Data Subjects' Perspectives on Emotion Artificial Intelligence Use in the Workplace: A Relational Ethics Lens

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The workplace has experienced extensive digital transformation, in part due to artificial intelligence's commercial availability. Though still an emerging technology, emotional artificial intelligence (EAI) is increasingly incorporated into enterprise systems to augment and automate organizational decisions and to monitor and manage workers. EAI use is often celebrated for its potential to improve workers' wellbeing and performance as well as address organizational problems such as bias and safety. Workers subject to EAI in the workplace are data subjects whose data make EAI possible and who are most impacted by it. However, we lack empirical knowledge about data subjects' perspectives on EAI, including in the workplace. To this end, using a *relational ethics* lens, we qualitatively analyzed 395 U.S. adults' open-ended survey (partly representative) responses regarding the perceived benefits and risks they associate with being subjected to EAI in the workplace. While participants acknowledged potential benefits of being subject to EAI (e.g., employers using EAI to aid their wellbeing, enhance their work environment, reduce bias), a myriad of potential risks overshadowed perceptions of potential benefits. Participants expressed concerns regarding the potential for EAI use to harm their wellbeing, work environment and employment status, and create and amplify bias and stigma against them, especially the most marginalized (e.g., along dimensions of race, gender, mental health status, disability). Distrustful of EAI and its potential risks, participants anticipated conforming to (e.g., partaking in emotional labor) or refusing (e.g., quitting a job) EAI implementation in practice. We argue that EAI may magnify, rather than alleviate, existing challenges data subjects face in the workplace and suggest that some EAI-inflicted harms would persist *even if* concerns of EAI's accuracy and bias are addressed.

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CCS Concepts: • **Human-centered computing** → **Empirical studies in HCI**.

Additional Key Words and Phrases: emotion artificial intelligence, emotion AI, emotion recognition, workplace, future of work, data subjects, workers, relational ethics, ethics

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1 INTRODUCTION

Emotion artificial intelligence (EAI) or automatic emotion recognition technology claims to detect and predict human emotion, affect, mood, and other interior states by applying affective computing

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and artificial intelligence techniques to a range of data (e.g., facial expressions; voice patterns and tones; body gait and gestures; text communication; biosignals) to "sense, learn about, and interact with human emotional life" [110]. As of 2022, the EAI market is approximately a $23 billion dollar global industry and is expected to grow to $43.3 billion by 2027 [53, 179]. Even Zoom, the video-conferencing powerhouse, recently announced plans to integrate emotion recognition in addition to its existing sentiment analysis features [88]. Though still a nascent technology [150], commercial adoption of EAI has spread widely in various domains including health, education, entertainment, and advertising [91, 110, 115, 125, 174]. One high-stakes context in which EAI has emerged is the workplace [99, 115, 165, 166, 169].

The Computer-Supported Cooperative Work (CSCW) and Human-Computer Interaction (HCI) scholarship have long been interested in the implications of technology integration in the workplace (e.g., [70, 124, 158]). Technological advancements have supported workplaces in digital transformations of their processes by incorporating AI to augment and automate organizational decisions and to monitor and manage workers [74, 90, 123, 132, 152]. A class of AI, EAI in particular is touted for its potential to improve corporate wellness programs (e.g., assess worker wellbeing or identify stressful workplace conditions [117, 126]), as well as to monitor and predict worker sentiment [95], monitor team performance [75, 116], and detect insider threats [128].

Scholars and advocates have questioned the validity, reliability, and accuracy of EAI's current capability to infer human emotion [18, 26, 79, 161] and have raised concerns surrounding EAI's potential to perpetuate bias along dimensions including race, gender, ability, and mental health status [115, 139, 144, 173, 188] to name a few. While important, with some exceptions [7, 99, 144, 174], much of the existing discourse leaves out data subjects'[1] perspectives and experiences. Existing research that centers data subjects identifies individual and societal risks associated with EAI use in social media [7] including the potential to amplify discrimination against marginalized groups [144] and privacy concerns regarding EAI use in educational contexts [174].

Data subjects in the workplace can be vulnerable [12, 164] to technological interventions (e.g., being subjected to EAI at work), as they may be subject to employer decisions that prioritize profitability [130] with little power to protect their own interests, raising questions about *who* EAI may serve or harm. It is, therefore, important to examine data subjects' perspectives on EAI use in the workplace as they "are better suited to recognize harm due to their epistemic privilege" [22]. Investigating data subjects' perceptions of EAI can uncover whether EAI's celebrated purposes are indeed beneficial (and to whom). Exposing EAI's potential implications can inform future decisions about EAI, and more broadly affective computing, development and use in the workplace. To this end, we address the following research questions:

- **RQ 1**: How do data subjects perceive EAI to impact them in the workplace?
- **RQ 2**: How do data subjects anticipate they might respond to the use of EAI in the workplace in practice?

We address these questions through a relational ethics lens [22]. A relational ethics lens centers the needs of those most impacted by a technology to critically examine its implications, challenging ideas of using AI to solve complex, social problems that often perpetuate harmful patterns of injustice and discrimination [22]. This approach is aligned with a growing body of scholarship [7, 23, 35, 69, 144] advocating to center the voices of those subjected to technologies in determining their impact, design, use, and regulation.

We conducted a survey with U.S. adults (N=395), partly representative of the U.S. population and oversampled for marginalized identities, a sampling approach used in past HCI scholarship

[1]Aligned with other scholars [69, 144], we use the term "data subjects" to refer to individuals whose data is used in and enables EAI and who EAI stands to impact in turn. In this study, we view participants as data subjects in the workplace.

[71]. Participants first answered vignette-based questions related to various potentially beneficial applications of EAI in the workplace. They then answered open-ended questions regarding what benefits and concerns, if any, they associated with EAI in the workplace as potential data subjects to EAI. This paper reports on our qualitative analysis of participants' open-ended text-based responses. We find that while data subjects acknowledge the potential ways EAI use in the workplace could benefit them (implied in our survey vignettes), those potential benefits are overshadowed by a myriad of potential perceived risks and harms. About 32% of participants, 71.7% of whom were participants who identified with a marginalized identity, did not deem EAI use in the workplace to be beneficial to them at all. Those that noted potential benefits (e.g., improved wellbeing, work environment, and performance and reduced bias), shared numerous concerns about the potential for employers to use EAI as a means to harm data subjects (e.g., harm wellbeing and employment status, bias and discrimination against data subjects). We found that conceptions of potential risks posed to data subjects further led to possibilities of conforming to (e.g., via emotional labor [40, 68]) or refusing EAI (e.g., quitting jobs) to mitigate EAI-inflicted harms.

We discuss 1) the wider social and institutional conditions in which public appreciation for AI (and EAI) as a solution to deep-rooted social problems masks the problems that EAI implementation can create, 2) EAI's implications for heightened power asymmetries and promoting unjust workplace outcomes, and 3) how key EAI-inflicted harms would still remain *even if* approaches to addressing concerns associated with its validity, bias, and accuracy are successful. Taken together, by centering data subjects, this work provides in-depth and empirical knowledge about EAI's social and ethical implications in a high-stakes context that has the potential to shape the future of work and workforce – an issue that is also of pressing societal importance. Indeed, the United States Office of Science and Technology Policy (OSTP) recently posted a request for information about technologies including those that provide "inference of attributes including individual mental and emotional states" to understand "stakeholders that are, or may be, impacted by their use or regulation" [151] – a discourse to which this work directly contributes.

2 LITERATURE REVIEW

In this section, we trace the foundations of EAI. We then review scholarship regarding EAI in the workplace and EAI's ethical and social implications including data subjects' attitudes toward EAI.

2.1 Emotions and the growth of emotion AI

EAI is a class of AI that is widely considered to have grown out of the field of Affective Computing, conceived by Rosalind W. Picard in 1995 to improve human interaction with technologies that can recognize and/or interact with human emotion [131]. Extending affective computing, EAI generates algorithmic automatic inferences about humans' emotional and affective states. The foundations of automatic emotion recognition can be traced back to various theories of emotion that aim to address what emotion is and how we come to know it. In 1884, American philosopher William James theorized emotion instances as secondary to the body's physiological reactions to events [84]. Separately, in 1885, Danish physician Carl Lange developed a similar theory that assumed physiological changes are antecedent to emotion. American philosopher John Dewey interpreted James and Lange's theories in a misrepresentation [17] that came to be known as the James-Lange Theory of Emotions [48]; though Dewey's James-Lange theory erroneously understood emotions as categories, rather than instances, that have distinct physiological states, the theory persisted [17, 62].

Building on biological and physiological assumptions of emotional expression, Paul Ekman studied the facial expressions of human emotions across cultures [51], and in 1999, introduced the Basic Emotion Theory. Ekman theorized that across cultures, humans universally express six basic emotions consisting of anger, disgust, fear, joy, sadness, and surprise [52]. Most EAI models classify humans' emotional expressions into basic emotion categories based on an individual's bodily expression, perpetuating Ekman's universalist assumptions and the James-Lange theory of emotion, which psychologist Barrett and colleagues have contested [18] among others. Critiques argue that emotion-adjacent research requires more careful consideration of how AI understands, responds to, and uses emotions [18].

With EAI's pervasiveness, critical scholars have argued for the importance of evaluating and attending to the assumptions encoded into and promised by EAI as emotions can vary across different identities, cultures, and backgrounds [18, 38, 86, 162, 177]. Historically, assumptions that an individual's inner states and traits can be inferred from bodily characteristics and expressions have facilitated the racist and misogynist pseudoscientific practices of physiognomy and phrenology, leading some scholars to argue that computer vision and machine learning approaches to read human emotion are "reanimations" of these harmful practices [159, 162] as they "infer or create hierarchies of an individual's body composition, protected class status, perceived character, capabilities, and future social outcomes based on their physical or behavioral characteristics" [162]. Drawing on this history, scholars argue that EAI can perpetuate harmful stereotypes and patterns of discrimination against data subjects [159, 162] including against individuals with a disability [177]. In an empirical investigation, Rhue shows that facial emotion recognition is racially biased, tagging Black faces with more negative emotions no matter how much one smiles [138]. Other forms of potential EAI-inflicted harms surfaced in past work include intrusions of privacy [7, 153], stigmatizing individuals' health conditions [115, 173] and triggering paranoia symptoms [98, 154]. However, we lack empirical investigations that provide insights into data subjects' perspectives on EAI in high-stakes contexts such as the workplace.

2.2 AI, emotion AI, and the workplace

The workplace has experienced increasingly heavy surveillance as a means to monitor and manage workers using data including personal and biometric data, social media data, Internet and email data, and location data [3, 9, 14, 45, 101, 112, 147, 148, 155, 157, 186]. In the workplace, AI and other automated systems are used as a form of surveillance [75, 95, 116, 145]. Data can then be repurposed to understand workplace culture [43], to understand and predict worker wellbeing, performance, engagement, satisfaction, and activity patterns [42, 45, 100, 101, 112, 147, 148, 155–157], to facilitate algorithmic recruitment and hiring [61, 87, 125, 134], and to improve insider threat detection [128]. Scholars have examined the social implications of AI broadly [10, 13, 31, 121, 140] and integrating AI in work [5, 59, 80, 175, 178, 185], a full review of which is outside the scope of this paper. In summary, while it is established that AI, broadly, can inflict harm in high-stakes contexts such as in criminal justice and health [31, 121, 140], investigating *E*AI's implications in particular is important as EAI infers a uniquely sensitive type of data that is vulnerable, complex, and prone to misuse [7]. For example, in social media, EAI and broadly algorithmic inferences of emotional states may be employed to monitor and infer mental health states of social media users [45, 47, 104] – information about one's emotions, mental health, or broadly affective phenomena, if inferred in the workplace, may raise questions and concerns such as discrimination, privacy, and ethics [29, 30, 115, 134]. EAI interfaces with human emotions which are core to social and private life, moderating our thoughts, behaviors, interactions, and decisions [41, 96, 184]. Additionally, the visibility and sharing of emotions and associated experiences can be consequential [8, 20, 37, 141–143].

The use of EAI and broadly algorithmic inferences of emotional and affective states surfaces ethical tensions and social implications that may vary dependent upon the various contexts in which it is deployed. For example, Chancellor et al. discuss issues with algorithmic predictions of peoples' mental and emotional states from social media data, identifying key tensions in the areas of inadequate ethical oversight, lack of scientific validity, and disparate impacts across stakeholders involved in the development, implementation, and use of such algorithms in social media [29, 30]. However, different tensions may surface in the use of AI systems that predict mental and emotional states in other contexts, especially if we center data subjects' perspectives. In this study, we focus on EAI's implications in the workplace, an environment increasingly adopting EAI [11, 63–65, 87, 90, 125, 128]. Integrating automated systems into the workplace has been in part due to the workplace being a leading stress source [60, 122]. Research has examined the causes of stress in the workplace such as work overload and role conflict [111] and the consequences of stress such as a decrease in productivity and performance [36, 92], in which employers may aim to address and mitigate tribulations that workers may face [65], for example, by analyzing worker interactions with technology [113]. As worker wellbeing can negatively impact productivity and performance [36, 92], employers are interested in EAI to better survey workers' emotional states as a means to improve worker wellbeing and work production as well as to expedite workplace decisions [11, 45, 87]. However, EAI's outputs and data subjects' self-reports of emotions in the workplace do not always align [86].

Absent from the discourse surrounding EAI use in the workplace is the perspective of those who would be subjected to it, including the benefits and harms they conceive of as a result of being subjected to EAI. Indeed, efforts to address the ethics of a technology's use begin with "a deep understanding of the potential benefits and harms of a system" [83]. Our paper contributes to this understanding by centering data subjects in the workplace through a relational ethics lens [22].

2.3 Ethical and social implications of emotion AI

Despite being framed as efficient and reliable systems [19, 88], AI ethicists argue that concerns around the "fairness, justice, and ethics of Artificial Intelligence (AI)" emerge from the "grave failures, limitations, harms, threats, and inaccuracies" of implementing AI in different domains [23]. The use of inherently limited EAI technologies to fully account for the complexities of human emotion, then, threatens to shape society in profound yet unknown ways. As such, it is important to address the ethical and social implications that emerge from the adoption of EAI.

A relational ethics lens in the context of algorithmic systems addresses and challenges harmful and unjust AI use by putting "the needs and welfare of the most impacted and marginalized at the center" [22]. To exist and function, EAI requires data subjects' data to create inferences about and potentially respond to their affective and emotional states [46, 89, 109]. However, we know little about how data subjects conceive of or would react to EAI at work. A relational ethics lens allows us to address this gap in the context of EAI in the workplace.

Outside the workplace context, scholars have recently taken steps to examine data subjects' views on EAI. U.K. surveys indicate discomfort with being subjected to EAI broadly [110]. In the social media context, data subjects have primarily negative attitudes towards EAI with concerns at the individual and societal levels [7, 69, 144]. Additionally, students have privacy concerns regarding EAI use in educational contexts [174]. Lastly, Mantello et al. conducted a survey to understand job-seekers' attitudes towards EAI and suggest that, if left unregulated, EAI may lead to increased stress among people with marginalized ethnicities, genders, and class as current EAI systems are unlikely to adequately account for human differences and particularities [99]. These studies both illustrate the importance of centering data subjects and highlight their legitimate concerns.

As applications of EAI in different domains grow, we contribute to a growing interdisciplinary discourse surrounding EAI's ethical and social implications [7, 38, 69, 110, 144, 161, 177] by examining data subjects' perspectives in the high-stakes context of the workplace.

3 METHODS

3.1 Recruitment and participation

This study draws from a dataset of U.S. adults' open-ended responses (*N*=395) collected as part of a survey studying data subjects' attitudes and perceptions of EAI. We recruited participants using Prolific, an online survey recruitment platform with a database of survey respondents pre-screened for specific criteria, allowing for recruitment of specific populations.

We developed our sample (*N*=395) in two steps. First, we collected a sample balanced for U.S. representativeness by sex, age and race/ethnicity (*N*=300) by using Prolific's representative sample feature, which automatically selects respondents with a distribution of age, sex, and race/ethnicity representative of the national population for sample sizes of at least 300. Due to the importance of accounting for marginalized communities' perspectives of EAI and aligned with relational ethics [22], we ran a separate recruitment by using Prolific's pre-screened criteria to allow us to oversample for participants who identified with mental illness(es), underrepresented genders, and people of color (*N*=455). For the qualitative analysis of open-ended questions (this paper's focus), we first randomly sampled open-ended responses from the oversampled dataset (*N*=109), which included participants who identified with at least one of the following marginalized identities: a person of color, gender minority (i.e., transgender, non-binary), and/or current or past lived experience with mental illness. We then combined the randomly sampled open-ended responses from the oversample with open-ended responses from the representative sample. Our methodological choice to oversample our representative dataset through random subsampling for people with mental illness(es), underrepresented genders, and people of color allowed us to include marginalized social groups that may be at increased risk of harm as EAI data subjects [139, 144, 188] whose perspectives may otherwise be eclipsed by a representative sample *alone*, while preserving the findings' generalizability to the sampled groups' perceptions of potential impacts of EAI use and balancing study resources with research goals [183]. We note that our goal for qualitatively analyzing the oversample was not to provide statistical results but to present themes surfacing in said analysis; we also note that in analyzing the oversample subset, we stopped observing new themes and therefore did not increase the oversample subset's size. Future work could use insights derived from this qualitative analysis to develop close-ended survey questions to determine the prevalence of findings about marginalized groups on a larger scale. After merging the representative sample and supplemented oversamples (*N*=409), we removed 14 respondents for disingenuous or blank responses and duplicates to the open-ended questions, resulting in a total of 395 analyzed responses with a representative sample of 289 participants and an oversample of 106 participants. For duplicate submissions, we preserved the participant's first submission and removed the other. Appendix B includes the full breakdown of the two samples. Appendix C includes participants' demographics.

3.2 Study design

Using factorial vignettes designed based on best practices [21, 85, 97, 102, 103, 172], participants were presented with 28 vignettes that asked them to rate their comfort level with their employer automatically detecting their emotional state from either (1) "records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it" or (2) "images or video of what you look like, based on your facial expressions" that were "recorded from your daily activities and device use," for 14 various purposes. Participants indicated their comfort level by answering each vignette using a visual analog scale (VAS) ranging from 1 (extremely uncomfortable) to 100 (extremely comfortable) – analyzing these data is outside the scope of this paper's contributions, but we provide this detail for transparency and context. To ensure respondents had a common understanding of what we meant by "emotional state," we included the following definition at the top of the survey: "Emotional state" refers to your emotions and moods, including but not limited to stress, anxiety, depression, boredom, calmness, fear, fatigue, attentiveness, happiness, sadness, disgust, surprise, and/or anger.

Purposes were informed by prior work's suggestions of purposes that people may perceive as beneficial applications of EAI and algorithms that infer emotional states (which may not be known as EAI), including to support academic research [144], detect or prevent harm to oneself or others [47, 144, 149], facilitate early detection of mental and neurological illnesses [47, 67], provide employers with increased understanding about workers at either individual and aggregate levels [45, 182], and provide more relevant and timely automated wellbeing interventions [107] with data-driven and presumably more accurate, less subjective insights about workers' mental health, emotions, and related affective phenomena [45, 86, 107, 144]. These aforementioned purposes also surface in descriptions of EAI in the workplace patents [119]. All participants saw the same vignettes in a randomized order to avoid ordering effects.

An example of a vignette presented to participants is as follows: *As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: diagnosing mental illness in employees earlier than otherwise possible.*

A complete list of vignettes and purposes for the workplace context is included in Appendix A. After completion of each vignette set, participants were asked to answer open-ended questions. These questions asked participants to describe what, if any, 1) benefits and 2) risks/concerns they associated with EAI in the workplace, and 3) aspects of their identity (broadly construed) that may have shaped their comfort with EAI in the workplace in their own perspective. This paper contributes findings from our analysis of participants' responses to these open-ended questions; as such, we provide only the necessary details about the survey's vignette portion that is relevant to the present inquiry. Though including data analysis of the survey's vignette portion can provide a quantitative underpinning, we focus on participants responses to open-ended questions to amplify their voices around their perceptions, feelings, and attitudes towards EAI use in the workplace.

We ran a pilot survey to test our design and determine whether any changes were necessary before data collection, including assessing respondent fatigue (i.e., measuring average time to complete and adding attention checks) and clarity of survey questions (i.e., adding open-ended questions that asked respondents to describe any parts of the survey they had questions about to ensure respondents interpreted survey questions in the way we meant). After we analyzed the pilot survey, we determined that no additional changes were necessary and the study design was ready for data collection.

A note on vignettes. Factorial vignettes are useful to elicit judgments and attitudes about phenomena [85]. While we designed vignettes based on real world stated purposes of EAI use in the workplace, our vignettes were speculative in the sense that we asked participants to imagine if their workplaces used the systems described in vignettes; this approach is well-established in factorial vignette designs [21, 103]. Indeed, speculation is a powerful tool for examining technologies' ethical implications [57] and uncovering whether technological designs meet the needs of those with whom they interact [187] by eliciting values toward emerging technologies such as EAI [6, 25, 27, 76, 181] where people may not be directly familiar with the technology or cognizant of being subjected to it [58], for example due to lack of transparency. The main critique of vignette-based approaches is that people may behave differently than how they say they will; however, there is evidence suggesting that people would in fact act similarly to how they imagine they would as well [81, 135].

Codebook themes	Alpha binary
Perceived potential benefits of EAI use in the workplace	0.735
Perceived potential concerns of EAI use in the workplace	0.85
Average alpha binary across relevant themes	0.7925

Table 1. Alpha binaries and average of alpha binaries of codebook themes relevant to this study

Regardless, because our goal was to surface participants' *attitudes* towards EAI use in the workplace – for which speculative vignettes are useful [181] – whether or not people *would* in practice behave the way they said they would is not a concern regarding our approach and findings. Furthermore, our vignette-based approach is aligned with algorithmic folk theory scholarship suggesting that what people *think* an algorithmic system does and how they feel about it is just as key as what the technology may *actually do* in practice [56, 180].

3.3 Analysis

We conducted iterative qualitative analysis to analyze participants' answers to three open-ended questions described in Section 3.2.

To develop a codebook, we conducted a first coding exercise on randomly selected open-ended responses to 50 out of the dataset's 395 participants' responses. Five coders trained in qualitative coding individually and independently open-coded a random subset of 50 participants' responses. They then met to discuss their codes, coding agreement, and observed themes overall. After this meeting, the last author developed an initial codebook by grouping open codes into parent codes (e.g., the parent code *benefit* was developed to capture all anticipated benefits surfaced in the analysis). In a second coding exercise, three of the five coders collaboratively iterated on the initial codebook and applied the revised codebook to a subset of another 35 randomly selected responses. Next, the three coders met with the last author to discuss their codes, resolve disagreements, and iteratively develop a finalized codebook.

Once we finalized the codebook, we established inter-rater reliability (IRR) [106] as follows. Two coders separately coded a newly selected random subset of 20 responses using the final codebook. Using functionality available in ATLAS.ti, we measured IRR with Krippendorff's alpha binary. Table 1 includes the alpha binary for the codebook themes relevant to this study and the average of the relevant alpha binary values. We established IRR after reaching a score above .75 [106], deemed as "acceptable," after two rounds of coding data and measuring IRR. To identify and resolve disagreements after the first round, the two coders met to discuss any discrepancies, shared perspectives and rationales, and reached consensus to ensure similar understanding and application of codes moving forward.

After we established IRR, we divided the remaining data among the same two coders. Though they used the established codebook in this final coding round, the two coders could add new codes to mark for discussion with the rest of the team. This choice ensured that our analysis remained open and flexible. However, no new codes surfaced in this process. After coding the remaining data, the whole research team met to identify and refine resulting themes surrounding data subjects' perceived risks and benefits associated with EAI in the workplace.

3.4 Limitations and opportunities

First, as described in Section 3.2, the survey design included open-ended questions presented to participants *after* rating their comfort being subject to EAI systems described in various vignettes. While care was taken to construct the wording of vignettes in a neutral way to the extent possible, the benefits implied by our vignettes' purposes of using EAI may have nevertheless biased participants' perceptions toward EAI in a positive way due to framing bias [1, 16, 129, 170, 171]. Conversely, it is also possible that our vignettes may have been perceived as controversial, which may have mitigated potential framing bias by provoking an immediate negative response. That said, the survey vignettes did not imply any potential risks or harms and so avoided potential (negative) priming effects when eliciting participants' concerns regarding EAI. We also note that the open-ended questions we analyzed were written in an intentionally flexible way, allowing participants to create their own conceptions of EAI's potential effects. This flexibility may have mitigated the possible influence of survey vignettes on participant perceptions. Additionally, demographic questions that could have influenced participants' responses were asked at the end of the survey.

Second, all participants regardless of their employment status and whether or not they have been subjected to EAI in the workplace are potential EAI data subjects (a group this work focuses on). That said, the majority of participants were current, former, or future employees. However, we did not collect information about *all* data subjects' characteristics that may be relevant to their perceptions of EAI (i.e., level of familiarity with distinct data types, level of literacy), as our sampling approach was constrained by the available pre-screened participant pools in Prolific and concerns of respondent fatigue. Moreover, data subjects' perceptions of EAI in the workplace may vary by factors such as industry/occupation that were not assessed in this study, and as such we do not claim that our findings are representative of workers as a whole. Future work could extend our findings such as by examining the perspectives of people who are *knowingly* subjected to EAI in the workplace, for example by conducting larger scale surveys and sampling specific sub-populations of workers to better understand how data subjects as well as work condition differences may shape perceptions of EAI.

Next, we acknowledge that by centering our study in the workplace context that is increasingly implementing EAI systems [74, 123, 132, 152], our findings may not generalize to other groups of data subjects who experience EAI use. While we present percentages to signal prevalence of marginalized participants' perceptions throughout our findings, such findings regarding marginalized groups may not generalize to all data subjects. Additionally, our findings may not be generalizable to other contexts in which EAI is/may be used such as education, healthcare, law enforcement, or criminal justice, as perceptions about technology and norms surrounding data sharing and emotional expression are contextually situated [86, 107, 118]. That said, our findings offer important insights regarding data subjects' perceptions of EAI in the high-stakes context of the workplace, and hope these insights encourage future work to explore ways in which data subjects in other domains could be impacted by EAI, as well as how data subjects' perceptions of EAI might be shaped by factors such as framing (i.e., if data subjects' perceptions of EAI may differ if the purpose for which it is used does not imply a benefit to data subjects – an effect that can encourage workers' participation in surveillance [3]).

Lastly, we note potential limitations regarding our sample and elaborate on our methodological choice to oversample the representative dataset. Oversampling is inextricably linked to representativeness in sampling. Socially dominant groups whose larger share of the population make up representative samples may obfuscate the perceptions of marginalized groups [105]. As a research study in the context of the workplace where emotion AI's data subjects (i.e., workers) have little power to consent to their interactions with this emerging technology, we felt it was important and timely to explore the perceptions of data subjects as a collective group, while ensuring that the perceptions of data subjects who identify as (1) a person of color, (2) underrepresented gender, and/or (3) living with mental illness were represented by first sampling for representativeness and then oversampling for attributes along these dimensions. While research questions examining differences in perceptions among these (and other) subpopulations are out of scope for this paper, future analysis could explore such differences.

4 FINDINGS

Notably, when asked what benefits to them, if any, they associated with EAI in the workplace, 32% of participants responded that they did not foresee *any* benefits – 71.7% of whom identified with a marginalized identity, which we define for purposes of this paper as data subjects that identified with at least one of the marginalized groups for which we oversampled: (1) person of color; (2) gender minority; (3) current or past lived experience with mental illness. For those participants that did acknowledge how EAI could potentially benefit them in the workplace, we find that EAI's potential benefits are overshadowed by a myriad of ethical and justice-related concerns that expose data subjects to potential harms. Using a relational ethics lens [22], we reveal how data subjects acknowledge potential benefits of EAI in the workplace yet fear employers' use of EAI may enact unjust and disproportionate EAI-inflicted harms to data subjects. We describe three ways data subjects perceive employers' use of EAI could potentially benefit or harm their 1) wellbeing; 2) work environment, performance, and employment status; and 3) employers' (im)partiality. Table 2 shows a breakdown of these potential impacts. Moreover, we found that as a result of these potential risks, participants foresee conforming to or refusing EAI in the workplace. Throughout the following sections, we include (1) the overall percentages of all participants who that shared each findings' theme and (2) what percentage is represented by participants who identified as having at least one marginalized identity to further amplify the voices and perspectives of marginalized participants.

In this section, we first describe findings from the large number of participants that did not perceive *any* benefit to them associated with EAI in the workplace. We then share findings organized around areas where data subjects anticipate potential benefits and risks of EAI in the workplace. We conclude by describing data subjects' potential practical responses to EAI in the workplace.

4.1 Data subjects perceiving no EAI-related benefits to them

Although participants acknowledged a variety of potential benefits of using EAI in the workplace (described in later sections), many participants reported that there would be no benefit to them at all. Even after responding to vignettes that suggested potentially beneficial workplace applications of EAI, about 32% of participants, 71.7% of whom were participants who identified with a marginalized identity (i.e., person of color, woman, transgender, non-binary, having or had a mental illness) did not note any benefit when asked to describe potential benefits they might receive from EAI in the workplace. Some participants pointedly responded with answers such as *"None"* and *"No benefit,"* while others shared that they viewed no benefit to EAI use in the workplace and, instead, raised concerns regarding how it can pose risks onto them. Participants specified a variety of concerns (outlined in later sections) including the potential for EAI use to harm their wellbeing, work environment, and employment status, and to create and amplify bias and stigma against them, especially for those with marginalized identities. Furthermore, participants expressed distrust against EAI use and anticipate conforming to or refusing its implementation in practice. For example, P103 said, *"I don't [see a benefit]. computers and such have not advanced enough to take the place of people in these things and every persons expressions and things are more subtle."* Additionally, P86, who has a mental health condition, stated, *"i don't think anything could be beneficial from the intrusion of employers into employees' personal health."* Participants such as P103 and P86 did not perceive any value to being subjected to EAI in the workplace, and their remarks point to their skepticism of the technological capabilities and employers' use of EAI. We also note that, although 32% of participants explicitly noted no benefit to EAI use at all, even participants who acknowledged a potential benefit went on to describe a myriad of potential risks that they may become exposed to.

Wellbeing Refers to whether and how employers care for data subjects' wellbeing	
Improve data subjects' wellbeing • Early health detection, diagnosis, and intervention • Increased support and awareness	**Harm data subjects' wellbeing** • Incorrect inferences of health conditions and misdiagnosis • Privacy loss
Work environment, performance, and status Describes how data could be used by employers to improve or harm the work environment, data subjects' performance, and employment status	
Improve work environment and performance • Workplace safety • Performance management	**Harm work performance and employment status** • Impair work performance • Negative employment outcomes
(Im)partiality Highlights if and how employers make partial or impartial decisions perceptions towards data subjects	
Reducing bias and stigma • Reducing bias against data subjects • Reducing stigma around data subjects' mental health and associated disclosures	**Creating and perpetuating bias and stigma** • Incorrect and inaccurate EAI-generated inferences • Bias and discrimination against data subjects • Perpetuating mental health stigma

Table 2. Breakdown of the three ways in which participants perceived employers' use of EAI to impact them

4.2 Wellbeing: employers using EAI-generated inferences to improve data subjects' wellbeing vs. harm data subjects' wellbeing

Participants' remarks pointed to how, as data subjects, they anticipated their wellbeing would be directly impacted by EAI use in the workplace. Perceptions of whether data subjects' wellbeing would be positively or adversely impacted by EAI were dependent upon the employers' use of the personal and sensitive emotional data the EAI application generated. Participants acknowledged the potential for employers to practice care when interacting with data subjects' emotion data (e.g., improving their wellbeing by identifying individuals in need of support and taking supportive action when support is needed); however, participants contrasted these potential benefits with concerns that employers would use EAI in ways that could potentially inflict harm to their wellbeing (e.g., inaccurate inferences, loss of privacy).

4.2.1 Improve data subjects' wellbeing. Producers and adopters of EAI claim to use data regarding peoples' emotional states to promote workplace and data subjects' overall wellbeing [115, 117, 126]. Resembling factorial vignettes that posited the purpose of EAI in the workplace to diagnose health conditions early, identify individuals in need of support, and provide data-driven understanding about employees, participants acknowledged EAI's potential to improve their wellbeing (e.g., early health detection, diagnosis, and intervention; increased support and awareness of data subjects' wellbeing) with the qualification *if* employers used EAI-generated inferences in ways that demonstrate care towards data subjects' wellbeing.

Early health detection, diagnosis, and intervention. 15.9% of participants, 79.4% of whom were participants who identified with a marginalized identity, noted EAI's potential to benefit them if EAI could diagnose a health condition early through health monitoring and detection. For instance, P314, who reported having a mental health condition being treated with medication, stated, *"... there are always undertones but at the same time it can detect if you really need help. Not only that but to also have your employer care about your mental health? That seems very beneficial because taking care of mental health will most likely help with performance of that individual."* P314 acknowledges how EAI in the workplace could potentially benefit her if employers used the technology in ways that provided care for her mental health, such as by detecting health conditions early (an outcome with positive consequences for one's work performance as well). P27 who was a multi-racial man looking for work, also stated, *"Anything that could diagnose cognitive decline earlier would be helpful not only to me, but to anyone with a brain. It could lead to much more positive health outcomes and a higher quality of life for those nearing retirement age,"* suggesting how participants anticipate the potential benefit of EAI aiding in the earlier diagnosis of health conditions to promote better health outcomes that may not otherwise be possible for them.

Some participants also described how early health detection and diagnosis can serve as a means to intervene in one's health conditions discovered and diagnosed by EAI. P57, who reported having a mental health condition, described EAI's potential to detect health conditions early as beneficial by providing necessary information they could use to intervene in their own wellbeing: *"Used responsibly, these could be a serious boon to mental health. If a system sees I'm having say... an OCD relapse before I do, I could take action earlier to stop it."* These examples highlight how participants acknowledge EAI use in the workplace to be potentially beneficial to them in detecting, diagnosing, and intervening in their potential health conditions which can potentially lead to an improved overall wellbeing in the workplace.

Increased support and awareness. 30.6% of participants acknowledged EAI's potential to provide the necessary information to employers to identify health conditions and provide support to manage said conditions, 82.6% of whom were participants who identified with a marginalized identity. P3, a non-binary person with a mental health condition, stated that EAI could be beneficial to them, *"if employers are fair and understanding of their worker's mental health and the importance of providing accommodations when needed...,"* illustrating how EAI may be potentially useful to data subjects if employers were to demonstrate care towards data subjects by providing resources to those in need.

P230, who disclosed having a mental health condition being treated with medication, noted how EAI could lead to potential wellbeing benefits by increasing one's self-awareness about their health, stating *"Yes, i feel like these systems would 100% benefit me, not only as a employee but also as a person.. For example, i could find more ways to cope with my bipolar depression, while at home and work."* In addition to promoting self-management through increased self-awareness, P230 further described how EAI health detection and monitoring could potentially lead to improved understanding about mental health and disabilities in the workplace as a whole, sharing *"I feel like its important for the work place to understand mental health and also disabilities, and I feel like this is amazing and so beneficial."* Here, P230 highlights the lack of understanding surrounding mental health and disabilities in the workplace, and the allure of EAI's potential to indirectly benefit data subjects by promoting data-driven understandings about mental health between data subjects and employers in the workplace.

These findings demonstrate that data subjects view EAI as a tool to potentially promote employers' understanding and awareness of data subjects' wellbeing while allowing for data subjects' self-awareness of possible health conditions and potentially providing data subjects with necessary resources and care that can improve their wellbeing. However, the potential for EAI to benefit data subjects is dependent upon employers' use of EAI-generated data that demonstrates care towards data subjects in the workplace. As the following section describes, participants described concerns of how employers' use of EAI data beyond the stated beneficial purposes could inflict harm to data subjects' wellbeing.

4.2.2 Harm data subjects' wellbeing. Despite the aforementioned potential benefits, our analysis reveals how data subjects contrasted their acknowledgement of EAI's potential to benefit their wellbeing with concerns that employers could use EAI-generated data in ways that would not demonstrate care toward data subjects, which could inflict harm to their wellbeing. Some noted the potential for negative wellbeing effects as a result of inaccurate inferences and subsequent misdiagnosed health condition(s), while others cited concerns that EAI would increase stress due to privacy loss. Therefore, many participants perceived the personal information EAI generates as irrelevant to their employers and that EAI in the workplace is contextually inappropriate.

Incorrect inferences of health conditions and misdiagnosis. 5% of participants noted that EAI use could lead to incorrect inferences of a data subjects' health condition, of whom 76.2% identified with a marginalized identity. These participants contested previous ideas of EAI use to aid in improving data subjects' wellbeing. As noted by P36 who reported having a mental health condition, *"I have a problem with the possibility of incorrectly assessing individuals. It would be a hell of a thing to get 5150*[2] *into a psych ward just because a computer thought you needed it,"* describing concerns regarding potential harms, including to one's wellbeing and autonomy, resulting from EAI's inaccurate inferences. Similarly, P84 said that EAI systems *"could easily misdiagnose my condition or make it seem as if I had a poor work experience even if that is not the case,"* illustrating concerns around how EAI could lead to both a misdiagnosis and negative assumptions towards an individual's work.

Privacy loss. 50.9% of participants, 36.7% of whom identified as having a marginalized identity, noted their concerns surrounding their privacy and how EAI use by employers could contribute to their worsened wellbeing. P96, who has a mental health condition that has not been formally diagnosed, expressed how EAI systems could *"gather sensitive information the employee wishes to be kept private, and they [EAI] just generally overstep boundaries,"* suggesting that participants consider emotion data to be personal and sensitive information and that EAI's deployment in the workplace would violate privacy boundaries that data subjects hold for their emotions in the work context. By rendering visible personal and sensitive information that one wishes to remain private, EAI may psychologically harm data subjects by inducing emotional disturbance or distress [33]. For example, P363, who disclosed having multiple health conditions, shared concerns regarding negative wellbeing implications as a result of EAI-induced privacy intrusions: *"The awareness that I am being analyzed would ironically have a negative effect on my mental health."* P363's concerns demonstrate that, despite EAI's claimed goals to infer and improve data subjects' wellbeing in the workplace [90, 115, 117, 126] as also observed in Section 4.2.1, EAI use can *"ironically"* lead to opposite effects in which data subjects' wellbeing may suffer as a result of losing control and privacy over their emotional states.

As many participants noted privacy concerns regarding EAI use, 20% therefore viewed EAI use as contextually irrelevant to employers and the workplace in general, 81% of whom identified with having a marginalized identity. P62, who has lived with anxiety and depression, noted, *"it makes me feel that it might be strange to have a system at work monitoring my mental health as these things may have nothing to do with my work, or what or how much I am accomplishing during my time at work."* P62's remarks point to how monitoring data subjects' wellbeing using EAI could

[2]The number of the section of the Welfare and Institutions Code that allows a person with a mental illness to be involuntarily detained for up to 72 hours.

generate unrelated inferences regarding their performance at work. P56, a white woman who was a full-time employee, also stated, *"It's an invasion of privacy. It's an employee's responsibility to seek out help not an employer's responsibility to pry into someone's personal life,"* demonstrating the belief that EAI is both invasive to data subjects' privacy and inappropriate for employers to attempt to improve data subjects' wellbeing. Participants noted how EAI-generated inferences are unsuitable for the workplace as it could lead to potential negative impressions of data subjects and feelings of uneasiness at and towards work, including for those living with mental health conditions. Overall, participants' remarks suggest that EAI's introduction in the workplace violates contextual integrity (i.e., by not adhering to contextually relevant and appropriate norms of information collection and sharing [118]).

Altogether, we find that participants acknowledged that employers' use of EAI could potentially improve or deteriorate data subjects' wellbeing, where either outcomes is dependent on how much employers care for, in practice, data subjects' wellbeing in the data subject-employer dynamic.

4.3 Work environment, performance, and status: improve work environment and performance vs. harm work performance and employment status

Many participants commented on how employers' use of EAI-generated inferences and associated data could improve or harm data subjects' work environment, performance, and employment status. While participants noted the potential for employers to use EAI in ways that could improve the work environment such as through maintaining a safe workplace and managing their workloads, participants contrasted these potential benefits with potential risks of employers using EAI in harmful ways (e.g., the potential for employers' use of EAI to impair their work performance, potential negative employment outcomes such as denying benefits or even termination).

4.3.1 Improve work environment and performance. EAI is touted for the possibility to enhance the workplace environment and employees' performance through purposes such as insider threat detection [128] and managing employees' work [65]. Participants acknowledged similar potential benefits, noting how employers could use EAI to improve the work environment by helping to maintain a safe work environment and improve data subjects' performance through performance management. Such conceptualizations are in conversation with survey vignettes positing EAI as a means to infer employees' risk of self-harm and harm towards others, assess employees' work performance, and alert employers when they need more support.

Workplace safety. 10.9% of participants remarked upon how EAI's inferences could be used to identify and protect people who may pose harm to themselves or others, 69.8% of whom were participants with a marginalized identity. P164 who was a woman looking for work stated, *"Personally, I think the most beneficial uses of these programs would be to detect potentially harmful/violent behavior,"* suggesting that EAI could help with sustaining a safe work environment. Some participants noted how EAI could be used to detect potential danger for both self-harm and harm posed on others. P77, a full-time employee, stated that EAI could potentially *"infer if employees could harm themselves and others"* and P391 who is looking for work stated, *"I do think in terms of safety it would be beneficial. If it's able to see if a coworkers has the potential to hurt themselves or another person I would want to know. It would prevent injury or in some cases death,"* pointing to a potential benefit of EAI to recognize potential harm and maintain safety which may, in turn, improve the workplace.

Performance management. 15.4% of participants also acknowledged the potential for employers to use EAI to improve the workplace for purposes such as assessing data subjects' performance and alerting employers when data subjects may be experiencing work overload, 75.4% of whom identified as having a marginalized identity. Some interpreted EAI as a form of performance management, suggesting how such purposes could improve data subjects' work conditions and outcomes. For example, P148 an African-American or Black man who was a full-time employee, stated *"Potentially, this system could help me when I am overrun with work and burnt out. The system could help alert my employers that I need something to improve my emotional wellbeing,"* suggesting that using EAI as part of work performance assessments could prompt employers to reduce or adjust data subjects' workloads without negative repercussions for the data subject, as implied by P148. To add, P245 stated that she has *"issues when it comes to working that could use some legitimate support. This could help [her] employer understand or at least be obligated to comply with offering that support or lenience,"* demonstrating how some participants recognize the potential for EAI use in the workplace to result in an increase in employers' support for data subjects.

Some participants noted that EAI as a performance management tool could be mutually beneficial for both data subjects and employers. As P120 described, using EAI to promote *"greater productivity in the work place"* could *"be a win-win."* A *"win-win"* in this context demonstrates how, for some participants, using EAI to identify gaps in support that data subjects may need to manage their workload and better perform, may benefit both data subjects and employers, potentially leading to improved work outcomes.

4.3.2 Harm work performance and employment status. Although many participants acknowledged how employers could theoretically use EAI in ways that improve the work environment and their performance, they also contrasted these potential benefits with concerns regarding the potential for EAI use to impair their work performance and lead to negative employment outcomes.

Impair work performance. 8.1% of participants noted how employers' use of EAI would impair their work performance, 80% of whom were participants who identified with a marginalized identity. P339 who is employed full-time, noted how *"Monitoring employee's attention or work with close scrutiny has been proven to lower productivity,"* contesting previously mentioned potential benefits of EAI use to monitor work to manage and improve data subjects' workloads and productivity. Some participants also mentioned how employers using EAI could potentially wrongly treat data subjects, deteriorating the workplace environment for data subjects. P42, who was a part-time employee, noted that employers' use of EAI could result in *"Lower self-esteem and bring embarrassment from being called out by an employer,"* pointing to how employers' EAI use could potentially harm how she performs and feels in her workplace, in contrast to promises of using EAI to promote better work conditions and outcomes.

Negative employment outcomes. 19.7% of participants expressed concerns regarding the potential for employers' use of EAI to create or intensify existing power imbalances between data subjects and their employers, which could, in turn, harm data subjects' employment status, 76.9% of whom identified with a marginalized identity. P10, who was a part-time employee, noted how EAI systems could potentially *"give a little too much power or authority to the employers,"* pointing to how she finds employers' use of EAI concerning. P115, who noted that she was looking for work, describes how EAI could give *"employers more access to personal, private data on their employees"* which could result in employers having more power over data subjects by using their *"personal, private data."*

Participants that mentioned the potential for exacerbated power imbalances were fearful of the dynamic they would have with employers if EAI were integrated into their workplace, pointing to how EAI use could potentially intensify already existing tensions in the employer-data subject relationship. For instance, P44, a full-time employee, describes how he viewed the current employer-data subject relationship in the workplace: *"The amount of control that employers already have over employees suggest there would be few checks on how this information would be used. Any 'consent' on employees is largely illusory in this context."* P44's remarks on the dynamics in the workplace highlight the power employers currently have which EAI could potentially intensify. Additionally, P44's remarks point to the potential for creating a false sense of security whereby data subjects giving consent to the use of EAI may be useless and *"illusory"* as employers could misuse EAI regardless with *"few checks"* in place.

These potential risks regarding power imbalances between data subjects and employers led 33.4% of participants, 77.3% of whom were participants who identified with a marginalized identity, to express concerns regarding employers potentially using EAI and their authority – reinforced by relying on EAI-generated inferences – as a means to make unjust employment decisions such as firing or denying benefits and promotions with implications for equal opportunity and safety. P245, who has a felony and has *"been labeled a felon [since she] got out in 2008,"* expressed concerns about what this might affect her if the system would *"block people by accidentally saying they're dangerous,"* and thereby equating having a felony with being a risk to others in the workplace, a phenomenon observed in prior work [77]. P245's remarks acutely demonstrate the existing biases she faces as someone with a felony, suggesting how using EAI in workplace safety initiatives may indeed not increase workplace safety and equal participation opportunities (or perceptions thereof) for some data subjects who already face unjust barriers in the workplace (e.g., those with a felony in their backgrounds). Whether a particular EAI system takes into account a data subject's past history or not, and whether it labels a former felon as dangerous is not our focus here, but what the concerns of a data subject in that position are. To add, P15, a full-time employee with a diagnosed mental health condition, mentioned that *"They [employers] could decide that I am no longer a good fit at work and fire me. Decide I'm not capable enough and not give me a raise, or think I'm not working enough,"* highlighting beliefs about several potential ways in which employers' use of EAI could impact data subjects' employment status. P50, also a full-time employee who has multiple health conditions, stated that *"This technology could very easily be used by employers to fire employees struggling with mental health issues or to hold them back from receiving promotions or raises. Employers could possibly use it to force employees into unpaid FMLA leave if the employer determines that the employee has mental health issues."* These examples are in stark contrast with potential benefits described earlier surrounding employers using EAI to better manage data subjects' workloads as well as to support and care for their wellbeing.

Taken together, these examples highlight participants' concerns around employers using EAI as a means to impair work performance and justify undesired employment decisions or negative and consequential perceptions of data subjects, posing harm to data subjects' employment status rather than improving their work environment or performance. Furthermore, these findings demonstrate that data subjects are wary of how employers would use EAI in practice to make high-stakes decisions, such as firing and denying them benefits.

4.4 (Im)partiality: reducing bias and stigma vs. creating and perpetuating bias and stigma

Participants noted the potential for employers to make impartial or partial decisions and perceptions when using EAI-generated inferences. We refer to (im)partiality as the degree to which employers make fair, unbiased decisions or perceptions regarding data subjects when using EAI. Participants acknowledged the potential benefit of employers using EAI in ways that demonstrate impartiality towards them such as reducing bias and removing barriers to disclosure surrounding mental health conditions. However, they also noted potential harms such as making false inferences regarding data subjects and creating and perpetuating bias and stigma against data subjects. In describing these concerns, participants highlighted their fear of employers overrelying on inaccurate and biased EAI systems.

4.4.1 Reducing bias and stigma. Research demonstrates that in general, the public's views are aligned with the popular allure of AI's potential to make unbiased and objective decisions [19, 44, 87]. Similarly, participants noted that EAI use in the workplace could lead to more unbiased decisions and perceptions (compared to traditional workplaces) concerning data subjects through reducing bias and stigma, in line with claimed purposes of implementing EAI and other algorithmic approaches to *avoid* human biases and subjectivity when assessing an employee's emotional state (i.e., through employer observations or employee self-reports), as suggested by one survey scenario.

Reducing bias against data subjects. 3% of participants acknowledged how employers could potentially use EAI to make fair and unbiased decisions and perceptions regarding them if the systems were trained and de-biased to account for differences in identities, 66.7% of whom identified with a marginalized identity. As P180 stated, EAI might be beneficial, *"assuming the software adjusts for those differences [across different identities] and still outputs correct and reliable data,"* suggesting that, the potential benefit of EAI for data subjects is contingent upon its technical accuracy and lack of bias, particularly for groups EAI is known to generate less accurate inferences for including women, disabled people, and people of color [50, 120, 138]. If the system were to reliably remove demographic biases, some participants saw its potential to mitigate the bias they experience in the workplace. As P228, a transgender East Asian woman who was looking for work, shared, *"It might benefit me if it avoids employers' human biases in making judgments so as to be more objective,"* demonstrating how the promise of objective and reliable use of EAI leads to a belief that EAI use could reduce subjectivity and bias in the workplace. Sharing how such promises of EAI to reduce human judgement and subjectivity might benefit data subjects, P194, a Black woman who reported having a mental health condition, stated that *"It may be better in getting past the common problems of discrimination in giving better readings."* These conceptions of EAI show the allure towards EAI's promises of objective and de-biased inferences to benefit data subjects by replacing human subjectivity and bias in the workplace.

Reducing stigma around data subjects' mental health and associated disclosures. 5% of participants, 80% of whom identiifed with a marginalized identity, acknowledged the potential for EAI use to help reduce stigma surrounding mental health and its disclosure in the workplace. As disclosure about mental health can often be a stigmatized topic [55, 146] with consequences including in the workplace, participants acknowledged how EAI use could potentially facilitate discussions surrounding mental health in the workplace, remove barriers to disclosure of mental health (or other health conditions) to employers, and lead to increased understanding and support for data subjects. For example, P28, who lives with multiple mental health conditions, stated, *"I think they [EAI systems] would benefit me in being able to speak about my wellbeing not directly...,"* demonstrating how EAI could potentially allow data subjects to disclose their emotional or physical states without having to directly talk about it by virtue of EAI making inferences about their health. To add, P311, a full-time employee with a mental health condition, noted the potential for EAI to aid in reducing stigma around mental health in the workplace, leading to more access to support and resources for data subjects: *"They could allow access to care that normally has a negative stigma attached to it without having to put yourself [out there.]"* These examples highlight participants' beliefs that EAI use in the workplace could potentially directly or indirectly facilitate disclosure of their mental health or wellbeing broadly which may potentially lead to employer support without risking stigmatization and bias.

Stigma, as a form of prejudice and of discriminatory nature, is associated with negative wellbeing effects [93, 94]; as such, while we include themes surrounding stigma here, we note that participants' concerns surrounding EAI's impact on increasing or reducing stigma is also relevant to EAI's potential wellbeing impacts suggested by participants, which we discuss in Section 4.2.

4.4.2 Creating and perpetuating bias and stigma. Although participants acknowledged the potential for EAI to be used in ways that could help reduce bias and stigma in the workplace, in contrast, they also raised concerns about the potential for employers to use EAI in harmful ways such as making false inferences about data subjects based on inaccurate EAI inferences, leading to bias, discrimination, and stigmatization against data subjects.

Incorrect and inaccurate EAI-generated inferences. 36% of participants noted the potential for EAI to produce inaccurate and incorrect inferences about data subjects that employers would then accept at face value, leading to partial and incorrect perceptions of data subjects, 72.7% of whom identified with a marginalized identity. P87, who was being treated for a mental health condition, described the understanding that *"all current AI systems depend heavily on their training material. They are often wrong when presented with information outside their training. It seems to me very difficult to provide a suitable large training set to cover the full gamut of human emotions,"* noting concerns regarding EAI's inability to infer all human emotions correctly. Additionally, P94, a Hispanic or Latino/a/x man employed full-time, stated that data subjects *"have just one more thing to worry about, the employer thinking the employee is suicidal or something because a system saw them make a weird facial expression,"* illustrating the belief that EAI could potentially produce inaccurate inferences regarding data subjects that employers could take as true, leading to potentially harmful consequences against them. To add, P328, a Hispanic or Latino/a/x woman employed part-time stated, *"Another concern I would have is it [EAI] being inaccurate. Or perhaps not doing enough help than they [employers] think it will. If it is so accurate in diagnosing and bringing attention problems, that might also have a negative side effect. If you were somewhat feeling okay that day but the system reads something different, it could bring attention to things that people were not thinking of in the first place and make them aware of their true emotions at an inconvenient setting."* P328's remarks point to concerns around inaccurate EAI-generated inferences about her, but also harm such as lack of control and agency around whether and when she directs attention to her internal states, even if accuracy concerns are resolved.

Bias and discrimination against data subjects. 15.9% of participants expressed concerns regarding employers using EAI in ways that could lead to bias against data subjects with a marginalized identity, disproportionately affecting data subjects along dimensions such as race, gender, class, disability, and sexuality, 85.7% of whom were participants who identified with a marginalized identity. For instance, P95, a disabled Black woman, mentioned that she would be concerned about EAI use in the workplace *"If they're [EAI systems] not programmed properly to consider race & culture."* She went on to describe how her identity as a *"poor/black/elderly/woman"* would lead to obstacles in *"getting real, honest, caring help from professionals... [and she has] to take into consideration that the bots are being programmed by people which most times, (maybe unintentional), use their bias."* P95's comments point to concerns regarding EAI's potential to perpetuate bias and discrimination against data subjects with marginalized identities and how said bias may impact the support and resources one would have access to. To add, P7, a transgender and non-binary white person, described how EAI systems could *"have the potential for both racial and gender biases, particularly against POC [people of color], women, and trans individuals. Who is deciding what expressions 'look violent' and how can one determine people as a threat just from the look on their face?..."* P7's remarks demonstrate concerns around how employers using EAI could potentially discriminate marginalized data subjects. As a result, participants noted EAI to be a potential means to take unfair actions towards marginalized groups and to justify such partial actions. P42, a white woman who was employed part-time, mentioned that *"there is already a bias in the workplace for minorities and women, these systems could be used as 'evidence' in any unjustness, or oppression, by blaming it on mental instability."* These examples point towards data subjects' concerns regarding employers using EAI to further perpetuate discrimination against marginalized data subjects in the workplace.

Perpetuating mental health stigma. 2.3% participants, 88.9% of whom were participants who identified with a marginalized identity, noted how EAI could potentially lead to perpetuating stigma of mental health and discrimination in the workplace, contrary to earlier acknowledgements of EAI reducing stigma and barriers to disclosure of mental health-related concerns in the workplace. P358, who has a formally diagnosed mental health condition stated that *"Mental health is stigmatized enough without allowing employers access to a computer program that thinks it can figure out mental health,"* implying, with skepticism about EAI's capabilities, that implementing EAI into the workplace could further stigmatize mental health.

Others described concerns surrounding being stigmatized for their accurately EAI-inferred mental health conditions. For example, P234, a Black woman with multiple mental health conditions, stated that, *"Unfortunately, there's a nasty stigma around mental health and you can be subjected to employee discrimination even though it's against the law. I can't afford to take that chance. I believe mental health is best left in the hands of medical professionals instead of employers with possible agendas."* P234's remarks demonstrate the fear of employers becoming aware of her mental health status due to EAI use, leading to stigmatization in the workplace and potentially causing her unjust harm and discrimination. These examples highlight data subjects' concerns regarding EAI in the workplace and the potential to perpetuate bias and stigma, contesting ideas of reducing bias and stigma as described in Section 4.3.1. Overall, participants who noted EAI's potential to perpetuate bias and stigma demonstrate the harms that could be posed to data subjects, especially specific groups of people such as those with marginalized and/or stigmatized identities.

All in all, to situate concerns regarding inaccuracy, stigma, and bias resulting from EAI use in the workplace, it is worth noting that 1.3% of participants also expressed concerns regarding the potential for employers to overly rely on EAI, 80% of whom identified with a marginalized identity. Participants were especially concerned with overreliance on systems that have no human input, expressed by 4.3% of participants, 67.4% of whom identified with a marginalized identity. For example, P103, a full-time employee, stated that EAI *"will be relied upon too much."* Similarly, P318 mentioned that implementing EAI would mean trusting *"employers to do the right thing too much,"* suggesting that relying on employers to effectively use EAI in supportive ways is not trivial. Employers' use of EAI systems without human input led to exacerbated concerns regarding overreliance. For example, P283, a white woman who was a full-time employee living with a mental health condition, stated that because they *"feel like computers cannot do what a human is able to do,"* employers over relying on EAI-generated inferences is problematic.

4.5 Data subjects' anticipated practical reactions to EAI use in their workplace

Participants described how they would respond to EAI if the systems were implemented into their workplace with many envisioning themselves to change their feelings or behavior, citing how they would partake in conforming to EAI expectations or rejecting the technology. Whether or not participants would actually engage in these activities in practice is difficult to know, especially with emerging technologies like EAI; however, these findings do illustrate participants' concerns regarding being subjected to EAI in the workplace.

4.5.1 Conforming. 7.6% of participants, 76.7% of whom identified with a marginalized identity, suggested that they would intentionally change their typical behavior and feelings in the workplace to conform to expectations of data subjects' behavior as prescribed by EAI, in an attempt to avoid being adversely affected by EAI. This is significant as it highlights how EAI implementation in the workplace may lead to data subjects losing control and autonomy over their own actions and emotions. For example, P360, a trans full-time employee with a mental health condition, stated, *"it would cause me to act differently than I normally do at work,"* highlighting the potential for EAI use to lead data subjects changing their behavior at work. P272, also a full-time employee, described that *"You could not be yourself and roll your eyes at your Supervisor or co-worker if you felt the urge, you would have a constant feeling that big brother is watching and you are not alone."* P272's association of EAI with "Big Brother," a fictional character from George Orwell's dystopian novel *1984* [127], highlights her fear of surveillance from higher authorities and the consequences from implementing EAI into the workplace. To add, P185, employed full-time, shared: *"It would affect me in that if I had to use the app for work, I would fake a smile or otherwise try to fool the software because I would not want my employer to know my mental state unless I wished them to,"* pointing to concerns regarding EAI use to violate data subjects' privacy, therefore changing her behavior by engaging in emotional labor [40, 68] to not provide her employer with private information about her emotional states. Similarly, P71 who is disabled and has multiple health conditions, stated that they would *"exert a massive amount of energy masking (engaging in neurotypical/expected behaviors when they aren't natural to me) even when alone in my office, which would make me very distracted and unproductive"* if EAI was implemented in the workplace. However, if they were unsuccessful, P71 continues, they could *"constantly be flagged by the software."* These remarks demonstrate the concern that conforming to EAI in the workplace may amplify negative impacts, especially on disabled data subjects, by constantly partaking in additional emotional labor to evade EAI inferences, leaving them exhausted. These examples illustrate that data subjects may live with EAI in the workplace by acting in ways that would deter the system's inferences about them or by otherwise conforming to normative workplace behavior expectations as encoded by EAI. However, participants feared how this reaction could lead to harmful impacts on their health and productivity, especially when disabled or otherwise marginalized in the workplace.

4.5.2 Refusing. 4.1% of participants who shared concerns about EAI-inflicted harms responded with feelings of distrust towards EAI technology, 62.5% of whom identified with a marginalized identity. Some stated broad feelings of distrust such as P26 who was employed full-time saying, *"I would not trust such a system."* Others explained why they felt such distrust towards EAI such as P12 who was employed part-time stating, *"I do not trust a computer program to accurately and benevolently diagnose and/or treat mental health issues. If I had a mental illness diagnosed through a computer, I would not trust that diagnosis,"* illustrating that reasons for participants' distrust included their perceptions of the technology's inability to accurately infer or diagnose health conditions.

Feelings of distrust and perceived EAI-induced risks led to anticipated refusal towards being subjected to EAI at the workplace. 3.5% of participants described that they would refuse EAI use such as by quitting their job, not accepting a job that uses such systems, or not giving consent to its use, 78.6% of whom identified with a marginalized identity. For instance, P124 who is retired stated, *"I see no possible way 'these systems' could benefit me, since I will never accept employment with any organization that uses them,"* demonstrating how some participants envisioned themselves to maintain their power and autonomy by rejecting jobs and organizations that use EAI. To add, P155 stated that, using EAI systems in the workplace, *"is an invasion of privacy that [they] would never agree to,"* further highlighting how participants would potentially reject giving consent to the use of EAI if they have the option to do so. P292, a part-time employee, also stated that if their workplace began using EAI systems, it would be a sign for them that *"it is time to find a new employer,"*. While these anticipated responses highlight negative attitudes towards being subjected to EAI at work, it is important to note that declining a job offer or quitting a job are highly privileged acts which many data subjects do not have and, therefore, would continue to work under conditions they find harmful; that is, assuming data subjects would be aware of being subjected to EAI in the workplace in the first place.

5 DISCUSSION

Data subjects' perceptions of EAI in the workplace, as we examined, challenge the dominant discourse surrounding EAI and its stated purposes to improve humans' environments and wellbeing, showing how EAI could ultimately harm the very conditions proponents of EAI claim it will improve [11, 47, 54, 87]. Centering data subjects as privileged knowers best suited to identify technological harms [22, 49], our findings suggest that EAI's potential benefits come at significant risk of harm to data subjects in the workplace: EAI could harm data subjects' wellbeing and the workplace environment just as well as it could improve it, amplify [167] the biases and stigmas it aims to mitigate, and threaten data subjects' autonomy and agency in a context where they have minimal opportunity to meaningfully consent to EAI technologies [15, 114, 137].

Our use of the relational ethics lens [22] demonstrates the generative possibilities of critical work. The following sections expand upon our findings to 1) examine wider social conditions in which public reverence for algorithmic systems as solutions masks the problems they create, 2) discuss EAI's implications for widened power asymmetries and promoting unjust outcomes in the workplace, and 3) highlight social harms from EAI that remain *in spite* of leading approaches to solve EAI's established problems.

5.1 The misleading allure of using EAI in the workplace

The attraction towards EAI as a solution to work-related problems may stem from public perceptions of AI's capability to efficiently and neutrally improve an environment [22], in tandem with the obstacles that workplaces experience and have historically experienced. For example, the workplace is an increasing source of stress resulting from issues such as work overload and role conflict [60, 111, 122] which designers and adopters of EAI may promise that the technology would alleviate [11, 87]. Of note, although our survey vignettes suggest potentially beneficial applications of EAI, as informed by prior work [47, 54, 86, 107, 144, 149, 182], nearly one third of participants did not acknowledge *any* benefit to EAI in the workplace; those that acknowledged EAI's potential benefits as implied by survey scenarios *still* contrasted them with concerns of EAI's potential to inflict harm. This is important to note as our findings could be interpreted to legitimize using EAI in the workplace by referencing potential benefits acknowledged by participants, which is not the goal of this study. Although developers, providers, and consumers (e.g., employers) of AI technology perpetuate the dominant narrative that AI (and EAI) offer objective solutions that benefit society [22, 28, 109, 161], our findings show how data subjects, the targets of EAI systems in the workplace most vulnerable to its harms [22], do not fall trap to the allure of EAI to solve work-related problems. Rather, as privileged knowers [49], data subjects contest dominant narratives surrounding EAI [11, 54, 87] with critical challenges to its purported benefits and by identifying its potential harmful effects, such as the perceived potential for negative impacts on their wellbeing, harm their work environment and employment status, and increased bias and discrimination by employers.

Data subjects' acknowledgements of the potential benefits of EAI in the workplace (e.g., to improve wellbeing, to reduce bias and stigma) exposes the obstacles that workers continue to endure to maintain their wellbeing and access equal opportunity in the workplace. Highlighting the lack of available resources to adequately meet their needs, data subjects noted how EAI could potentially mitigate these obstacles, yet they remained concerned that EAI would likely not lead to these benefits *in practice* due to potential partiality, bias, and heightened surveillance they may experience as a result of being subjected to EAI at work. This is because the human and institutional forces that foreshadow and accompany technologies' introduction shape said technologies' impact [167].

Indeed, our findings reveal how EAI may magnify, rather than alleviate, existing challenges data subjects face in the workplace. Toyama's amplification theory [167] reconciles these narratives, describing how technologies amplify the underlying structural and institutional forces that are limited in their capacity and intent to address existing inequalities and injustices in the workplace [34, 130]. Under the amplification theory, EAI's effect on the workplace is not simply additive [2, 167], moving the needle in regards to employees' wellbeing, equal access, and power relations in either positive or negative direction, but "a tool that multiplies human capacity in the direction of human intent" [167]. As past work suggests, corporate stakeholders are deficient in their commitment to address workplace conditions that hinder employees' ability to maintain and improve their wellbeing [130] and access care and justice in the workplace [34], motivated by a singular goal to maximize organizational resources "heedless of the well-being" of its employees [34]. Applying the amplification theory to our findings (i.e., unjust and detrimental employment decisions informed by EAI, widened power imbalance between employers and employees), we suggest that EAI can widen power imbalances and amplify existing injustices in its attempt to substitute EAI for organizations' missing capacity and intent to promote equity and wellbeing in the workplace.

Therefore, we suggest that the risks and harms associated with EAI in the workplace render EAI a poor and dangerous solution to address the deeper and structural issues of inadequate wellbeing support and unjust treatment in the workplace. Some problems may just not be solvable by technological interventions [4, 73].

5.2 Implications for power and justice with EAI in the workplace

If EAI amplifies the power asymmetry between employees and employers, what might that effect look like in practice? We offer insights into how data subjects in the workplace foresee potential harms and may renegotiate the terms of power in an EAI-enabled work environment that risks inflicting significant and wide-ranging harms to data subjects. Our findings suggest data subjects of EAI in the workplace anticipate how they would use their remaining power to avoid some EAI-inflicted harms by conforming to (e.g., changing emotional displays) or refusing (e.g., quitting or rejecting a job) EAI's integration in their workplace, an environment already contextually bounded by deep power asymmetries.

As a form of workplace surveillance, our findings suggest that EAI in the workplace may worsen employee wellbeing, extending prior work that has identified non-algorithmic workplace surveillance to harm workers' wellbeing and raising ethical questions in regards to workers' wellbeing and privacy in the workplace environment [14, 116, 145]. In data subjects' anticipated efforts to evade EAI's harms from extensive surveillance by conforming their outward displays of emotion to meet their job's emotional expectations, these acts would take the form of emotional labor [40, 68, 78], a term coined by Arlie R. Hochschild in 1983 to describe how people may act or display emotions to suit others' expectations [78]. In the traditional workplace, emotional labor is associated with negative consequences such as burnout, increased stress, and decreased job satisfaction [24, 133]. However, we argue that by engaging in emotional labor to bypass some EAI-inflicted harms, data subjects could be exposed to other harms posed on their actual or genuine emotional states (e.g., increased stress) as participants in this study described their anticipation to conforming to expectations placed onto them by the workplace environment. We suggest that these EAI-inflicted harms would be unjustly exacerbated for some data subjects along dimensions of industry/job, gender, race, and (dis)ability; for example, service workers [163], women [163], autistic people [82], and racial minorities [72] have higher emotional labor expectations to meet in the traditional workplace, which we expect EAI use would only reinforce.

To discuss how data subjects anticipate themselves to refuse EAI technology in the workplace altogether to avoid EAI-inflicted harms, we borrow the term *refusal* from the Feminist Data Mainfest-No, a collaboratively written set of refusals of harmful data regimes and commitments to new data futures [32]. Potential refusal strategies surfaced in our analysis included denying consent to being subjected to EAI in the workplace and rejecting or quitting a job that implements or plans to implement EAI. While potentially powerful, it is important to note that such refusal is a highly privileged act that data subjects may not be able to do in practice. Refusing EAI may risk data subjects' livelihood by leading to negative employment outcomes such as losing a job or staying unemployed. These potential unjust outcomes further emphasize the need to include data subjects in the design and implementation processes of EAI as failing to do so can disproportionately affect those who, although may wish to refuse, cannot refuse the technology in practice without facing harms to their livelihood.

As data subjects' anticipated efforts to avoid EAI-inflicted harm by conforming to or refusing the technology, we suggest the potential for EAI in the workplace to, instead, expose data subjects to unavoidable harm. Ethical and responsible EAI must square with these harmful and unjust implications [136, 144], such as by exploring how data subjects' privacy may be protected and preserved with any EAI technologies in the workplace.

5.3 More accurate and less biased EAI: then what?

EAI has been contested for qualities such as validity, accuracy, and bias [18, 138, 162] as well as privacy invasion [7]. In response, some have called for banning EAI altogether (which have not been effective to date) [39]. Others offer technical fixes in an attempt to improve EAI to make it more accurate and less biased [66, 108], which some note is inherently impossible [162, 176]. Yet, emotion AI development, scholarship, and practice continues to grow.

We posit that even if EAI's technical inaccuracy and bias concerns are somehow addressed in the future, there are still EAI-inflicted harms that increased accuracy may indeed exacerbate or that debiased systems would not actually mitigate, as highlighted by participants' concerns around potential privacy harm, conformity and emotional labor, and other perceived potential risks; that increased algorithmic accuracy may harm, rather than benefit, certain communities is echoed in prior work [168, 176], albeit not within the context of EAI. For example, more accuracy in EAI may exacerbate privacy loss concerns [69] as well as emotional labor performances, as seen in participants' concerns in conforming or resisting to EAI implementation, which may have disparate impacts. Other harms inflicted by EAI in the workplace, such as reduced wellbeing and heightened power imbalances between data subjects and employers with employers gaining more control and authority over data subjects, would still persist and may be amplified, regardless of how much more accurate and debiased future EAIs might be. As suggested in Section 5.2 in tandem with our findings highlighting participants' anticipated risks from being subjected to EAI at work, the harms EAI can inflict on data subjects in the workplace may be inescapable consequences.

In spite and as a result of efforts to mitigate or preempt EAI's established social harms, EAI's harms persist, raising the larger question of whether EAI can defensibly be implemented in the workplace *at all.*

6 CONCLUSION

Using a relational ethics lens, we investigated data subjects' perspectives regarding being subjected to EAI in the workplace. Approximately one third of data subjects did not foresee any benefit to them stemming from EAI use in the workplace. Others who acknowledged potential benefits, contrasted them with potential harms. Data subjects noted how EAI use could potentially contribute to improved wellbeing, work environment, performance, and employment status as well as reduced bias and stigmatization in the workplace; however, they also perceived the potential for employers to use EAI in ways that could lead to harms posed to data subjects (e.g., negative wellbeing effects, harm work performance and employment status, increased bias and discrimination). These potential harms further led to anticipations of how data subjects might react to the implementation of EAI in practice, noting how they would conform to or refuse it. We argue that EAI may magnify, rather than alleviate, existing challenges (e.g., wellbeing, bias) data subjects face in the workplace and suggest that some EAI-inflicted harms would persist even if EAI's contested qualities (e.g., validity, bias, accuracy) are addressed. This work makes novel empirical contributions to scholarship surrounding EAI's social and ethical implications in a high-stakes context that has the potential to shape the future of work, while also directly responding to calls by the U.S. Office of Science and Technology Policy to better understand EAI and impacted groups' perspectives on it.

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REFERENCES

[1] Idris Adjerid, Alessandro Acquisti, Laura Brandimarte, and George Loewenstein. 2013. Sleights of privacy: Framing, disclosures, and the limits of transparency. In *Proceedings of the ninth symposium on usable privacy and security*. 1–11.

[2] Philip Agre. 1998. Yesterday's tomorrow. *Times Literary Supplement* 3, 7 (1998), 98.

[3] Ifeoma Ajunwa, Kate Crawford, and Jason Schultz. 2017. Limitless worker surveillance. *Calif. L. Rev.* 105 (2017), 735.

[4] Oscar Alvarado, Elias Storms, David Geerts, and Katrien Verbert. 2020. Foregrounding Algorithms: Preparing Users for Co-design with Sensitizing Activities. In *Proceedings of the 11th Nordic Conference on Human-Computer Interaction: Shaping Experiences, Shaping Society*. 1–7.

[5] Saleema Amershi, Dan Weld, Mihaela Vorvoreanu, Adam Fourney, Besmira Nushi, Penny Collisson, Jina Suh, Shamsi Iqbal, Paul N Bennett, Kori Inkpen, et al. 2019. Guidelines for human-AI interaction. In *Proceedings of the 2019 chi conference on human factors in computing systems*. 1–13.

[6] Tawfiq Ammari, Sarita Yardi Schoenebeck, and Meredith Ringel Morris. 2014. Accessing social support and overcoming judgment on social media among parents of children with special needs. In *Eighth International AAAI Conference on Weblogs and Social Media*.

[7] Nazanin Andalibi and Justin Buss. 2020. The human in emotion recognition on social media: Attitudes, outcomes, risks. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–16.

[8] Nazanin Andalibi and Andrea Forte. 2018. Announcing pregnancy loss on Facebook: A decision-making framework for stigmatized disclosures on identified social network sites. In *Proceedings of the 2018 CHI conference on human factors in computing systems*. 1–14.

[9] Elizabeth Anderson. 2017. *Private government*. Princeton University Press.

[10] McKane Andrus and Sarah Villeneuve. 2022. Demographic-Reliant Algorithmic Fairness: Characterizing the Risks of Demographic Data Collection in the Pursuit of Fairness. *arXiv preprint arXiv:2205.01038* (2022).

[11] Neal M Ashkanasy and Catherine S Daus. 2002. Emotion in the workplace: The new challenge for managers. *Academy of Management Perspectives* 16, 1 (2002), 76–86.

[12] Benjamin Baez. 2002. Confidentiality in qualitative research: Reflections on secrets, power and agency. *Qualitative research* 2, 1 (2002), 35–58.

[13] Aparna Balagopalan, Haoran Zhang, Kimia Hamidieh, Thomas Hartvigsen, Frank Rudzicz, and Marzyeh Ghassemi. 2022. The Road to Explainability is Paved with Bias: Measuring the Fairness of Explanations. *arXiv preprint arXiv:2205.03295* (2022).

[14] Kirstie Ball. 2010. Workplace surveillance: An overview. *Labor History* 51, 1 (2010), 87–106.

[15] Kirstie S Ball and Stephen T Margulis. 2011. Electronic monitoring and surveillance in call centres: a framework for investigation. *New technology, work and employment* 26, 2 (2011), 113–126.

[16] Andrew Ballard. 2019. Framing bias in the interpretation of quality improvement data: evidence from an experiment. *International Journal of Health Policy and Management* 8, 5 (2019), 307.

[17] Lisa Feldman Barrett. 2017. *How emotions are made: The secret life of the brain*. Pan Macmillan.

[18] Lisa Feldman Barrett, Ralph Adolphs, Stacy Marsella, Aleix M Martinez, and Seth 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.
[19] Michael Bartl and Johann Füller. 2020. *The rise of emotion AI: Decoding flow experiences in sports.* Springer, Cham. 219–229 pages.
[20] Natalya N Bazarova, Yoon Hyung Choi, Victoria Schwanda Sosik, Dan Cosley, and Janis Whitlock. 2015. Social sharing of emotions on Facebook: Channel differences, satisfaction, and replies. In *Proceedings of the 18th ACM conference on computer supported cooperative work & social computing*. 154–164.
[21] Jaspreet Bhatia, Travis D Breaux, Joel R Reidenberg, and Thomas B Norton. 2016. A theory of vagueness and privacy risk perception. In *2016 IEEE 24th International Requirements Engineering Conference (RE)*. IEEE, 26–35.
[22] Abeba Birhane. 2021. Algorithmic injustice: a relational ethics approach. *Patterns* 2, 2 (2021), 100205.
[23] Abeba Birhane, Elayne Ruane, Thomas Laurent, Matthew S. Brown, Johnathan Flowers, Anthony Ventresque, and Christopher L. Dancy. 2022. The forgotten margins of AI ethics. In *2022 ACM Conference on Fairness, Accountability, and Transparency*. 948–958.
[24] Céleste M Brotheridge and Alicia A Grandey. 2002. Emotional labor and burnout: Comparing two perspectives of "people work". *Journal of vocational behavior* 60, 1 (2002), 17–39.
[25] Jed R Brubaker, Lynn S Dombrowski, Anita M Gilbert, Nafiri Kusumakaulika, and Gillian R Hayes. 2014. Stewarding a legacy: responsibilities and relationships in the management of post-mortem data. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 4157–4166.
[26] De'Aira Bryant and Ayanna Howard. 2019. A comparative analysis of emotion-detecting AI systems with respect to algorithm performance and dataset diversity. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society*. 377–382.
[27] John M Carrol. 1999. Five reasons for scenario-based design. In *Proceedings of the 32nd annual hawaii international conference on systems sciences. 1999. hicss-32. abstracts and cd-rom of full papers*. IEEE, 11–pp.
[28] Stephen Cave and Seán S ÓhÉigeartaigh. 2018. An AI race for strategic advantage: rhetoric and risks. In *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*. 36–40.
[29] Stevie Chancellor, Michael L Birnbaum, Eric D Caine, Vincent MB Silenzio, and Munmun De Choudhury. 2019. A taxonomy of ethical tensions in inferring mental health states from social media. In *Proceedings of the conference on fairness, accountability, and transparency*. 79–88.
[30] Stevie Chancellor and Munmun De Choudhury. 2020. Methods in predictive techniques for mental health status on social media: a critical review. *NPJ digital medicine* 3, 1 (2020), 1–11.
[31] Alexandra Chouldechova. 2017. Fair prediction with disparate impact: A study of bias in recidivism prediction instruments. *Big data* 5, 2 (2017), 153–163.
[32] Marika Cifor, Patricia Garcia, T. L. Cowan, Jasmine Rault, Tonia Sutherland, Anita Say Chan, Jennifer Rode, Anna Lauren Hoffman, Niloufar Salehi, and Lisa Nakamura. 2019. *Feminist Data Manifest-No.* https://www.manifestno.com/
[33] Danielle Keats Citron and Daniel J Solove. 2021. Privacy harms. *GWU Legal Studies Research Paper* 2021-11 (2021).
[34] Celeste M Condit. 2018. 13. The Supra-Cyborg: The Rise of Global Governing Corporatocracies. In *Biocitizenship*. New York University Press, 274–306.
[35] Sasha Costanza-Chock. 2020. *Design justice: Community-led practices to build the worlds we need.* The MIT Press.
[36] Peter Cotton and Peter M Hart. 2003. Occupational wellbeing and performance: A review of organisational health research. *Australian Psychologist* 38, 2 (2003), 118–127.
[37] Roddy Cowie. 2015. Ethical issues in affective computing. *The Oxford handbook of affective computing* (2015), 334–348.
[38] Kate Crawford et al. 2021. Time to regulate AI that interprets human emotions. *Nature* 592, 7853 (2021), 167–167.
[39] Kate Crawford, Roel Dobbe, Theodora Dryer, Genevieve Fried, Ben Green, Elizabeth Kaziunas, Amba Kak, Varoon Mathur, Erin McElroy, Andrea Nill Sánchez, et al. 2019. AI now 2019 report. *New York, NY: AI Now Institute* (2019).
[40] Russell Cropanzano, Howard M Weiss, and Steven M Elias. 2003. The impact of display rules and emotional labor on psychological well-being at work. In *Emotional and physiological processes and positive intervention strategies*. Emerald Group Publishing Limited.
[41] Antonio R. Damasio. 2006. *Descartes' error: emotion, reason and the human brain* (rev. ed. with a new preface ed.). Vintage, London. OCLC: 255585811.
[42] Vedant Das Swain, Koustuv Saha, Hemang Rajvanshy, Anusha Sirigiri, Julie M Gregg, Suwen Lin, Gonzalo J Martinez, Stephen M Mattingly, Shayan Mirjafari, Raghu Mulukutla, et al. 2019. A multisensor person-centered approach to understand the role of daily activities in job performance with organizational personas. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 4 (2019), 1–27.
[43] Vedant Das Swain, Koustuv Saha, Manikanta D Reddy, Hemang Rajvanshy, Gregory D Abowd, and Munmun De Choudhury. 2020. Modeling organizational culture with workplace experiences shared on glassdoor. In *Proceedings of the 2020 CHI conference on human factors in computing systems*. 1–15.

[44] Thomas Davenport, Abhijit Guha, Dhruv Grewal, and Timna Bressgott. 2020. How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science* 48, 1 (2020), 24–42.
[45] Munmun De Choudhury and Scott Counts. 2013. Understanding affect in the workplace via social media. In *Proceedings of the 2013 conference on Computer supported cooperative work*. 303–316.
[46] Munmun De Choudhury, Michael Gamon, and Scott Counts. 2012. Happy, nervous or surprised? classification of human affective states in social media. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 6. 435–438.
[47] Mandar Deshpande and Vignesh Rao. 2017. Depression detection using emotion artificial intelligence. In *2017 international conference on intelligent sustainable systems (iciss)*. IEEE, 858–862.
[48] John Dewey. 1895. The theory of emotion. *Psychological review* 2, 1 (1895), 13.
[49] Catherine D'ignazio and Lauren F Klein. 2020. *Data feminism*. MIT press.
[50] Artem Domnich and Gholamreza Anbarjafari. 2021. Responsible AI: Gender bias assessment in emotion recognition. *arXiv preprint arXiv:2103.11436* (2021).
[51] Paul Ekman. 1971. Universals and cultural differences in facial expressions of emotion.. In *Nebraska symposium on motivation*. University of Nebraska Press.
[52] Paul Ekman. 1999. Basic emotions. *Handbook of cognition and emotion* 98, 45-60 (1999), 16.
[53] Engre Engineer Element. 2022. *Emotional Artificial Intelligence Market 2022 - 2030: Global Size, Trends, Growth Insight*. https://engre.co/news/articles/emotional-ai-market-2022-2030/
[54] Darren Ellis and Ian Tucker. 2020. *Emotion in the digital age: Technologies, data and psychosocial life*. Routledge.
[55] Hadar Elraz. 2018. Identity, mental health and work: How employees with mental health conditions recount stigma and the pejorative discourse of mental illness. *Human Relations* 71, 5 (2018), 722–741.
[56] Motahhare Eslami, Aimee Rickman, Kristen Vaccaro, Amirhossein Aleyasen, Andy Vuong, Karrie Karahalios, Kevin Hamilton, and Christian Sandvig. 2015. " I always assumed that I wasn't really that close to [her]" Reasoning about Invisible Algorithms in News Feeds. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*. 153–162.
[57] Casey Fiesler. 2021. Innovating like an optimist, preparing like a pessimist: Ethical speculation and the legal imagination. *Colo. Tech. LJ* 19 (2021), 1.
[58] Janet Finch. 1987. The vignette technique in survey research. *Sociology* 21, 1 (1987), 105–114.
[59] Yoko E Fukumura, Julie McLaughlin Gray, Gale M Lucas, Burcin Becerik-Gerber, and Shawn C Roll. 2021. Worker perspectives on incorporating artificial intelligence into office workspaces: implications for the future of office work. *International Journal of Environmental Research and Public Health* 18, 4 (2021), 1690.
[60] Gallup. 2022. *State of the Global Workplace: 2022 Report*. https://www.gallup.com/workplace/349484/state-of-the-global-workplace.aspx#ite-393218
[61] R Geetha and Sree Reddy D Bhanu. 2018. Recruitment through artificial intelligence: a conceptual study. *International Journal of Mechanical Engineering and Technology* 9, 7 (2018), 63–70.
[62] Maria Gendron and Lisa Feldman Barrett. 2009. Reconstructing the past: A century of ideas about emotion in psychology. *Emotion review* 1, 4 (2009), 316–339.
[63] Laurie Giddens, Ester Gonzalez, and Dorothy Leidner. 2019. Unintended Consequences of Wearable Fitness Devices in Corporate Wellness Programs. In *Proceedings of the 2019 on Computers and People Research Conference*. 4–4.
[64] Laurie Giddens, Dorothy Leidner, and Ester Gonzalez. 2017. The role of Fitbits in corporate wellness programs: Does step count matter? (2017).
[65] Ron Z Goetzel, Ronald J Ozminkowski, Lloyd I Sederer, and Tami L Mark. 2002. The business case for quality mental health services: why employers should care about the mental health and well-being of their employees. *Journal of occupational and environmental medicine* (2002), 320–330.
[66] Hila Gonen and Yoav Goldberg. 2019. Lipstick on a pig: Debiasing methods cover up systematic gender biases in word embeddings but do not remove them. *arXiv preprint arXiv:1903.03862* (2019).
[67] Gregorio González-Alcaide, Mercedes Fernández-Ríos, Rosa Redolat, and Emilia Serra. 2021. Research on emotion recognition and dementias: Foundations and prospects. *Journal of Alzheimer's Disease* 82, 3 (2021), 939–950.
[68] Alicia A Grandey. 2000. Emotional regulation in the workplace: A new way to conceptualize emotional labor. *Journal of occupational health psychology* 5, 1 (2000), 95.
[69] Gabriel Grill and Nazanin Andalibi. 2022. Attitudes and Folk Theories of Data Subjects on Transparency and Accuracy in Emotion Recognition. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW1 (2022), 1–35.
[70] Jonathan Grudin and Steven Poltrock. 2013. Computer supported cooperative work. *The Encyclopedia of Human-Computer Interaction, 2nd Ed.* (2013).
[71] Oliver L Haimson, Daniel Delmonaco, Peipei Nie, and Andrea Wegner. 2021. Disproportionate removals and differing content moderation experiences for conservative, transgender, and black social media users: Marginalization and moderation gray areas. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–35.

[72] Roxanna Harlow. 2003. " Race doesn't matter, but...": The effect of race on professors' experiences and emotion management in the undergraduate college classroom. *Social psychology quarterly* (2003), 348–363.
[73] Christina Harrington and Tawanna R Dillahunt. 2021. Eliciting tech futures among Black young adults: A case study of remote speculative co-design. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–15.
[74] Nader Henein, Helen Poitevin, and Bart Willemsen. 2021. Gartner: Practical Privacy - Managing HR Data. https://www.gartner.com/document/3995881?ref=solrAll&refval=278163520
[75] Alexander P Henkel, Stefano Bromuri, Deniz Iren, and Visara Urovi. 2020. Half human, half machine–augmenting service employees with AI for interpersonal emotion regulation. *Journal of Service Management* (2020).
[76] Andrew C High, Anne Oeldorf-Hirsch, and Saraswathi Bellur. 2014. Misery rarely gets company: The influence of emotional bandwidth on supportive communication on Facebook. *Computers in Human Behavior* 34 (2014), 79–88.
[77] Crosby Hipes. 2019. The impact of a felony conviction on stigmatization in a workplace scenario. *International Journal of Law, Crime and Justice* 56 (2019), 89–99.
[78] Arlie Russell Hochschild. 1983. *The managed heart.* Routledge.
[79] Xin Hu, Jingjing Chen, Fei Wang, and Dan Zhang. 2019. Ten challenges for EEG-based affective computing. *Brain Science Advances* 5, 1 (2019), 1–20.
[80] Claretha Hughes, Lionel Robert, Kristin Frady, and Adam Arroyos. 2019. Artificial intelligence, employee engagement, fairness, and job outcomes. In *Managing technology and middle-and low-skilled employees*. Emerald Publishing Limited.
[81] Rhidian Hughes. 1998. Considering the vignette technique and its application to a study of drug injecting and HIV risk and safer behaviour. *Sociology of Health & Illness* 20, 3 (1998), 381–400.
[82] Amy E Hurley-Hanson, Cristina M Giannantonio, and Amy Jane Griffiths. 2020. *Autism in the workplace: Creating positive employment and career outcomes for Generation A.* Springer.
[83] Brian R Jackson, Ye Ye, James M Crawford, Michael J Becich, Somak Roy, Jeffrey R Botkin, Monica E de Baca, and Liron Pantanowitz. 2021. The ethics of artificial intelligence in pathology and laboratory medicine: principles and practice. *Academic Pathology* 8 (2021), 2374289521990784.
[84] William James. 1884. What is an emotion?
[85] Guillermina Jasso. 2006. Factorial survey methods for studying beliefs and judgments. *Sociological Methods & Research* 34, 3 (2006), 334–423.
[86] Harmanpreet Kaur, Daniel McDuff, Alex C Williams, Jaime Teevan, and Shamsi T Iqbal. 2022. "I Didn't Know I Looked Angry": Characterizing Observed Emotion and Reported Affect at Work. In *CHI Conference on Human Factors in Computing Systems*. 1–18.
[87] Simran Kaur and Richa Sharma. 2021. Emotion AI: integrating emotional intelligence with artificial intelligence in the digital workplace. In *Innovations in Information and Communication Technologies (IICT-2020)*. Springer, 337–343.
[88] Kate Kaye. 2022. *Companies are using AI to monitor your mood during sales calls. Zoom might be next.* https://www.protocol.com/enterprise/emotion-ai-sales-virtual-zoom
[89] Yelin Kim, Honglak Lee, and Emily Mower Provost. 2013. Deep learning for robust feature generation in audiovisual emotion recognition. In *2013 IEEE international conference on acoustics, speech and signal processing*. IEEE, 3687–3691.
[90] Dimitri Kraft, Kristof Van Laerhoven, and Gerald Bieber. 2021. CareCam: Concept of a new tool for Corporate Health Management. In *The 14th PErvasive Technologies Related to Assistive Environments Conference*. 585–593.
[91] Adam DI Kramer, Jamie E Guillory, and Jeffrey T Hancock. 2014. Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences* 111, 24 (2014), 8788–8790.
[92] Christian Krekel, George Ward, and Jan-Emmanuel De Neve. 2019. Employee wellbeing, productivity, and firm performance. *Saïd Business School WP* 4 (2019).
[93] Bruce G Link and Jo C Phelan. 2001. Conceptualizing stigma. *Annual review of Sociology* (2001), 363–385.
[94] Bruce G Link and Jo C Phelan. 2006. Stigma and its public health implications. *The Lancet* 367, 9509 (2006), 528–529.
[95] Liyuan Liu, Sanjoosh Akkineni, Paul Story, and Clay Davis. 2020. Using HR analytics to support managerial decisions: a case study. In *Proceedings of the 2020 ACM Southeast Conference*. 168–175.
[96] George Loewenstein and Jennifer S Lerner. 2003. The role of affect in decision making. (2003).
[97] Ruth Ludwick, Marion Elizabeth Wright, Richard Allen Zeller, Dawn W Dowding, William Lauder, and Janice Winchell. 2004. An improved methodology for advancing nursing research: Factorial surveys. *Advances in Nursing Science* 27, 3 (2004), 224–238.
[98] David D Luxton, Russell A McCann, Nigel E Bush, Matthew C Mishkind, and Greg M Reger. 2011. mHealth for mental health: Integrating smartphone technology in behavioral healthcare. *Professional Psychology: Research and Practice* 42, 6 (2011), 505.
[99] Peter Mantello, Manh-Tung Ho, Minh-Hoang Nguyen, and Quan-Hoang Vuong. 2021. Bosses without a heart: socio-demographic and cross-cultural determinants of attitude toward Emotional AI in the workplace. *AI & society*

(2021), 1–23.

[100] Gloria Mark, Shamsi T Iqbal, Mary Czerwinski, and Paul Johns. 2014. Bored mondays and focused afternoons: the rhythm of attention and online activity in the workplace. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 3025–3034.

[101] Gloria Mark, Shamsi T Iqbal, Mary Czerwinski, Paul Johns, Akane Sano, and Yuliya Lutchyn. 2016. Email duration, batching and self-interruption: Patterns of email use on productivity and stress. In *Proceedings of the 2016 CHI conference on human factors in computing systems*. 1717–1728.

[102] Kirsten Martin. 2016. Do privacy notices matter? Comparing the impact of violating formal privacy notices and informal privacy norms on consumer trust online. *The Journal of Legal Studies* 45, S2 (2016), S191–S215.

[103] Kirsten E Martin. 2012. Diminished or just different? A factorial vignette study of privacy as a social contract. *Journal of Business Ethics* 111, 4 (2012), 519–539.

[104] Ricardo Martins, José João Almeida, Pedro Rangel Henriques, and Paulo Novais. 2021. Identifying Depression Clues using Emotions and AI.. In *ICAART (2)*. 1137–1143.

[105] Nora McDonald and Andrea Forte. 2020. The politics of privacy theories: Moving from norms to vulnerabilities. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–14.

[106] Nora McDonald, Sarita Schoenebeck, and Andrea Forte. 2019. Reliability and inter-rater reliability in qualitative research: Norms and guidelines for CSCW and HCI practice. *Proceedings of the ACM on human-computer interaction* 3, CSCW (2019), 1–23.

[107] Daniel McDuff, Eunice Jun, Kael Rowan, and Mary Czerwinski. 2019. Longitudinal Observational Evidence of the Impact of Emotion Regulation Strategies on Affective Expression. *IEEE Transactions on Affective Computing* 12, 3 (2019), 636–647.

[108] Dan McQuillan. 2020. Non-fascist AI. (2020).

[109] Andrew McStay. 2018. *Emotional AI: The rise of empathic media.* Sage.

[110] Andrew McStay. 2020. Emotional AI, soft biometrics and the surveillance of emotional life: An unusual consensus on privacy. *Big Data & Society* 7, 1 (2020), 2053951720904386.

[111] Susan Michie. 2002. Causes and management of stress at work. *Occupational and environmental medicine* 59, 1 (2002), 67–72.

[112] Tanushree Mitra, Michael Muller, N Sadat Shami, Abbas Golestani, and Mikhil Masli. 2017. Spread of employee engagement in a large organizational network: a longitudinal analysis. *Proceedings of the ACM on Human-Computer Interaction* 1, CSCW (2017), 1–20.

[113] Lillio Mok and Ashton Anderson. 2021. The Complementary Nature of Perceived and Actual Time Spent Online in Measuring Digital Well-being. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–27.

[114] Ramiro Montealegre and Wayne F Cascio. 2017. Technology-driven changes in work and employment. *Commun. ACM* 60, 12 (2017), 60–67.

[115] Scott Monteith, Tasha Glenn, John Geddes, Peter C Whybrow, and Michael Bauer. 2022. Commercial Use of Emotion Artificial Intelligence (AI): Implications for Psychiatry. *Current Psychiatry Reports* (2022), 1–9.

[116] Phoebe V Moore. 2018. Tracking affective labour for agility in the quantified workplace. *Body & Society* 24, 3 (2018), 39–67.

[117] Salla Muuraiskangas, Marja Harjumaa, Kirsikka Kaipainen, Miikka Ermes, et al. 2016. Process and effects evaluation of a digital mental health intervention targeted at improving occupational well-being: lessons from an intervention study with failed adoption. *JMIR mental health* 3, 2 (2016), e4465.

[118] Helen Nissenbaum. 2004. Privacy as contextual integrity. *Wash. L. Rev.* 79 (2004), 119.

[119] A nonymous. 2021. Automated Emotion Recognition in the Workplace: How Proposed Technologies Reveal Potential Futures of Work Data Inputs, Promised Outputs, and Proposed Actions in Emotion Recognition Patents. (2021).

[120] Selin E Nugent and Susan Scott-Parker. 2021. Recruitment AI has a Disability Problem: anticipating and mitigating unfair automated hiring decisions. https://doi.org/10.31235/osf.io/8sxh7

[121] Ziad Obermeyer and Sendhil Mullainathan. 2019. Dissecting racial bias in an algorithm that guides health decisions for 70 million people. In *Proceedings of the conference on fairness, accountability, and transparency*. 89–89.

[122] The American Institute of Stress. n.d.. *Workplace Stress.* https://www.stress.org/workplace-stress

[123] Claudia Ogriseg. 2017. GDPR and Personal Data Protection in the Employment Context. *Labour & Law Issues* 3, 2 (Dec. 2017), 1–24. https://doi.org/10.6092/issn.2421-2695/7573 Publisher: University of Bologna.

[124] Gary M Olson and Judith S Olson. 2000. Distance matters. *Human–computer interaction* 15, 2-3 (2000), 139–178.

[125] Gloria Omale. 2019. Gartner Identifies Three Most Common AI Use Cases in HR and Recruiting. https://www.gartner.com/en/newsroom/press-releases/2019-06-19-gartner-identifies-three-most-common-ai-use-cases-in-

[126] Serena Oppenheim. 2019. How The Corporate Wellness Market Has Exploded: Meet The Latest Innovators In The Space. https://www.forbes.com/sites/serenaoppenheim/2019/06/11/how-the-corporate-wellness-market-has-exploded-meet-the-latest-innovators-in-the-space/ Section: Healthcare.

[127] George Orwell. 1949. *1984*. Signet Classic.
[128] Maria Payri, Michael Cohn, and Ilene R Shaw. 2013. How often is employee anger an insider risk I? Detecting and measuring negative sentiment versus insider risk in digital communications. *The Journal of Digital Forensics, Security and Law: JDFSL* 8, 1 (2013), 39.
[129] Thomas V Perneger and Thomas Agoritsas. 2011. Doctors and patients' susceptibility to framing bias: a randomized trial. *Journal of General Internal Medicine* 26, 12 (2011), 1411–1417.
[130] Jeffrey Pfeffer, Stacie Vilendrer, Grace Joseph, Jason Kim, and Sara J Singer. 2020. Employers' Role in Employee Health: Why They Do What They Do. *Journal of Occupational and Environmental Medicine* 62, 11 (2020), e601–e610.
[131] Rosalind W Picard. 2000. *Affective computing*. MIT press.
[132] Helen Poitevin. 2015. Gartner: Workplace Analytics Needs Digital Ethics. https://www.gartner.com/document/3164927?ref=authrightrec&refval=3887785
[133] Karen Pugliesi. 1999. The consequences of emotional labor: Effects on work stress, job satisfaction, and well-being. *Motivation and emotion* 23, 2 (1999), 125–154.
[134] Manish Raghavan, Solon Barocas, Jon Kleinberg, and Karen Levy. 2020. Mitigating bias in algorithmic hiring: Evaluating claims and practices. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 469–481.
[135] Naila Rahman. 1996. Caregivers' sensitivity to conflict: The use of the vignette methodology. *Journal of Elder Abuse & Neglect* 8, 1 (1996), 35–47.
[136] Inioluwa Deborah Raji, Andrew Smart, Rebecca N White, Margaret Mitchell, Timnit Gebru, Ben Hutchinson, Jamila Smith-Loud, Daniel Theron, and Parker Barnes. 2020. Closing the AI accountability gap: Defining an end-to-end framework for internal algorithmic auditing. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 33–44.
[137] Daniel M Ravid, David L Tomczak, Jerod C White, and Tara S Behrend. 2020. EPM 20/20: A review, framework, and research agenda for electronic performance monitoring. *Journal of Management* 46, 1 (2020), 100–126.
[138] Lauren Rhue. 2018. Racial influence on automated perceptions of emotions. *Available at SSRN 3281765* (2018).
[139] Lauren Rhue. 2019. *Understanding the Hidden Bias in Emotion-Reading AIs*.
[140] Rashida Richardson, Jason M Schultz, and Kate Crawford. 2019. Dirty data, bad predictions: How civil rights violations impact police data, predictive policing systems, and justice. *NYUL Rev. Online* 94 (2019), 15.
[141] Bernard Rimé. 2009. Emotion elicits the social sharing of emotion: Theory and empirical review. *Emotion review* 1, 1 (2009), 60–85.
[142] Bernard Rimé, Catrin Finkenauer, Olivier Luminet, Emmanuelle Zech, and Pierre Philippot. 1998. Social sharing of emotion: New evidence and new questions. *European review of social psychology* 9, 1 (1998), 145–189.
[143] Bernard Rimé, Dario Paez, Patrick Kanyangara, and Vincent Yzerbyt. 2011. The social sharing of emotions in interpersonal and in collective situations: Common psychosocial consequences. In *Emotion regulation and well-being*. Springer, 147–163.
[144] Kat Roemmich and Nazanin Andalibi. 2021. Data subjects' conceptualizations of and attitudes toward automatic emotion recognition-enabled wellbeing interventions on social media. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–34.
[145] Alex Rosenblat, Tamara Kneese, and Danah Boyd. 2014. Workplace surveillance. *Open Society Foundations' Future of Work Commissioned Research Papers* (2014).
[146] Nicolas Rüsch, Matthias C Angermeyer, and Patrick W Corrigan. 2005. Mental illness stigma: Concepts, consequences, and initiatives to reduce stigma. *European psychiatry* 20, 8 (2005), 529–539.
[147] Koustuv Saha, Manikanta D Reddy, Stephen Mattingly, Edward Moskal, Anusha Sirigiri, and Munmun De Choudhury. 2019. Libra: On linkedin based role ambiguity and its relationship with wellbeing and job performance. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–30.
[148] Koustuv Saha, Asra Yousuf, Louis Hickman, Pranshu Gupta, Louis Tay, and Munmun De Choudhury. 2021. A social media study on demographic differences in perceived job satisfaction. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–29.
[149] Samiha Samrose, Wenyi Chu, Carolina He, Yuebai Gao, Syeda Sarah Shahrin, Zhen Bai, and Mohammed Ehsan Hoque. 2019. Visual cues for disrespectful conversation analysis. In *2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII)*. IEEE, 580–586.
[150] Dagmar Schuller and Björn W Schuller. 2018. The age of artificial emotional intelligence. *Computer* 51, 9 (2018), 38–46.
[151] Science and Technology Policy Office. 2021. *Notice of Request for Information (RFI) on Public and Private Sector Uses of Biometric Technologies*. https://www.federalregister.gov/documents/2021/10/08/2021-21975/notice-of-request-for-information-rfi-on-public-and-private-sector-uses-of-biometric-technologies

[152] Donna Scott, Irving Tyler, and Dale Kutnick. 2020. Master These Core Enterprise Capabilities to Advance Your Digital Transformation. https://www.gartner.com/document/3985104?ref=solrAll&refval=288221761
[153] Elaine Sedenberg and John Chuang. 2017. Smile for the camera: Privacy and policy implications of emotion AI. *arXiv preprint arXiv:1709.00396* (2017).
[154] Jussi Seppälä, Ilaria De Vita, Timo Jämsä, Jouko Miettunen, Matti Isohanni, Katya Rubinstein, Yoram Feldman, Eva Grasa, Iluminada Corripio, Jesus Berdun, et al. 2019. Mobile phone and wearable sensor-based mHealth approaches for psychiatric disorders and symptoms: systematic review. *JMIR mental health* 6, 2 (2019), e9819.
[155] N Sadat Shami, Michael Muller, Aditya Pal, Mikhil Masli, and Werner Geyer. 2015. Inferring employee engagement from social media. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. 3999–4008.
[156] N Sadat Shami, Jeffrey Nichols, and Jilin Chen. 2014. Social media participation and performance at work: a longitudinal study. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 115–118.
[157] N Sadat Shami, Jiang Yang, Laura Panc, Casey Dugan, Tristan Ratchford, Jamie C Rasmussen, Yannick M Assogba, Tal Steier, Todd Soule, Stela Lupushor, et al. 2014. Understanding employee social media chatter with enterprise social pulse. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*. 379–392.
[158] Meredith M Skeels and Jonathan Grudin. 2009. When social networks cross boundaries: a case study of workplace use of facebook and linkedin. In *Proceedings of the ACM 2009 international conference on Supporting group work*. 95–104.
[159] Rory W Spanton and Olivia Guest. 2022. Measuring Trustworthiness or Automating Physiognomy? A Comment on Safra, Chevallier, Gr\ezes, and Baumard (2020). *arXiv preprint arXiv:2202.08674* (2022).
[160] Katta Spiel, Oliver L Haimson, and Danielle Lottridge. 2019. How to do better with gender on surveys: a guide for HCI researchers. *Interactions* 26, 4 (2019), 62–65.
[161] Luke Stark and Jesse Hoey. 2021. The ethics of emotion in artificial intelligence systems. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*. 782–793.
[162] Luke Stark and Jevan Hutson. 2021. Physiognomic artificial intelligence. *Available at SSRN 3927300* (2021).
[163] Ronnie J Steinberg and Deborah M Figart. 1999. Emotional labor since: The managed heart. *The Annals of the American Academy of Political and Social Science* 561, 1 (1999), 8–26.
[164] V Suchitra Mouly and Jayaram K Sankaran. 1997. On the study of settings marked by severe superior-subordinate conflict. *Organization Studies* 18, 2 (1997), 175–192.
[165] Gavin Tay and Bern Elliot. 2019. Maverick* Research: Emotion AI Will Become You Without Your Knowledge. https://www.gartner.com/document/3975557?ref=gfeed
[166] Gavin Tay, Annette Zimmerman, and Bern Elliot. 2021. Maverick* Research: Emotional Wellness Will Rescue Your Organization and Distributed Workforce. https://www.gartner.com/document/4000627?ref=solrAll&refval=286373907
[167] Kentaro Toyama. 2011. Technology as Amplifier in International Development. In *Proceedings of the 2011 IConference* (Seattle, Washington, USA) *(iConference '11)*. Association for Computing Machinery, New York, NY, USA, 75–82. https://doi.org/10.1145/1940761.1940772
[168] Nicol Turner Lee and Caitlin Chin. 2022. *Police surveillance and facial recognition: Why data privacy is imperative for communities of color.* Technical Report. https://www.brookings.edu/research/police-surveillance-and-facial-recognition-why-data-privacy-is-an-imperative-for-communities-of-color/
[169] Anushree Verma. 2020. Hype Cycle for Sensing Technologies and Applications, 2020. https://www.gartner.com/document/3987226?ref=solrAll&refval=287771061
[170] Ari Ezra Waldman. 2018. *Privacy as trust: Information privacy for an information age.* Cambridge University Press.
[171] Ari Ezra Waldman. 2020. Cognitive biases, dark patterns, and the 'privacy paradox'. *Current opinion in psychology* 31 (2020), 105–109.
[172] Lisa Wallander. 2009. 25 years of factorial surveys in sociology: A review. *Social science research* 38, 3 (2009), 505–520.
[173] Colin G Walsh, Beenish Chaudhry, Prerna Dua, Kenneth W Goodman, Bonnie Kaplan, Ramakanth Kavuluru, Anthony Solomonides, and Vignesh Subbian. 2020. Stigma, biomarkers, and algorithmic bias: recommendations for precision behavioral health with artificial intelligence. *JAMIA open* 3, 1 (2020), 9–15.
[174] Qiaosi Wang, Shan Jing, David Joyner, Lauren Wilcox, Hong Li, Thomas Plötz, and Betsy Disalvo. 2020. Sensing Affect to Empower Students: Learner Perspectives on Affect-Sensitive Technology in Large Educational Contexts. In *Proceedings of the Seventh ACM Conference on Learning@ Scale*. 63–76.
[175] Deborah L Wells, Robert H Moorman, and Jon M Werner. 2007. The impact of the perceived purpose of electronic performance monitoring on an array of attitudinal variables. *Human Resource Development Quarterly* 18, 1 (2007), 121–138.
[176] Sarah Myers West, Meredith Whittaker, and Kate Crawford. 2019. Discriminating systems. *AI Now* (2019).
[177] Meredith Whittaker, Meryl Alper, Cynthia L Bennett, Sara Hendren, Liz Kaziunas, Mara Mills, Meredith Ringel Morris, Joy Rankin, Emily Rogers, Marcel Salas, et al. 2019. Disability, bias, and AI. *AI Now Institute* (2019).

[178] Alex C Williams, Harmanpreet Kaur, Gloria Mark, Anne Loomis Thompson, Shamsi T Iqbal, and Jaime Teevan. 2018. Supporting workplace detachment and reattachment with conversational intelligence. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–13.

[179] Business Wire. 2022. *Global Emotion Detection and Recognition Market (2022 to 2027) - Growing Partnerships and Widening Ecosystems Presents Opportunities - ResearchAndMarkers.com.* https://www.businesswire.com/news/home/20220420005613/en/Global-Emotion-Detection-and-Recognition-Market-2022-to-2027---Growing-Partnerships-and-Widening-Ecosystems-Presents-Opportunities---ResearchAndMarkets.com

[180] Richmond Y Wong, Deirdre K Mulligan, and John Chuang. 2017. Using science fiction texts to surface user reflections on privacy. In *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers*. 213–216.

[181] Richmond Y Wong, Ellen Van Wyk, and James Pierce. 2017. Real-fictional entanglements: Using science fiction and design fiction to interrogate sensing technologies. In *Proceedings of the 2017 Conference on Designing Interactive Systems*. 567–579.

[182] Stephen Wood, Valerio Ghezzi, Claudio Barbaranelli, Cristina Di Tecco, Roberta Fida, Maria Luisa Farnese, Matteo Ronchetti, and Sergio Iavicoli. 2019. Assessing the risk of stress in organizations: getting the measure of organizational-level stressors. *Frontiers in Psychology* 10 (2019), 2776.

[183] Hirokazu Yoshikawa, Thomas S Weisner, Ariel Kalil, and Niobe Way. 2008. Mixing qualitative and quantitative research in developmental science: Uses and methodological choices. *Developmental psychology* 44, 2 (2008), 344.

[184] Paul Thomas Young. 1961. Motivation and emotion: A survey of the determinants of human and animal activity. (1961).

[185] Angie Zhang, Alexander Boltz, Chun Wei Wang, and Min Kyung Lee. 2022. Algorithmic management reimagined for workers and by workers: Centering worker well-being in gig work. In *CHI Conference on Human Factors in Computing Systems*. 1–20.

[186] Kathryn Zickuhr. 2021. Workplace Surveillance Is Becoming the New Normal for US Workers. *Washington Center for Equitable Growth. https://equitablegrowth. org/research-paper/workplace-surveillance-is-becomingthe-new-normal-for-us-workers/. Institute for Research on Labor and Employment University of California, Berkeley* 2521 (2021), 94720–5555.

[187] John Zimmerman and Jodi Forlizzi. 2017. Speed dating: providing a menu of possible futures. *She Ji: The Journal of Design, Economics, and Innovation* 3, 1 (2017), 30–50.

[188] Annuska Zolyomi and Jaime Snyder. 2021. Social-emotional-sensory design map for affective computing informed by neurodivergent experiences. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–37.

7 APPENDICES

A SURVEY VIGNETTES FOR THE WORKPLACE CONTEXT

The 14 purposes for which EAI is deployed and informed our survey design are **bolded**. The 14 purposes were repeated twice.

(1) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **inferring the mental health state of employees. Inferences of an individual's mental health will not be made; only at a group level**.

(2) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **inferring the mental health state of employees individually**.

(3) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **diagnosing mental illness in employees earlier than otherwise possible**.

(4) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **diagnosing neurological disorders, such as dementia or ADHD, in employees earlier than otherwise possible**.

(5) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **identifying employees in need of mental health support, to better plan organizational mental health resources**.

(6) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **developing an intelligent computer program, such as a chat bot, that can conduct mental health therapy with employees, including you**.

(7) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **inferring moments employees may be in need of emotional support, and responding with an intelligent computer program designed to help employees improve their wellbeing, such as offering wellbeing tips**.

(8) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states

using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **sharing that information with academic researchers to help them learn more about mental health, as part of a research partnership**.

(9) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **giving employers data-driven insights into employees' wellbeing**.

(10) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **automatically alerting your employer when employees may need support, including you**.

(11) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **inferring whether employees are at risk of harming themselves**.

(12) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **inferring whether employees are at risk of harming others**.

(13) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **avoiding subjectivity in other methods of your employer learning about your emotional state, like a survey or your employer's observations**.

(14) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) recorded from your daily activities and device use, for the purpose of: - **assessing the work performance of individual employees**.

(15) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- inferring the mental health state of employees. Inferences of an individual's mental health will not be made; only at a group level.**

(16) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- inferring the mental health state of employees individually.**

(17) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- diagnosing mental illness in employees earlier than otherwise possible.**
(18) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- diagnosing neurological disorders, such as dementia or ADHD, in employees earlier than otherwise possible.**
(19) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- identifying employees in need of mental health support, to better plan organizational mental health resources.**
(20) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- developing an intelligent computer program, such as a chat bot, that can conduct mental health therapy with employees, including you.**
(21) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- inferring moments employees may be in need of emotional support, and responding with an intelligent computer program designed to help employees improve their wellbeing, such as offering wellbeing tips.**
(22) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- sharing that information with academic researchers to help them learn more about mental health, as part of a research partnership.**
(23) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- giving employers data-driven insights into employees' wellbeing.**
(24) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- automatically alerting your employer when employees may need support, including you.**
(25) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states

using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- inferring whether employees are at risk of harming themselves.**

(26) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- inferring whether employees are at risk of harming others.**

(27) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- avoiding subjectivity in other methods of your employer learning about your emotional state, like a survey or your employer's observations.**

(28) As an employee, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with your employer using a computer program to automatically detect your emotional states using records of images or video of what you look like, based on your facial expressions recorded from your daily activities and device use, for the purpose of: **- assessing the work performance of individual employees.**

B BREAKDOWN OF SAMPLE INCLUDED IN THIS PAPER

Sample	**Number of participants, *n***
Representative sample	289
Mental health oversample*	37
Gender oversample**	
Trans	6
Non-binary	26
Trans, non-binary	2
Race/ethnicity oversample***	
African-American or Black	11
Asian-American	1
East Asian	2
Hispanic or Latino/a/x	11
Indigenous American or First Nations	1
Multi-racial	9
Total participants	395

Table 3. Full breakdown of the sample included in this paper.

*Participants were asked "Please describe your mental health status. Select all the apply." to the following options: *I have a mental health condition and it has not been formally diagnosed; I have a mental health condition that has been formally diagnosed; I am being treated for a mental health condition, and that treatment includes medication; I am being treated for a mental health condition, not with medication; I do not have a mental health condition; I used to have a mental health condition and I no longer do; I have multiple mental health conditions. Some are diagnosed, some are not; I have multiple mental health conditions. I take medication for some, and do not for others.*

**Participants were asked "Please describe your gender. Select all that apply." to the following options: *Woman, Man, Trans, Non-binary, Prefer not to disclose, Prefer to self-describe (open-ended textbox).* These options were selected according to [160].

***Participants were asked "Please describe your race/ethnicity. Select all that apply." to the following options: *African, African-American or Black, Asian-American, East Asian, Hispanic or Latino/a/x, Indigenous American or First Nations, Middle Eastern, South Asian, Southeast Asian, White, Not listed, please specify (open-ended textbox), Prefer not to answer.*

C BREAKDOWN OF PARTICIPANTS' DEMOGRAPHICS

Demographics	**Number of participants, *n***
Gender	
Woman	202
Man	364
Non-binary	34
Trans	11
Race/ethnicity	
African	5
African-American or Black	62
Asian-American	27
East Asian	27
Hispanic or Latino/a/x	39
Indigenous American or First Nations	8
Middle Eastern	3
Not listed	7
South Asian	2
Southeast Asian	5
White	269
Age*	
18-24	96
25-34	83
35-44	61
45-54	50
55-64	58
65+	45
Employment status**	
Employed full-time	176
Employed part-time	61
Not in the paid workforce	100
Looking for work	47
Other	25
Highest level of education or degree completed***	
Some grade school	2
High school graduate	52
Some college	97
Technical, vocational, or trade school	5
Associate degree in college	41
Bachelor's degree in college	115
Master's degree	64
Professional degree	14
Doctoral degree	5

Table 4. Note: Some percentages may add up to more than our sample number of 395 because participants could be in multiple gender and race/ethnicity categories and experiencing more than one employment event at once. Additionally, 3 participants did not report their age.

*Participant age ranges were provided by the recruitment service Prolific and validated with a prescreening survey questions that asked participants' year of birth.

**Participants were asked "Please indicate your current employment status. Select all that apply." to the following options: *Employed Full-Time, Employed Part-Time, Looking for work, Not in the paid workforce (retired, full-time caregiving, full-time student etc), Other (open-ended textbox)*

***Participants were asked "What is the highest level of school you have completed or the highest degree you have received?" to the following options: *No formal school, Some grade school, High school graduate (high school diploma or equivalent including GED), Some college, Technical, vocational, or trade school, Associate degree in college (2-year), Bachelor's degree in college (4-year), Master's degree, Professional degree (JD, MD), Doctoral degree*

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