantified Workplace. *Body and Society* 24, 3 (2018), 39–67. https://doi.org/10.1177/1357034X18775203 cited By 44.

[106] D. Naous and T. Mettler. 2022. Mental Health Monitoring at Work: IoT Solutions and Privacy Concerns. *Communications in Computer and Information Science* 1626 CCIS (2022), 37–45. https://doi.org/10.1007/978-3-031-14832-3_3 cited By 1.

[107] G. Newlands. 2021. Algorithmic Surveillance in the Gig Economy: The Organization of Work through Lefebvrian Conceived Space. *Organization Studies* 42, 5 (2021), 719–737. https://doi.org/10.1177/0170840620937900 cited By 133.

[108] S. Nižetić, N. Pivac, V. Zanki, and A.M. Papadopoulos. 2020. Application of smart wearable sensors in office buildings for modelling of occupants' metabolic responses. *Energy and Buildings* 226 (2020). https://doi.org/10.1016/j.enbuild.2020.110399 cited By 29.

[109] U.S Bureau of Labor Statistics. 2023. Construction deaths due to falls, slips, and trips increased 5.9 percent in 2021. https://www.bls.gov/opub/ted/2023/construction-deaths-due-to-falls-slips-and-trips-increased-5-9-percent-in-2021.htm. (2023).

[110] M.J. Page, J.E. McKenzie, P.M. Bossuyt, I. Boutron, T.C. Hoffmann, C.D. Mulrow, L. Shamseer, J.M. Tetzlaff, E.A. Akl, S.E. Brennan, R. Chou, J. Glanville, J.M. Grimshaw, A. Hróbjartsson, M.M. Lalu, T. Li, E.W. Loder, E. Mayo-Wilson, S. McDonald, L.A. McGuinness, L.A. Stewart, J. Thomas, A.C. Tricco, V.A. Welch, P. Whiting, and D. Moher. 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *Systematic Reviews* 10, 1 (2021). https://doi.org/10.1186/s13643-021-01626-4 cited By 3712.

[111] H. Park, D. Ahn, K. Hosanagar, and J. Lee. 2021. Human-ai interaction in human resource management: Understanding why employees resist algorithmic evaluation at workplaces and how to mitigate burdens. *Conference on Human Factors in Computing Systems - Proceedings* (2021). https://doi.org/10.1145/3411764.3445304 cited By 29.

[112] D. Patel, D. Shah, and M. Shah. 2020. The Intertwine of Brain and Body: A Quantitative Analysis on How Big Data Influences the System of Sports. *Annals of Data Science* 7, 1 (2020), 1–16. https://doi.org/10.1007/s40745-019-00239-y

cited By 60.

[113] M. Peruzzini and M. Pellicciari. 2017. A framework to design a human-centred adaptive manufacturing system for aging workers. *Advanced Engineering Informatics* 33 (2017), 330–349. https://doi.org/10.1016/j.aei.2017.02.003 cited By 112.

[114] B. Plester, J. Sayers, and C. Keen. 2024. Health and wellness but at what cost? Technology media justifications for wearable technology use in organizations. *Organization* 31, 2 (2024), 358–380. https://doi.org/10.1177/13505084221115841 cited By 5.

[115] S. Pütz, V. Rick, A. Mertens, and V. Nitsch. 2022. Using IoT devices for sensor-based monitoring of employees' mental workload: Investigating managers' expectations and concerns. *Applied Ergonomics* 102 (2022). https://doi.org/10.1016/j.apergo.2022.103739 cited By 10.

[116] M. Raghavan, S. Barocas, J. Kleinberg, and K. Levy. 2020. Mitigating bias in algorithmic hiring: Evaluating claims and practices. *FAT* 2020 - Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (2020), 469–481. https://doi.org/10.1145/3351095.3372828 cited By 257.

[117] K. Roemmich, T. Rosenberg, S. Fan, and N. Andalibi. 2023. Values in Emotion Artificial Intelligence Hiring Services: Technosolutions to Organizational Problems. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW1 (2023). https://doi.org/10.1145/3579543 cited By 3.

[118] K. Roemmich, F. Schaub, and N. Andalibi. 2023. Emotion AI at Work: Implications for Workplace Surveillance, Emotional Labor, and Emotional Privacy. *Conference on Human Factors in Computing Systems - Proceedings* (2023). https://doi.org/10.1145/3544548.3580950 cited By 8.

[119] Malak Saleh. 2023. The NFL and Amazon are using AI to invent new football stats. https://www.engadget.com/the-nfl-and-amazon-are-using-ai-to-invent-new-football-stats-173508576.html. (2023).

[120] Mark C Schall Jr, Richard F Sesek, and Lora A Cavuoto. 2018. Barriers to the adoption of wearable sensors in the workplace: A survey of occupational safety and health professionals. *Human factors* 60, 3 (2018), 351–362. https://doi.org/10.1177/0018720817753907

[121] M. Sharma, N.M. Suri, S. Kant, and M.S. Alam. 2022. Analyzing environmental heat stress under changing work conditions: A sensor-based monitoring solution. *Human Factors and Ergonomics In Manufacturing* 32, 5 (2022), 389–405. https://doi.org/10.1002/hfm.20960 cited By 0.

[122] R. Shelby, S. Rismani, K. Henne, A. Moon, N. Rostamzadeh, P. Nicholas, N. Yilla-Akbari, J. Gallegos, A. Smart, E. Garcia, and G. Virk. 2023. Sociotechnical Harms of Algorithmic Systems: Scoping a Taxonomy for Harm Reduction. *AIES 2023 - Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society* (2023), 723–741. https://doi.org/10.1145/3600211.3604673 cited By 4.

[123] M. Soto, C. Satterfield, T. Fritz, G.C. Murphy, D.C. Shepherd, and N. Kraft. 2021. Observing and predicting knowledge worker stress, focus and awakeness in the wild. *International Journal of Human Computer Studies* 146 (2021). https://doi.org/10.1016/j.ijhcs.2020.102560 cited By 14.

[124] L. Stark, A. Stanhaus, and D.L. Anthony. 2020. "I Don't Want Someone to Watch Me While I'm Working": Gendered Views of Facial Recognition Technology in Workplace Surveillance. *Journal of the Association for Information Science and Technology* 71, 9 (2020), 1074–1088. https://doi.org/10.1002/asi.24342 cited By 39.

[125] A. Stojadinović, N. Stojanović, and L. Stojanović. 2015. Industry paper: Dynamic monitoring for improving worker safety at the workplace: Use case from a manufacturing shop floor. *DEBS 2015 - Proceedings of the 9th ACM International Conference on Distributed Event-Based Systems* (2015), 205–216. https://doi.org/10.1145/2675743.2771881 cited By 4.

[126] J. Taborri, M. Bordignon, F. Marcolin, M. Donati, and S. Rossi. 2019. Automatic identification and counting of repetitive actions related to an industrial worker. *2019 IEEE International Workshop on Metrology for Industry 4.0 and IoT, MetroInd 4.0 and IoT 2019 - Proceedings* (2019), 394–399. https://doi.org/10.1109/METROI4.2019.8792887 cited By 9.

[127] L. Tirabeni. 2023. Bounded Well-Being: Designing Technologies for Workers' Well-Being in Corporate Programmes. *Work, Employment and Society* (2023). https://doi.org/10.1177/09500170231203113 cited By 0.

[128] Guilherme Tortorella, Flavio S Fogliatto, Maneesh Kumar, Vicente Gonzalez, and Matthew Pepper. 2023. Effect of Industry 4.0 on the relationship between socio-technical practices and workers' performance. *Journal of Manufacturing Technology Management* 34, 1 (2023), 44–66. https://doi.org/10.1108/JMTM-04-2022-0173

[129] Kevin Truong. 2019. AARP Foundation files class action suit against Yale University over employee wellness program. https://medcitynews.com/2019/07/aarp-foundation-files-class-action-suit-against-yale-university-over-employee-wellness-program/. (2019).

[130] Amy Vatcha. 2020. Workplace surveillance outside the workplace: an analysis of e-monitoring remote employees. *EDITORIAL–From the Faculty Editor* 4 (2020).

[131] J. Vitak and M. Zimmer. 2023. Surveillance and the future of work: exploring employees' attitudes toward monitoring in a post-COVID workplace. *Journal of Computer-Mediated Communication* 28, 4 (2023). https://doi.org/10.1093/jcmc/zmad007 cited By 1.

[132] A. Wang, S. Barocas, K. Laird, and H. Wallach. 2022. Measuring Representational Harms in Image Captioning. *ACM International Conference Proceeding Series* (2022), 324–335. https://doi.org/10.1145/3531146.3533099 cited By 17.

[133] E.A. Watkins. 2020. Took a pic and got declined, vexed and perplexed: Facial recognition in algorithmic management. *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW* (2020), 177–182. https://doi.org/10.1145/3406865.3418383 cited By 6.

[134] N. Wouters, R. Kelly, E. Velloso, K. Wolf, H.S. Ferdous, J. Newn, Z. Joukhadar, and F. Vetere. 2019. Biometric mirror: Exploring values and attitudes towards facial analysis and automated decision-making. *DIS 2019 - Proceedings of the 2019 ACM Designing Interactive Systems Conference* (2019), 447–461. https://doi.org/10.1145/3322276.3322304 cited By 16.

[135] F.U. Zaman, M.T. Zaman, M.A. Alam, and M.G.R. Alam. 2021. Multi-modal Emotion Recognition for Determining Employee Satisfaction. *2021 IEEE Asia-Pacific Conference on Computer Science and Data Engineering, CSDE 2021* (2021). https://doi.org/10.1109/CSDE53843.2021.9718373 cited By 0.

[136] A. Zhang, A. Boltz, C.W. Wang, and M.K. Lee. 2022. Algorithmic Management Reimagined For Workers and By Workers: Centering Worker Well-Being in Gig Work. *Conference on Human Factors in Computing Systems - Proceedings* (2022). https://doi.org/10.1145/3491102.3501866 cited By 36.

[137] Michael Zhang. 2021. Canon Uses AI Cameras That Only Let Smiling Workers Inside Offices. https://petapixel.com/2021/06/17/canon-uses-ai-cameras-that-only-let-smiling-workers-inside-offices/. (2021).

[138] W. Zhao, R. Lun, C. Gordon, A.-B.M. Fofana, D.D. Espy, M.A. Reinthal, B. Ekelman, G.D. Goodman, J.E. Niederriter, and X. Luo. 2017. A Human-Centered Activity Tracking System: Toward a Healthier Workplace. *IEEE Transactions on Human-Machine Systems* 47, 3 (2017), 343–355. https://doi.org/10.1109/THMS.2016.2611825 cited By 61.

[139] G. Zhou, V. Aggarwal, M. Yin, and D. Yu. 2021. Video-based AI Decision Support System for Lifting Risk Assessment. *Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics* (2021), 275–282. https://doi.org/10.1109/SMC52423.2021.9659025 cited By 0.

[140] M. Züger, C. Corley, A.N. Meyer, B. Li, T. Fritz, D. Shepherd, V. Augustine, P. Francis, N. Kraft, and W. Snipes. 2017. Reducing interruptions at work: A large-scale field study of FlowLight. *Conference on Human Factors in Computing Systems - Proceedings* 2017-May (2017), 61–72. https://doi.org/10.1145/3025453.3025662 cited By 59.