Emotion AI at Work: Implications for Workplace Surveillance, Emotional Labor, and Emotional Privacy

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ABSTRACT

Workplaces are increasingly adopting emotion AI, promising benefits to organizations. However, little is known about the perceptions and experiences of *workers* subject to emotion AI in the workplace. Our interview study with (*n*=15) US adult workers addresses this gap, finding that (1) participants viewed emotion AI as a deep privacy violation over the privacy of workers' sensitive emotional information; (2) emotion AI may function to enforce workers' compliance with emotional labor expectations, and that workers may engage in emotional labor as a mechanism to preserve privacy over their emotions; (3) workers may be exposed to a wide range of harms as a consequence of emotion AI in the workplace. Findings reveal the need to recognize and define an individual right to what we introduce as *emotional privacy*, as well as raise important research and policy questions on how to protect and preserve emotional privacy within and beyond the workplace.

CCS CONCEPTS

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

KEYWORDS

emotion AI, emotional AI, emotion recognition, affective computing, artificial emotional intelligence, passive sensing, emotional labor, privacy, workplace, future of work, surveillance

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1 INTRODUCTION

Aided by emotion artificial intelligence (AI), which broadly refers to technologies that "sense, learn about, and interact with human emotional life" [103], workplace surveillance is expanding to include automatic monitoring of worker emotion, mood, affect, and related constructs [157]. Through computational and artificial intelligence methods (i.e., statistical analysis, affective computing, and machine learning [54, 70, 71, 85, 117, 140]), emotion AI techniques can be applied to various types of input data (i.e., biological sensors, facial micro-expressions, physiological and speech signals, and text semantics [43, 127]), aiming to generate inferences about and/or interact with human emotion. Emotion AI promises organizations the ability to better know, manage and monitor employees' interior states and traits in ways that support organizational goals, including improved productivity, mitigated security and safety risks, increased customer loyalty and sales, and improved corporate wellness [20, 62, 72, 80, 113, 141, 143, 144, 147]. By one industry estimate, 50% of US employers will use emotion AI to monitor their employees' mental wellbeing by 2024 [144].

Commercially available emotion AI-enabled enterprise systems feature diverse capabilities [19]. Some are fully extractive, whereby employees are surreptitiously subject to emotion monitoring as part of larger workforce analytics programs that collect, aggregate and process data from a variety of enterprise sources (i.e., digital communications, IT security infrastructure, wearable sensors, eye trackers, external social media, and geolocation data), and mined for insights into workers' interiority, including energy levels, wellbeing, sentiment, personal preference, opinion, and emotions [118]. Systems may be designed to make data accessible to organizational leadership (i.e., supervisors, department heads), while others may be more limited in scope and access. For example, IT security programs may use emotion inferences to screen for insider threats to workplace safety and security, with access to that data under tighter access controls [27]. More obtrusive forms of emotion monitoring include wearables that use bio-sensors and physiological signals that aim to infer employees' affective and emotional states in real-time, which may be implemented to influence worker behavior [107, 119]. Despite the increasing commercial availability and adoption of emotion AI in the workplace [89, 107, 118, 144], claims that emotion AI improves organizational outcomes [143, 144] are not scientifically well-established [124]. Emotion AI is still nascent with critiques surrounding its accuracy, scientific validity, ethics, societal implications, and legality [7, 14, 37, 38, 123, 128, 136, 140].

Prior work suggests that commercial applications of emotion AI threaten the privacy of its data subjects, carrying potential for privacy risks including data misuse and abuse [7, 103, 123] that

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when exploited may bring harm to individuals targeted by emotion AI systems. Furthermore, people interacting with emotion AI may be vulnerable to manipulation, and adapt their behavior without cognizance [143]. These privacy risks may be particularly prevalent in the US workplace, where employer surveillance practices perpetuate and reify social inequality [11, 130, 137], and workers' exposure to and interaction with emotion AI-enabled workplace monitoring may occur regularly [157]. Industry guidance suggests that organizations implementing emotion AI address their potential to internally exploit these flaws by adopting policies that reflect the "especially sensitive nature of this data and individuals' right to be free from emotional manipulation" and prohibit uses of emotion data that might induce "disadvantageous outcomes for workers" [143]. However, as both emotion AI applications and employer surveillance practices remain shielded behind the opacity of organizational operations, we lack 1) an empirical understanding of the implications of emotion AI-enabled workplace surveillance that foregrounds *workers*' perspectives – an important party directly impacted by emotion AI use in the workplace; and 2) legal protections or regulatory safeguards that enforce, recognize, or even define an individual right to privacy over emotions – ends to which our work contributes.

Acknowledging the inherent power asymmetry between organizations and workers, the perspectives of workers who are or may be subject to and impacted by emotion AI in their everyday work interactions is key to developing an understanding of the ethical and social implications of emotion AI in the workplace. Workers' location on the weaker end of the power spectrum render them best suited to identify its harms and injustices [17, 49, 111]. To this end, we conducted semi-structured interviews with US adult workers (n=15) to address the following questions: What are workers' general perceptions of emotion AI in the workplace (RQ1)? In what ways do workers experience or anticipate behavioral adaptations in response to emotion AI in the workplace (RQ2)? What consequences do workers experience or anticipate associated with emotion AI in the workplace (RQ3)?

We contribute four novel insights. First, we contribute an understanding of workers' perceptions that emotion AI violates workers' *emotional privacy,* a term we introduce to describe privacy over one's emotions. Second, drawing on the sociological theory of emotional labor [74], our analysis finds that emotion AI in the workplace may function both as a tool to surveil employees' emotions and enforce workers' compliance with perceived expectations of emotional labor. Third, we find that workers may perform emotional labor as a way to preserve their emotional privacy. Lastly, we identify how emotion AI-enabled workplace surveillance can expose workers to a range of harms including privacy and emotional labor-induced harms. These findings demonstrate the need for critical attention to emotion AI's social and ethical implications, in and beyond the workplace, including research and policy on how to define, preserve, and protect emotional privacy. While we discuss implications for policy and design, we note that because many of emotion AI-enabled harms that we identify in this work cannot be mitigated through either technical or policy solutions, we advocate for approaches such as critical refusal [61] in the first place.

2 BACKGROUND AND RELATED WORK

In this section, we review prior work on workplace surveillance, emotion AI at work, and emotion AI's adverse consequences that inform our study.

2.1 Workplace Surveillance of Workers' Interiority

Surveillance of employees' interior states precedes today's digitally mediated surveillance practices. In the 1920s, employers started using surveys, interviews, and other methods to penetrate workers' "conscious barriers and [bring] out latent or unconscious sentiments," gaining insight into employees' thoughts, feelings, and emotions under the guise of improving the workplace [79]. As scientific and technological advancements grew, so too did employers' surveillance practices to probe employees' interiority. By the 1960s, employer use of psychological and personality tests to traverse borders between the worker as presented and the worker's psyche to reveal the "otherwise invisible inner man" was commonplace [67, 78], and by the late 1970s, employer use of lie detector tests (i.e., voice stress analyzers, psychological stress evaluators, and polygraphs) to identify employee deception was widespread [78].

Though the emergence of these increasingly invasive surveillance practices were met with public concern over employee privacy [10, 40, 60, 104, 133], US employers have by and large continued to expand their surveillance practices unrestrained, with electronic performance monitoring via methods including key stroke logging, computer screen capture, network logs, phone monitoring, and video surveillance emerging in the 1980s and continuing through today [11]. One notable exception constraining workplace surveillance is the passage of the Employee Polygraph Protection Act (EPPA) of 1988 that banned lie detector use by most private employers [10].

Advances around emotion recognition technologies have spurred employer desires to monitor and manage workers' interiority. Increasingly, employee monitoring practices have converged with aims to promote worker wellbeing. Intelligent systems promise to analyze enterprise data for inferences of worker emotions and related affective constructs in efforts to advance goals including work-life balance and worker happiness [24, 83, 152]. However, worker emotions are influenced by the workplace context [69], and emotion recognition technologies fail to adequately account for the contingency of emotions to the workplace context [82, 101]. For example, a recent study using automatic emotion recognition methods to infer worker emotions suggests that leading emotion metrics (i.e., detecting dominant emotions) fail to consider the nuances of emotional expression at work and to accurately detect emotions in line with subjects' self-reports [82].

Given the expansion of workplace monitoring practices to include the detection and monitoring of workers' affective phenomena (i.e., emotion, mood, and core affect [53]), as well as the contextual sensitivity of these constructs to the workplace [65], our study investigates workers' general perceptions of emotion AI (RQ1).

2.2 Emotion AI in the Workplace

The purpose of workplace monitoring is not simply to monitor employees' behavior and activities, but to also *shape* them [2]. Through its alleged capabilities to automatically infer, analyze, and/or respond to workers' affective phenomena at scale, emotion AI-enabled workplace technologies promise to support organizations in better managing organizational outcomes by influencing employee emotion and related constructs [143, 144].

Workers' affective phenomena and organizational outcomes are mutually constitutive. As drivers of human behavior and decision-making [44, 94, 155], workers' emotions, moods, and affects influence organizational outcomes and events including sales [1], productivity [15, 50, 122], workplace violence [13], and insider threats [75]. Employer interest in shaping workers' affective phenomena to support organizational goals is underscored by the wide range of organizational purposes for which emotion AI in the workplace is adopted, including monitoring and managing workers' emotion, mood, and affect to detect and mitigate safety and compliance risks; monitor and improve employee wellness, productivity, and engagement levels; analyze and predict employee behavior; and automatically deliver real-time support, management, and coaching to employees [20, 62, 72, 80, 113, 141, 143, 144, 147].

Alongside this organizational interest, HCI scholars have been interested in affective systems, including the development of affective computing as a field [117] and its successor, emotion AI, which often rely on cognitivist approaches to understanding human affective phenomena and related behavior [18, 26]. More recently, HCI scholars have advanced generally applicable developments such as real-time emotion recognition from facial expressions [102], improved machine reading of non-displayed emotions [114], and inferring emotions from head and eye movements in virtual reality applications [154]. Additionally, HCI researchers have designed context-specific applications of emotion AI for the workplace. For example, recent work has leveraged emotion AI to promote happiness and productivity in the workplace by mediating breaks [83], enhance communication with audiences during online presentations [106], and develop post-meeting feedback systems to improve meeting effectiveness and inclusivity [126]. Among other HCI scholars, Boehner et al. critique the cognitivist approaches found in such algorithmic models of emotion, and argue for the conceptualization of emotions as socially constructed [129]. Acknowledging such critiques, a growing body of HCI work continues to examine the ethical and social implications of emotion AI and other algorithmic systems interfacing with affective phenomena [7, 29, 123, 135].

Regardless of the use case, emotion AI in the workplace generates *emotion data* [7] about workers – inferences of workers' emotions, moods, affects, and other interior states and traits – providing employers with information that they may leverage to inform organizational strategy, drive workforce decisions, and manage employees more precisely. Critical scholarship centering the perspectives of data subjects targeted by emotion AI systems indicates that such sensitive information may be misused in ways that leave data subjects vulnerable to manipulation and harm [7, 123]. Yet, little is known about how the collection and sharing of workers' inferred emotional information may impact worker behavior beyond shaping it to support organizational outcomes. This work contributes to addressing this gap by investigating workers' perceived behavioral changes in response to emotion AI in the workplace (RQ2).

2.3 Adverse Consequences of Emotion AI

While the potential benefits of emotion AI to organizations are well-established [143, 144], its effects on workers and associated social and privacy implications remain relatively unknown, though there is some indication that people have negative attitudes toward emotion AI. The importance of examining worker attitudes and perceptions is aligned with recent work suggesting that AI in the workplace can have negative effects on workers. For example, AI implementation can displace organizational responsibilities onto workers [105], and expose workers to unwanted monitoring and productivity management practices that risk employee privacy [58]. Regarding emotion AI specifically, recent work suggests that people have negative attitudes about it [7, 123], including general discomfort [103] in the workplace. Notably, in a scenario-based survey regarding peoples' privacy attitudes toward video analytics technologies (one common source of emotion AI input data), Zhang et al. found that people were more uncomfortable and less willing to consent to video analytics that detect employee mood to predict productivity than their aggregated preferences across all surveyed scenarios [156]. Mantello et al. similarly found that job seekers have negative attitudes toward emotion AI in the workplace; their findings indicate that cultural background shapes attitudes toward emotion AI, suggesting that emotion AI may disproportionately induce stress and anxiety among workers of disadvantaged ethnicities, gender, and income classes [98].

To ensure fair treatment of workers, emotion AI technologies should be used fairly and ethically [143]. Fair and ethical use of emotion AI may include commitments by actors deploying emotion AI systems that it is meaningfully consented to [23]; that its (potentially biased, unreliable, and inaccurate [14, 38, 110, 120]) information is transparent and contestable [31, 66, 143]; and that its use does not widen power asymmetries, such as those already present between workers and their employers [4, 31]. Yet, so far, the use of emotion AI in workplaces remains largely unconstrained and unregulated, and in the modern US workplace, the growing adoption of emotion AI-enabled workplace surveillance is predicted to become the new norm [157]. In generating deeply private and sensitive emotion data that is prone to manipulation and misuse, emotion AI threatens the autonomy of its data subjects [7, 99, 123]. Like with emotion AI's predecessors for workplace surveillance (Section 2.1), workplace conditions of weak worker power within the US [157] place workers in a position whereby they may be unable to meaningfully consent to – or protest – the inference and collection of their emotion data in the workplace [55, 125], even if they are aware of the practice [11]. Indeed, US workers are provided with insufficient privacy protection in the workplace [125], and are thus particularly vulnerable to privacy harms posed by ubiquitous workplace monitoring that has expanded to surveillance of workers' emotion and affect [157]. Yet, we lack an understanding of the privacy implications of emotion AI in the workplace that is grounded in the experiences and perceptions of *workers.*

To understand emotion AI's privacy implications, we must first understand privacy theories. Altman's privacy regulation theory regards privacy as a temporal and dynamic process of regulating interpersonal boundaries with others to achieve one's (or one's social group's) desired privacy levels [5], compared against their actual privacy levels. Further refining Altman's theory, Petronio's communication privacy management theory (CPM) posits that such processes are underpinned by the belief that individuals own, and thus have a right to control flows over, their private information [116]. According to CPM, ownership of private information is shared with those whom information is shared, and privacy violations occur when rules regarding the management of that information are perceived to be broken [116]. Conversely, Nissenbaum's theory of contextual integrity (CI) posits that privacy is afforded with appropriate information flows, dictated by contextually specific norms; under CI, privacy violations occur when such norms are not followed [108]. Considering these privacy theories, emotion AI may implicate workers' privacy if the boundaries, rules, and norms around emotional information sharing in the workplace are ruptured, which may then expose workers to harms. Following Citron and Solove's privacy harms taxonomy (not specifically developed in the context of AI) [33], such harms may include physical, economic, reputational, psychological, autonomy, discrimination, and relationship harms.

Motivated by these gaps in knowledge about the privacy implications of emotion AI in the workplace, and informed by these privacy theories (as further described in Section 3.3), our study investigates emotion AI's risks of adverse consequences as perceived by the workers subject to and affected by emotion AI (RQ3).

3 METHODS

We conducted semi-structured interviews (n=15) with adult workers in the US both with *(n=6)* and without (*n=9)* cognizant experience subject to emotion AI in their workplace.

3.1 Interview Protocol

We designed a semi-structured interview protocol with four phases. In phase 1, we established an understanding of the respondent's workplace and the monitoring tools in place. In phases 2 and 3, we covered respondents' anticipated or experienced responses to emotion AI in their workplace, individually and to workers/the workplace as a whole. In phase 4, we asked privacy-related questions if the respondent had not yet mentioned privacy-related concerns. We designed the protocol to begin with general topics and questions, and then lead to more specific and sensitive topics to avoid influencing the participant's answers and to establish rapport to help facilitate disclosure. Interviews lasted approximately 90 minutes and participants received a $35 honorarium for their participation.

Our sample included workers with and without cognizant experience subject to emotion AI, as emotion AI might be used without workers' explicit knowledge, a key challenge in studying this technology (i.e., existing data streams may feed into emotion AI without that being disclosed to the employee). Between the two groups, our protocol differed only in that for those without cognizance of emotion AI in their workplace, we used scenario-based interviewing grounded in an understanding of workers' general experience with employer monitoring established in phase 1. For example, if a participant without cognizance of emotion AI in their workplace indicated that their employer used video surveillance cameras, we asked the participant to imagine that those video cameras were equipped with computational capabilities to automatically detect, predict, and/or respond to their emotions, feelings, moods, and/or other internal states or traits. Past work has similarly used participants' personal experience to ground scenario prompts regarding emerging technologies in real-life events [6, 7, 22, 123]. To avoid potential bias associated with terms such as "AI," "surveillance," or "mental health," these terms were not introduced to the respondent unless they used these terms first.

We conducted interviews between June and October 2021 and recorded them via Zoom video conferencing software. Participants who were uncomfortable with being recorded on video conducted an audio only interview. We used Zoom's live transcription feature to automatically transcribe interviews, then manually revised transcripts for accuracy before data analysis.

As an interview study on the sensitive and charged topic of emotions, AI surveillance, and the workplace, it was important to take steps to acknowledge and mitigate potential researcher bias and social desirability bias throughout the interview process. To avoid leading participants to respond in a negative way, we took particular care to ensure questions were asked in neutral ways, consciously avoiding prescribing meaning or assumptions upon the respondent by adopting participants' language (i.e. vocabulary choices) in follow-up questions, and when appropriate, repeating back our understanding to the respondent to confirm their agreement with our understanding of their responses [146]. In addition, we encouraged participants to respond with in-depth, narrative style responses, remaining flexible with the order of interview questions to follow the respondent's lead, a technique to reduce researcher bias [59, 146, 149]. By reserving potentially priming questions (i.e., privacy-related questions) for the end of the interview, and only asking those questions if the participants had not brought up those topics earlier in the interview first, we were able to stem researcher bias. A copy of our interview protocol is provided in Appendix B.

3.2 Sampling and Recruitment

To capture a wide range of worker perspectives about the emergent use of emotion AI in the workplace, we sought to gather participant experiences and backgrounds along dimensions of gender, race/ethnicity, age, industry/occupation, and cognizance of emotion AI in their workplace. Participation included workers both with (n=6) and without (n=9) cognizant experience subject to emotion AI in their workplace, denoted with alphanumeric codes of Pc and Pn, respectively. Table 1 includes participants' demographic information. Of note, occupations of participants with cognizance of emotion AI were predominantly public-facing roles (i.e., customer service representatives), suggesting these occupations may either be more likely to be subject to emotion AI, or simply more likely to be aware of it given the emotional demands of their occupation. Toward the end of data analysis, we identified no new themes and did not need to refine constructed theories, at which point we ended recruitment.

For sample diversity, we recruited participants from three sources: 1) occupation-related subreddits (i.e. r/supplychain), after gaining moderator approval; 2) the Prolific recruitment service; and 3) Facebook Ads. We solicited participants via an online recruitment message, which directed interested participants to a pre-screening survey to establish eligibility for the interview, determine cognizance of emotion AI at work, and gather demographic information to facilitate diverse participant selection.

We included a link to the pre-screening survey in our recruitment messages. The pre-screening survey collected information from interested respondents, including their cognizance of being subjected to emotion AI in the workplace, their demographic information (using best practices, i.e., [134]), various types of information collected and/or processed about them at work (i.e., information about what they look like, how they feel, their mental health state), the source of that data (i.e., phone, email, CCTV, microphones), and how that data was collected and/or processed (i.e., digitally recorded by the respondent in a self-report, automatically analyzed by a technological tool or device). To mitigate potential self-selection bias of those respondents highly concerned with workplace emotion AI, we recruited respondents aware of employer monitoring in general, rather than emotion AI specifically. We determined that those who indicated their employers inferred information about their internal states and/or traits automatically through a technological tool or device that inferred that information had cognizant experience with emotion AI. A copy of our pre-screening survey is provided in Appendix A.

We reached out to eligible respondents via email, which contained detailed information about our study's protocol and data management practices, and included a copy of our consent document. We asked eligible respondents to review the information provided and, if they wished to proceed, respond to schedule an interview. We obtained additional verbal consent from each participant at the beginning of each interview session and answered any questions they had.

Our institution's IRB determined this study exempt from oversight. Given the higher risk to which participants may have been exposed from participating in a study about their employer's practices [9, 142], we received IRB approval to classify our study under a higher tier to waive individual documentation requirements that otherwise would have provided our institution with information that could link participants' identities with participation in our study.

Participant	Gender	Age Group	Race/ Ethnicity	Industry/ Occupation
Pc1	woman	45-54	white	K-12 teacher
Pc2	man	35-44	Black Latine	customer service representative
Pc3	man	25-34	Latine white	customer service representative
Pc4	woman	18-24	Asian	research and development associate
Pn5	woman	45-54	Black	manufacturing team lead
Pc6	woman	35-44	Black	customer service representative
Pc7	woman	35-44	Black	healthcare aide
Pn8	woman	55-64	Black	K-12 teacher
Pn9	man	25-34	white	custodian
Pn10	man	35-44	white	insurance claims adjuster
Pn11	woman	35-44	white	social worker
Pn12	man	25-34	Latine	media services associate
Pn13	woman	25-34	white	audit manager
Pn14	man	45-54	white	immigration officer
Pn15	woman	25-34	white	K-12 staff

Table 1: Participant demographic table
Pc = with cognizance of emotion AI; Pn = not cognizant of emotion AI

3.3 Data Analysis

We imported de-identified interview transcripts and analytical memos written after each interview into NVivo, a qualitative data analysis software. Drawing upon grounded theory, the first author inductively analyzed interview data using interpretivist approaches to allow themes and patterns to emerge from the data rather than "imposing them prior to data collection and analysis" [36, 112], and met with the full research team weekly during the analysis for regular discussion and refinement of identified themes.

We initially open coded the data, ensuring developed codes remained close to the data and reflected participants' language and meaning [30, 145]. The first author took a line-by-line approach when open coding to help ensure a critical and focused analytic process and to identify actions, processes, gaps, and leads in the data to pursue [30]. The first author paid special attention to respondents' language to create *in vivo* codes, thus grounding the analysis in participants' worlds and ensuring the analysis aligned with participants' meanings [30].

Following open coding of the first few interview transcripts, we began to identify themes. The first author triangulated the themes that emerged from interview transcripts with those noted in interview memos to create thematic codes according to the identified themes, then grouped existing open codes under the newly developed thematic codes. This exercise resulted in a hierarchically structured codebook with open codes organized by theme, which was then used to code the remaining data using a combined open coding and thematic coding approach. As data analysis continued, we scrutinized and refined emergent theories by constantly comparing newly analyzed data against thematic codes [139]. This method ensured open codes reflected member meaning, and could be regrouped as patterns and themes emerged, diverged, and were refined throughout the analysis.

Finally, the first author employed selective coding to organize thematic codes around a core concept of privacy perceptions, impacts, and harms and connected them to related concepts and theories [76] (see Section 2.3). General perceptions were strongly connected to privacy theories of contextual integrity [109], privacy regulation [5] and communication privacy management [116]. Perceived impacts codes were related to the sociological concept of emotional labor [74]. Perceived consequences codes closely resembled the typology of privacy harms recently introduced by Citron and Solove [33]; to facilitate scholarship clarity and consistency when identifying privacy harms, we chose to adopt the privacy harms typology and mapped harms codes accordingly where relevant. We did not set out to use these theories in our analysis to begin with, rather we observed that our initial analysis pointed to parallels in our analysis and these theories. Our findings' connection to these theories are summarized in each findings section.

3.4 Limitations

As an interview study, the standard limitations of self-report data apply. Additionally, many participants did not know whether they were subject to emotion AI at their workplace (n=9); we conducted scenario-based interviews with this group. Scenario-based (i.e., speculative) methods are sometimes criticized for their findings' construct validity and generalizability to real-life experience. As described in Section 3.1, we ensured that scenarios were grounded in participants' actual experiences with workplace monitoring and followed best practices, noting that these methods are powerful in studying values toward emerging technologies [6, 7, 22, 28, 73]. As our analysis revealed consistent thematic overlap between the two groups, our confidence in the validity of our findings remains high.

While this study does not aim for generalizability, the small sample size (n=15) and representation of job types is a limitation and as such our results may not generalize to workers broadly. Indeed, the impact of emotion AI on some occupations, such as those not conventionally subject to management of their emotions, may be different from impacts identified in this work. Nonetheless, the fine-grained and in-depth nature of our interviews and subsequent analytic process allowed us to, rather than gaining validity through enumeration [42], provide generative insights regarding emotion AI's privacy implications in the workplace that are grounded in the experiences and perceptions of those who are or may be targeted and most impacted by this emerging technology, despite our study's small sample size. Future work could draw on these insights to examine workers' perspectives on emotion AI with larger sample sizes and other methods such as surveys, for example, to assess attitudes across identity lines and occupations.

4 FINDINGS

We first describe the general perceptions of emotion AI in the workplace held by participants in our study, finding that (1) participants experienced and anticipated emotion AI in the workplace as a deep privacy intrusion that inappropriately probes private and sensitive information about their emotions, suggesting that emotion AI in the workplace breaches the contextual norms that govern the appropriate flow of emotional information in the workplace [109]. In describing participants' boundary management processes [5, 116] around whether and to what extent their emotional information is inferred and shared in their workplace, we (2) show how participants perceived emotion AI to violate these boundaries.

Second, our findings integrate the sociological concept of emotional labor [74] to show that (3) emotion AI-enabled workplace surveillance may function to enforce workers' compliance with emotional labor expectations and that (4) workers may engage in emotional labor as a mechanism to preserve privacy over their emotions, as indicated by participants.

Lastly, our analysis draws on participants' perceptions of and experiences with emotion AI in the workplace to (5) reveal how emotion AI-enabled workplace surveillance can expose workers to a wide range of harms on account of its emotional surveillance and enforcement of emotional labor.

4.1 Perceptions of Emotion AI in the Workplace: Privacy Violation and Emotional Labor Enforcement

The main theme across participants' perceptions regarding emotion AI encompassed privacy concerns. Our findings suggest that workers may reasonably expect that they have privacy to their emotions in the workplace, and establish how participants perceived emotion AI in the workplace to violate their privacy over their emotions.

4.1.1 Emotional Inferences are Inappropriate and Irrelevant to Employers. The predominant concern underlying participants' perceptions of emotion AI was the perceived *inappropriateness* of their employer digitally monitoring and algorithmically inferring workers' emotions and related affective constructs. Participants understood employers' attention to their outward expression as it relates to professionalism, but described how the use of emotion AI to monitor their outward expressions in order to infer their interior emotions was irrelevant and inappropriate.

For example, Pn12 did not want employers to infer his emotions and noted how what should matter to employers is job performance, not employees' emotions: *"Don't worry about how I feel, just let me do my job…if you're getting the output that you need, if I'm performing the way you need me to whether I [actually] feel bad, sad, good or happy, it shouldn't really make a difference."* Pn12 emphasized that workers' inner emotions should not be of concern to employers, and questioned why the company even *"cares how I feel about XYZ as long as I'm working, I'm doing my job."* Here, Pn12 establishes the perceived irrelevancy and inappropriateness of worker emotions to appropriate employer concerns. Echoing this point, Pn8 noted that detection of workers' emotions inappropriately exceeds the scope of the transactive relationship between workers and employers: *"because you pay me to work, you don't pay me to have conversations about how I'm feeling."*

These perceptions of emotion AI's irrelevance and inappropriateness in the workplace suggest that emotion AI in the workplace may breach contextual norms regarding appropriate information sharing in the workplace – a violation of contextual integrity [109].

4.1.2 Emotion Data Sensitivity. Participants described how their emotions are not only private, but a particularly sensitive type of private information. Participants noted that the decision whether and to what extent to share their inner emotions should be an individual decision, and likened their emotions to components of their individual health and body.

As such, participants compared the emotion data generated by emotion AI to other sensitive information types, such as biometric and health data. Workers like Pn9 described how they view records of their emotions *"just like your medical information"* and that *"it* *should be kept private"* as such, while others like Pn11 suggested that emotion data *"should be regarded as like mental health information."* Pn11 questioned the distinction between emotion data and mental health information, asking *"whether it be depression and anxiety, you know, so why is [emotion data] any different than those?"*

Given the perceived sensitivity of emotion data, participants perceived emotion AI's inference of emotions as an especially flagrant type of privacy intrusion. As Pn9 described it, use of emotion AI to infer worker emotions is not simply a general violation of privacy, but *"a total invasion of your privacy, like in an acute way."* These findings indicate that workers may perceive the emotion data that emotion AI generates as particularly private and sensitive, and expect that emotion data is handled in accordance with its heightened sensitivity.

4.1.3 Emotion AI Violates Boundaries Over Emotional Information. Participants described how conventional disclosure practices regarding how they felt at work were a personal choice that allowed them to control boundaries around whether and to what extent they shared how they felt with employers. Participants perceived emotion AI to traverse those boundaries and erode workers' ability to manage their privacy over their emotional information.

For example, Pn11 compared emotion AI to employee feedback surveys that asked employees to share with their employers how they felt. Pn11 described how such self-reports were acceptable ways for employers to obtain this information as they preserved employee control over what and to what extent they shared their emotional information, but that using emotion AI to automatically infer what workers feel violates this personal boundary: *"If you want to ask me a question, and I choose to answer it, that's fine. But to... basically put me under a microscope and see how I'm writing things, or how my body's responding to different things [to infer that information]... I don't like."* Here, Pn11 highlights participant concerns around the automatic and continuous nature of emotion AI-enabled workplace surveillance.

Yet, participants' concerns were not only how and to what degree they were monitored, but *what* was monitored – their emotions. Demarcating clearly between expressed and felt emotion, participants described how emotion AI inferring their emotions beyond whether and to what extent they choose to express them transgresses those boundaries. As Pn9 put it, emotion AI inferring their *"deeper"* felt emotions is akin to *"spying"* that crosses *"a huge privacy boundary."* By traversing boundaries between expressed and felt emotion and bypassing workers' ability to manage those boundaries, participants perceived emotion AI's inferences as an intrusion of their interiority that extracts emotional information they perceived as inherently their own; as Pn11 put it, *"That's mine. I don't need someone monitoring that. It's my information. It's my emotions."* Indeed, participants emphasized that the core issue at stake in inferring their emotions was not simply disclosing emotions they otherwise wanted to conceal, as if there were something to hide [131], but that it was problematic because it eroded workers' autonomy to manage privacy over their emotional information. As explained by Pn8, even emotion AI's inferences of a worker's positive emotions can be troublesome: *"it could show that I'm really happy, that I enjoy what I'm doing. And I don't know that anybody needs to know that either."*

Participants' perceptions indicate that the automatic, continuous, and intrusive nature of emotion AI-enabled workplace surveillance inferring information about workers' interior emotions and affect may be profoundly unsettling to workers. All together, they illustrate how workers' boundary management over the disclosure of their emotional information [5, 116] is circumvented by emotion AI's automatic inferences, and how those inferences may violate workers' desired privacy over their emotions by providing workers with an *actual* level of privacy over their emotions that is less than *desired* (see Section 2.3 for further detail about Altman's concept of actual and desired privacy).

4.2 Behavioral Responses to Emotion AI-enabled Workplace Surveillance: Emotional Labor to Preserve Privacy Over Emotions

Integrating the sociological concept of emotional labor – inducing and suppressing feelings to convey a particular emotion as required by their job [74], our findings of participants' anticipated and experienced behavioral responses to emotion AI suggest that it may operate as a surveillance tool that enforces workers' compliance with workplace expectations around workers' emotion management. In addition, our analysis of participants' perceptions and experiences finds that workers may engage in emotional labor [74] not only to comply with perceived expectations of their emotional expression, but also as an impression management strategy [64] that influences what others perceive them to feel while managing and preserving privacy over what is known about their emotions. As such, our findings suggest that workers may engage in emotional labor to preserve their privacy over their emotions, to the extent that the performance of emotional labor can afford.

4.2.1 Emotional Surveillance Enforces Emotional Labor Expectations. Participants with cognizant experience of emotion AI in their workplace characterized it as an emotional surveillance tool that enforced their compliance with workplace expectations of their emotional labor [74]. Offering an illustrative example, Pc6, a customer service representative, shared that if the emotion AI that monitored customer calls inferred that *"you're not perky enough,"* it would intervene by nudging the employee to induce more positive emotion: *"you get a whisper, 'Hey, we need you to smile more, you got this!'"*

Aware of the continuous monitoring of their emotions and enforcement of emotional labor expectations, but without visibility to what information is generated or how it is used, participants described how this information asymmetry enforced a constant expectation that workers convey a positive affect out of fear of how the emotion AI would detect their non-compliance with emotional labor expectations and, consequently, how its inferences could be used against them by their employers. As described by Pc7, emotion AI acts as an *"authority"* that holds workers *"liable"* to *"do [their] best"* and *"discipline"* them to *"obey the rules"* – including rules around emotion management.

Participant descriptions of the use of emotion AI to systematically monitor worker emotions and enforce expectations of emotional labor provide support for an understanding of emotion AI as a tool that enables emotional surveillance [95]. These findings indicate that under emotion AI-enabled workplace surveillance and the information asymmetry it generates, workers may assume the need to constantly practice the emotional labor they perceive is expected of them.

4.2.2 Emotional Labor as Privacy Practice. Building on our findings established in Section 4.1.3 that emotion AI violates workers' privacy over their emotions, we find that workers may engage in emotional labor as a way to *preserve* privacy over their emotional information in response to emotion AI. Participants described how the emotional labor of inducing and suppressing their emotions at work protected them by allowing them to manage what and to what extent their employers knew about how they felt. Participants experienced and anticipated how emotion AI further erodes the privacy afforded by emotional labor through automatic inferences of their emotions. Thus, emotion AI not only enforces adherence to emotional labor expectations but simultaneously also penetrates workers' ability to use emotional labor to protect their interior emotions.

Participants with cognizant experience subject to emotion AI in their workplace described how they modified their emotional expressions in response to emotion AI-enabled workplace surveillance in order to convey a particular emotion readable to the machine. These participants shared how this practice was not simply to comply with perceived emotional labor expectations, but also to manage what information was inferred by the emotion AI and subsequently shared with their employers. Pc1, a teacher whose tone of voice and facial expressions during remote instruction were analyzed for emotion inferences as part of performance metrics, shared how emotion AI would reveal information to her employer that she did not want to share, such as disagreement with an automated lesson plan, as her expressions *"sometimes will say"* how she feels even if she chose not to explicitly express it. Consequently, Pc1 shared how she had *"to really be in control of [her] facial expressions"* and vocal tone to avoid the emotion AI from inferring emotions such as stress or being upset (i.e., *"modify"* and *"lower"* her vocal tone). Experiences like P1's suggest that workers may manage their emotional expressions not simply to comply with workplace expectations of emotional labor, but also as a privacy behavior that utilizes the boundary between expressed and felt emotion to manage what is known about how they feel to their employers.

As such, participants anticipated how emotion AI's inferences would disrupt the preservation of privacy over their emotions afforded by emotional labor. For example, Pn14, an immigration officer for the federal government, described the *"mentally distressing"* emotional labor expectations of his job that required officers to *"grind it and just keep going"* when confronted with administrative demands that conflicted with their personal values. Pn14 described how it was unsafe for officers to voice how they felt, and feared that if emotion AI were used in his workplace, it could expose him and his fellow officers as employees that did not support the organizational changes (i.e., detecting officers that did not *"like the way it was being presented, or what was being laid down to us,"*) which in turn could jeopardize their employment.

These findings suggest that workers may engage in emotional labor practices of inducing and suppressing emotions not solely as a requirement of their occupation, *but also* as a mechanism to manage and maintain privacy over their emotions in order to maintain stability and security in their jobs. Through automatic and continuous monitoring practices that bypass the affordances of emotional labor for protecting privacy, emotion AI then can disrupt workers' practices for managing their privacy over their emotions.

4.3 Perceived Harms of Emotion AI-enabled Workplace Surveillance

Participants experienced and anticipated how emotion AI in the workplace and its inferences of worker emotions exposes employees to a multitude of harms. Mapping our analysis to Citron and Solove's general taxonomy of privacy harms [33], which was not developed specifically in the context of AI, we identify both parallels with this typology as well as emotional labor-induced harms expressed by our participants that the typology does not quite capture: amplification of emotional labor's negative effects, disparate effects of emotional labor amplification, and chilling effects to workers' own, felt emotions.

4.3.1 Privacy Harms. We first discuss how emotion AI implicates established privacy harms, in alignment with Citron and Solove's privacy harm taxonomy [33].

Psychological Harm. Psychological harms refer to negative mental responses experienced as a result of privacy violations [33]. Participants shared how the practice of emotion AI-enabled surveillance can induce emotional disturbance and distress, harming workers' psychological wellbeing with negative effects including worry, stress, and paranoia.

Pc3, whose call center analyzed recordings from employees' web cameras to monitor their emotions, shared how he maintained *"a sense of...worrying"* throughout his experiences being subject to emotion AI. Pn15, who did not have cognizant experience with emotion AI in particular but did have experience with her employer maintaining digital records of observed employee emotions, described how if she was aware that she was subject to emotion AI, it would be *"very stressful, and it would make it so that the only place I could really relax is outside of work...and I would have felt very unhappy at the workplace."* Similarly, Pn10 anticipated that *"if [he] knew it was happening, [he] would be a bit paranoid"* and Pn11 noted that she *"would feel like [she's] under a microscope, like people are watching"* which would *"put [her] back on guard."* These examples illustrate how emotion AI's surveillance itself can result in direct harms to workers' psychological wellbeing.

Autonomy Harm. Autonomy harms involve constraints on people's freedom to make choices [33]. In line with findings from Section 4.1.3 that emotion AI violates workers' privacy over their emotional information, participants emphasized how being subjected to emotion AI would acutely harm their autonomy by automatically extracting and sharing inherently personal information about their emotions, which could expose them to emotional manipulation by their employers. Moreover, participants shared how they perceived employer efforts to obtain consent to emotion AI as coercive, suggesting that standard employer monitoring consent practices (i.e., asking an employee to sign a notice consenting to emotion AI) may be perceived as coercive, and should not be viewed as worker consent to the privacy violations imposed by emotion AI in the workplace.

For example, Pn9 described their emotional information as deeply personal, and believed that individuals alone should have the ability to exercise choice in sharing it. Pn9 stated that *"I think it should be up to your own person to decide what information... about your health and body"* is shared, and that the decision to share that information should be decided *"not [by] your employer...or anyone else."* Pn9 exemplifies participant perceptions that in eroding workers' privacy over their emotional information, emotion AI can harm workers' autonomy over when and how they share their emotions.

While obtaining consent for emotion AI to collect or infer workers' emotional information may arguably mitigate its autonomy harms, our findings suggest that this may be insufficient as it may be perceived as coercive rather than freely given consent. Of note, Pc3 was the only participant with cognizance of emotion AI in their workplace who noted their employer sought their consent, specifically to use *"camera tracking"* to monitor call center workers' emotions. Pc3 found this to be coercive, as employees felt obligated to sign the consent document because their job was on the line. Pc3 explained that *"everyone just felt obliged because it was an all-in-or-nothing sort of situation...everyone, if they wanted to keep their employment, they had to sign that document."* Underscoring the coercive nature of seeking consent to emotion AI-enabled workplace surveillance, Pc3 shared that a coworker had to leave the organization because *"they didn't sign the document on their own accord."*

Our findings suggest that the dissemination of workers' emotional information may leave workers vulnerable to emotional manipulation by their employers. For example, Pn12 anticipated how the use of emotion AI would indirectly manipulate workers to *"think a lot more...company-oriented things"* once awareness of the emotion monitoring grew. Yet, employers may use this information to directly influence workers' emotions as well. Pc1 reported that her employer used emotion inferences and metrics to *"coach"* teachers by informing them that they weren't expressing themselves *"the right way"* and warn that they *"might not get rehired"* if teachers did not embody the emotional expectations their employer demanded. Demonstrating how workers' emotional information can expose workers to emotional manipulation, Pc1 reported that their employer would use emotion data to influence teachers to feel how the district wanted them to feel: *"That's not how you should be feeling about [your lesson plans]. This is the way you should be approaching this. This is the way you should think."*

By denying workers the ability to control what is known about their felt emotions and in a context where workers do not have a free choice to consent to the practice, emotion AI-enabled workplace surveillance harms workers' autonomy by coercing workers to relinquish control over their private emotions to their employer. In addition, it poses a risk of future harm to workers' autonomy by revealing emotional information that employers can then use to manipulate workers into aligning their feelings with the interests of the organization. Importantly, these effects of introducing emotion AI are happening regardless of emotion AI's precision in recognizing emotions, a point we discuss further in Section 5.1.

Physical Harm. Physical harms characterize privacy violations that injure one's body [33]. Participants described how the stresses and psychological harms of emotion AI collecting and sharing information about workers' emotions can manifest physically, injuring workers' physical wellbeing.

For example, participants with cognizant experience with emotion AI described how it can deplete workers of physical energy and vitality. As illustrated by Pc6, being subject to emotion AI *"drains the snot out of [her]."* Likewise, Pc3 explained that *"it takes away from people's energy that could be used towards more productive things for both themselves and the company while working."* These examples illustrate how emotion AI can physically harm workers by stripping them of physical energy. What's more, this effect may impair worker productivity, which may pose an economic risk of harm to employees as well as employers.

Noting the close relationship between emotional and physical health, Pn8 anticipated how being required to use emotion AI at her workplace would just make her angry, which could in turn impair her physical wellness: *"You have a piece of equipment on me, that can tell people that I'm angry about something, annoyed about something, probably more anger, because my blood pressure will probably go up."* Pn8's observation highlights how the physiological responses to emotion monitoring can adversely impact one's physical wellness. Even if those changes are temporary (i.e., temporary blood pressure spikes), they can lead to longer term consequences (i.e., organ damage [68, 96]).

Economic Harm. Economic harms are the result of privacy violations that lead to monetary loss [33]. Participants described experiences and concerns related to economic harms resulting from the processing of their emotional information, as the revealed information may hinder future job opportunity or result in job loss. Particularly, participants were concerned that emotional information inferred by emotion AI could be used to make employment decisions or to justify performance evaluation decisions – upon which raises, promotions, and bonuses often depend.

Illustrating how using emotion data in performance evaluations can economically harm workers, Pc3 described how a colleague's performance review, which included metrics aggregated from video-based emotion tracking along with other data sources to infer employee satisfaction and engagement, suggested that the employee was not satisfied with their job. As a result, Pc3 explained that management then began to doubt whether the employee was *"up to the role,"*. Pc3 expressed disdain for his employer *"questioning a person's ability to continue [the job] based on...minimal information"* derived from emotion AI inferences, threatening workers' job security. In addition, workers shared concern that use of emotion AI's inferences in performance reviews could result in the loss of economic opportunity, such as denying a promotion or raise. For example, Pn11 worried their emotion data would lead to a poor performance review and pass them for a potential promotion, on the grounds that *"I wasn't necessarily happy or something like that."* Participants' shared experiences and concerns suggest that certain uses of emotion AI (i.e., in performance evaluations) can expose workers to economic harm.

Reputational Harm. Reputational harms involve injuries to one's reputation or standing [33]. Touching on concerns about emotion

AI's reliability and validity, participants reported that inferences of felt emotion are invalid and unreliable to assess how employees feel due to the high variation of emotions experienced in the workplace, the indistinguishability of emotions felt about work from other contexts, and technical inaccuracy. Participants expressed concern about consequences to their reputation as a result of misleading or inaccurate emotion AI inferences.

Pn10 described a recent example where his felt emotions varied significantly throughout the week, *"feeli[ing] very angry and concerned and just paranoid"* at the beginning of the week due to a higher than usual workload, but felt *"very happy"* by the end of the week as he *"got everything caught up,"* ending the week feeling accomplished. Pn10 highlights here how workers can experience felt emotions more deeply and extreme than they express them, an emotional phenomena that can be attributed to one's care for consequences [57]. By conflating workers' felt emotion with its modulated emotional expression, Pn10 worried that the *"extremes that you would get"* could confer a misleading impression of one's overall emotional wellness to their employer.

What's more, Pn10 worried that the blurred boundaries between the personal and the professional would render emotion AI's inferences about workers' emotional lives at work indistinguishable from their personal ones [65]. Pn10 emphasized that emotions felt while at work are often related to private life events rather than work concerns, such as recent *"bad news about a family member"* or upset at something relatively *"dumb"* like the cancellation of a favorite TV character, raising concern that the inferred emotional information may give his employer the wrong impression of how he feels as only *"some of [his] emotional responses are going to be work related."*

In addition, participants shared concerns that emotion AI's technical inaccuracies may create a false impression about workers. As a supervisor at a production facility with workplace hazards (i.e., pneumatic air and dangerous machinery), Pn5 acknowledged how emotion AI could improve workplace safety (i.e., detecting fatigue to reduce workplace accidents), yet remained concerned about emotion AI's potential to injure an employee's reputation as a result of potentially inaccurate inferences. Referring to her personal concerns, Pn5 reported that she doesn't *"have the most friendliest face,"* describing that she could feel *"happy as I don't know what,"* yet others may misread her face as *"stoic...or upset."* Given her experience with others misreading her emotions from her facial expressions, Pn5 was concerned the emotion AI would as well: *"I wouldn't want it misreading....if the human can do it, then I know a piece of technology could do it, so that's not cool in my opinion."* Consequently, Pn5 was concerned of what *"everybody would think of [her]"* if the emotion AI continued to misread her emotions negatively. Marking the significant difference between felt emotion and expressed emotion, Pn5 also shared concerns that detecting felt emotion would lead to unreliable and invalid predictions about workers: *"I'm so mad I want to shoot someone. So that don't mean I'm gonna go ahead and do it."* Describing the effects inaccurate inferences would have on workers as *"probably [her] biggest fear,"* Pn5 expressed concern that emotion AI's inaccuracy could unfairly harm workers' reputation in the workplace, and worried about what other potential consequences this might entail for workers: *"will it spill over? ...what's the consequence behind how you feeling?"*

In addition to reputational harms, Pn5's concerns raise important implications for employer liability, as employers may be compelled to act on certain inferences (i.e., anger) so they are not held liable for negligence in case that person threatens workplace safety and/or security (i.e., inflicts violence). As the algorithmic detection of anger has been shown to exhibit racialized bias [77, 120], employer interventions could involve unjust actions taken against workers of color erroneously detected as angry that not only harm a workers' reputation, but as recent scholarship has observed, potentially expose them to dangerous interactions with law enforcement as well [123].

Participants' insights illustrate how emotion inferences are likely a poor construct to assess employee wellness, which can mislead others to have a false impression of workers and unfairly harm workers' reputation. In addition, they suggest that the detection of some affective phenomena (i.e., fatigue) carry different risk profiles than others (i.e., anger), which may expose workers to additional harms (i.e., discrimination and economic harms).

Relationship Harm. Relationship harms concern injury to personal and professional relationships [33]. Participants shared experiences and concerns with how emotion AI in the workplace can damage trust and amplify tension between employers and employees and limit the capacity for workers to engage with and support each other, injuring professional relationships between and amongst workers and their employer.

Participants reported how they perceived the organizational decision to implement emotion AI in the workplace as a suggestion that their employer does not trust them. Pc3 described how the implementation of emotion AI in their workplace fostered *"a sense of distrust"* and *"disconnect between [workers] and [their employer]."* Similarly, Pc7 shared that after emotion AI was introduced, she and her colleagues immediately wondered, *"why is the organization not trusting us?"* As a consequence, participants shared that this sense of distrust would damage the professional relationship between workers and employers. For example, Pn12 shared that they *"would probably feel disregarded"* by their employer if they were to implement emotion AI in their workplace, and anticipated how *"a lot of people...would probably be really put off by the fact that a company is willing to roll something out...that kind of privacy violation tool."*

In addition, participants indicated that the decision to adopt emotion AI could amplify pre-existing tensions between workers and employers. For example, Pn11 perceived emotion AI in the workplace as an inauthentic way to promote wellness that, in effect, shifted the employers' responsibility to manage a workplace environment that is conducive to worker wellbeing onto individual workers. Likening emotion AI to employee wellness initiatives (i.e., encouraging workers to practice self-care), Pn11 underscored the hypocrisy of employers that *"drive [workers] for profits"* using emotion AI to promote an *"individual responsibility to take care of yourself"* instead of addressing underlying workplace conditions that can impair workers' wellbeing as a *"whole disconnect...that doesn't really line up for [her]."* Pn11's observations suggest that worker responses to the implementation of emotion AI – even when presented positively as a way to promote wellness – can exacerbate already present tensions in the employer-employee relationship regarding employee wellness.

Moreover, participants shared how emotion AI could constrain relationships between workers. As Pc3 described, *"everyone always complains about it...how ridiculous it is,"* but that they had to do so carefully. Pc3 explained that workers were careful to only bring up concerns with each other in-person *"when just having conversation"* so that their concerns were not digitally recorded or inferred by the organization. Moreover, Pc3 described how his boss would sometimes hear their conversations, but would *"remain neutral"* as their boss was not in a position to advocate employees' concerns. Pc3's experience suggests that emotion AI-enabled workplace surveillance may damage the professional relationship among workers as well, by limiting workers' capacity to support and engage with each other, and potentially suppress dissent among them.

Discrimination Harm. Discrimination harms perpetuate social inequalities of disadvantaged groupin ways that leave "a searing wound of stigma, shame, and loss of esteem...knowing that one is viewed as less than human, as not worthy of respect" [33]. Participants described experiences and perceptions of how emotion AI-enabled workplace surveillance can perpetuate and obscure gender-based discrimination in the workplace.

For instance, Pc7 described how her colleague experienced negative emotions related to her pregnancy, explaining how *"pregnancy comes with...so many things going on around the body"* that can negatively affect how one feels while at work. Pc7's colleague had not yet disclosed her pregnancy to their employer, so when their employer expressed concern about her negative emotions and the *"mistakes"* she made by failing to engage with patients warmly enough, the colleague felt *"forced"* to disclose her pregnancy to explain away the emotion AI's inferences about her negative emotional state. The unwanted disclosure of pregnancy to their employer that Pc7's colleague felt forced to reveal as a consequence of emotion AI-enabled workplace surveillance ultimately gave their employer a way to evade anti-discrimination requirements. Instead of modifying their expectations to accommodate the employee's pregnancy, their employer tied emotional expression to work performance (i.e., compliance with emotional labor expectations) and eventually gave the colleague a choice to either *"quit their job, or improve"* the negative emotions they experienced as part of their pregnancy that manifested in their interactions with patients. Describing the difficulty her colleague experienced in attempting to manage her pregnancy-related negative emotions how their employer expected, particularly when subject to emotion AI-enabled workplace surveillance, Pc7 explained that *"once she realized that [emotion monitoring] was going on...it kind of like changed her attitude in a way, because now you are acting under force, and pressure."* Though Pc7 indicated that her colleague *"really tried her best"* to improve, the colleague ultimately had to leave the organization. This example suggests that emotion AI can harm workers by inducing disclosure about private matters (e.g., pregnancy) that may then be used by employers to justify discriminatory practices.

Underscoring the concerning potential for emotion AI-enabled workplace surveillance to perpetuate and obscure discrimination, Pn13, a manager, anticipated how emotion AI could be beneficial to her organization by affording managers information about employees that could be used to justify employment decisions that otherwise lacked documented support. For example, Pn13 described *"a situation a couple of years ago where we had to terminate a [female] employee, and it was without cause,"* noting that emotion AI could be useful to employers in similar situations. Pn13 shared that it would be useful for *"IT management use it on an as-needed basis"* because it would offer employers *"concrete data"* to *"build a case"* against a worker they wished to terminate (who otherwise would have been fired without cause). Explaining further, Pn13, a woman herself, shared that *"females are stereotyped to have more emotion"* and that women *"need to, you know, keep your emotions out of the workplace."* Pn13 described her *"negative experiences"* as a manager working with womens' emotions in the workplace, such as *"disagreeing with a manager, and not wanting to do what they ask, resulting in storming off."* Pn13 thought emotion AI-enabled workplace surveillance could be particularly beneficial to the organization if it could detect *"emotions in the workplace from females that were extreme, and over the top and inappropriate."* P13's remarks here demonstrate the stigma surrounding womens' emotionality in the workplace, and the eagerness employers may have in adopting emotion AI-enabled surveillance systems that afford employers information they can wield to legitimize otherwise risky employment decisions (i.e., firing a woman without cause) and potentially shield them from discrimination claims.

4.3.2 Emotional Labor Harms. While many of the harms experienced and anticipated by participants align with Citron and Solove's privacy harms taxonomy as discussed in Section 4.3.1, emotion AI and its interaction with emotional labor also surfaces harms that exhibit nuanced qualities that do not neatly align with the taxonomy. We identify three harmful aspects to emotion AI as a surveillance mechanism to enforce emotional labor: (1) enhanced enforcement of compliance with emotional labor amplifies emotional labor's negative effects; (2) negative effects of emotional labor disparately endured by workers of marginalized identities and backgrounds (i.e., Black women as presented in our sample); (3) chilling effects to workers' own, felt emotions.

Emotion AI Amplifies Emotional Labor's Negative Effects on the Worker. Participants described how the automatic, continuous emotion monitoring provided by emotion AI worsened, or could worsen, the adverse impact to their wellbeing they already experienced from the emotional labor they performed at work through constant discipline and enforcement of emotion rules, in effect amplifying these known negative effects of emotional labor [74] that are only partially recognized by the privacy harms taxonomy [33].

For example, Pn11 anticipated how emotion AI's emotional surveillance would heighten the emotional labor they already practiced as a mental healthcare provider. Pn11 noted how difficult it would be to continue to express care and concern for her clients under under emotion AI-enabled workplace surveillance: *"rather than being present with my clients, so I wouldn't not only have to watch my emotions and my reactions, and also still be present for the clients, but then I would have to also be on guard to whatever this technology is trying to infer about me."* Here, Pn11 highlights how both emotion AI's enforcement of emotional labor expectations *and* emotion AI's surveillance of worker emotions can amplify the already difficult performance of emotional labor and associated negative effects, in effect harming workers' wellbeing, but also divorcing workers from their own emotional experience.

For participants, the negative psychological effects of continuously complying with emotional labor expectations under emotion AI-enabled surveillance carried a deeper quality than psychological disturbance and distress, leading to a sense of alienation that can estrange workers from their own selves and those around them [74, 100]. For example, Pc6 shared how the distress of being subject to emotion AI's constant emotional surveillance and emotional labor enforcement inducing feelings like hopelessness and fear reduced her sense of purpose to datified performance indicators: *"I'm like getting nowhere, that all of this stuff is counted against my metrics."* Likewise, Pn15 worried about the self-estrangement that could emerge from being subject to emotion AI, as it would prevent her from *"being able to be [her] full self."* Pn15 described how she *"would have been disappointed"* in herself for suppressing who she was and how she felt.

In summary, emotion AI's automatic surveillance of worker emotions affords employers the continuous, perfect enforcement of emotional labor, which can amplify its negative effects to workers' wellbeing. While this harm shares similarities to psychological and possibly physical privacy harms [33], it entails harms of worker alienation and self-estrangement that are amplified as a result of emotion AI-enabled workplace surveillance's enforcement of emotional labor compliance that are not captured by Citron and Solove's typology. Indeed, the experience of estrangement from one's own private self and emotions is an "important occupational hazard, because it is through our feelings that we are connected with those around us" [74].

Disparate Effects of Emotion AI's Emotional Labor Enforcement. Our findings suggest the negative effects workers may experience under emotion AI-enabled workplace surveillance as an emotional labor enforcement tool may be disproportionately felt by workers of marginalized identities and backgrounds. In particular, the experiences of Black women with emotion AI in their workplaces suggests that the negative effects from its use as an emotional labor enforcement tool may be more severe for Black women, who disproportionately endure challenging customer interactions as doubly women *and* workers of color [41]. While emotion AI can amplify this discrimination harm [33], its interaction with emotional labor involves a nuanced effect whereby workers may disproportionately endure emotional labor to *confront* the discrimination that harms them.

Pc6 described how her employer monitored her video and call-based interactions with customers in real-time to ensure that workers *"stay upbeat and make [them] really be positive and energetic through the whole conversation."* Pc6 reported that this expectation was enforced even in the face of challenging interactions, which for Pc6 included racist and sexist customers who met her with disdain and sometimes even refused her support upon recognizing her identity as a Black woman. Describing the distress of having to provide support to these customers, Pc6 shared how difficult it was to maintain positivity *"when your insides are crying because of the poor, poor attitudes that you have to deal with all day,"* knowing that their emotions were monitored to make sure of it. Pc7, a Black woman and healthcare aide whose employer similarly used real-time video and audio-based emotion analytics to monitor interactions with patients, reported similar distress from enduring emotional surveillance in the face of racist customer interactions. Pc7 shared that *"there's also some patients who don't like Blacks...so they will like insult you, they'll treat you badly"*; though Pc7 would always *"try [her] best"* to convey positivity and make the patient happy, she described how sometimes it was too much to endure when *"you cannot take it anymore."*

Both Pc7 and Pc6 described how they made sense of their experiences enduring emotional labor as ways to challenge racism, spinning them in a positive light. For example, Pc6 shared that even if she had *"someone that's racist, I want to provide the best experience ever so that I can make you change your viewpoint on how you feel about someone of my complexion"* and *"change the narrative that your experience with a Black person was the best that you have had in a long time."* Similarly, Pc7 described how maintaining calmness and positivity toward difficult patients could challenge patient prejudice: by refusing to respond to racism and contempt with anger, Pc7 believed that she *"chose to do the right thing"* by concealing the negative emotions that such racist encounters provoke, allowing her to *"be the bigger person."* Such sense-making processes demonstrate the additional burdens and consequent discriminatory effects Black women and possibly other workers of color may take on in order to reproduce the constant positive emotional labor required of their jobs under emotion AI-enabled workplace surveillance.

Harms from emotion AI's disparate negative effects from emotional labor enforcement share similarities to established discrimination privacy harms [33] in that they may disproportionally affect workers of marginalized identities and backgrounds, yet differ in that it does not create the same mark of shame and stigma. Pc6 and Pc7's experiences instead reveal how they perform emotional labor to *challenge* societal prejudices and their stigmatized associations. The disparate effects workers may experience from emotion AI then stem from the additional labor marginalized workers disproportionally endure on account of societal discrimination.

Emotional Surveillance's Chilling Effects on Felt Emotion. Concerned that emotion AI could detect that the emotions they outwardly expressed in accordance with their job's emotional expectations did not align with their inner, felt emotions, participants with cognizance of emotion AI-enabled workplace surveillance experienced chilling effects to their own felt emotions in order to align their emotions with perceived workplace emotional expectations. More than amplifying constraints to workers' autonomy and the psychological harms this restriction may involve [33], we find these chilling effects to workers' felt emotion to involve concerns that may be ignored by a categorization that insufficiently captures the complexities of human emotion that include, but also exceed, limits to free choice and rational thought [57].

For example, Pc1 described how the continuous emotional surveillance and emotional labor enforcement they experienced under emotion AI prevented her from *experiencing*, not just displaying, human, negative emotions. Pc1 shared that under constant emotion monitoring to enforce expectations that teachers maintain a positive demeanor, she felt she was not even allowed to experience negative emotions while at work – regardless of how she expressed them outwardly. Contextualizing her experience as a high school teacher, Pc1 shared examples of everyday interactions that would reasonably induce negative feelings: *"teenagers, they're going to try* *to tell you that you look fat one day, or they're gonna...ask if you have a boyfriend, or they're going to tell you that their mom is younger than you."* Pc1 explained how these difficult interactions *"push you to learn how to handle [them]"* and not visibly *"get angry."* But, under emotional surveillance and emotional labor enforcement, *"if you did get a little heated one day and have a bad day, definitely you would be investigated."* As a result, Pc1 found it difficult to not even be able to *feel* negative emotion, out of fear her employer would investigate her as a result. Similarly, Pc7 shared how she was unable to feel certain emotions as a result of her employer's emotion AI-enabled emotional surveillance, describing how the *"pressure [of] wanting to feel something that is outside the organization, or just something that you are just by yourself,"* but couldn't, was *"overwhelming"* due to the *"constraining"* effects of emotional surveillance.

These experiences demonstrate how emotion AI-enabled workplace surveillance can chill worker autonomy over their inner, felt emotions. This harm extends beyond established definitions of autonomy harm [33] as the point of contention goes further than concerns of undermining peoples' choices and restricting lawful human behavior, rather it involves manipulating and re-orienting worker affect and emotions in ways that limit the bounds of human emotional life.

5 DISCUSSION AND CONCLUSION

Emotion AI is often celebrated for its potential to improve the safety and culture of organizations and the wellbeing of the employees that compose them [118, 144]. Yet, our examination of workers' perceptions of and experiences with emotion AI illustrates a starkly different story: one where workers are subject to invasive emotional surveillance that enhances the control employers have over workers' emotional lives [8, 46, 74] and amplifies the adverse consequences workers may experience from emotional labor enforcement and privacy intrusion. Even in the increasingly privacy-invasive modern workplace [8, 157], we find that participants perceived emotion AI to enable an especially intolerable form of surveillance that erodes workers' privacy and control over their own emotions. Employers' unrestrained ability to monitor and manipulate their employees' emotions with emotion AI-enabled workplace surveillance threatens to degrade the value of and shift social norms around privacy at perhaps the most fundamental level of human experience: what we refer to as *emotional privacy*.

Our findings call for industry, policy, and research to contend with emotion AI's erosion of emotional privacy. To that end, we first discuss our conceptual contribution of emotional privacy to illustrate how emotion AI destabilizes privacy over one's emotional life, and argue that emotional information and freedom from emotional manipulation are worthy of preservation and protection – within and beyond the workplace. We conclude with implications of our findings regarding emotional privacy for policy and design.

5.1 Emotion AI Erodes Emotional Privacy

Documenting how employers engage in surveillance practices to monitor and manage employee emotions, Arlie Hochschild introduced the sociological concept of "emotional labor" in 1979 to describe the phenomenon of corporate control and commodification of workers' emotions. Hochschild's arguments proved to be politically potent [21] and were followed by an impressive breadth of scholarship that largely focused upon emotional labor's adverse effects [90]. Yet, less attention has been paid to the privacy implications of emotional labor, which Hochschild referred to as "the best account of how deep institutions can go into an individual's emotional life while apparently honoring the worker's right to 'privacy' " [74].

Hochschild depicts the interiority that remains deep inside workers as an "inner jewel" that evades the gaze of even the most authoritative employer [74]. As our findings suggest, emotional labor can function as a mechanism to manage and preserve one's privacy over this inner jewel, yet, emotion AI that automatically infers workers' emotions enables employers to break this shield and access the inner jewel of workers' interiority. In so doing, as our study finds, emotion AI erodes peoples' ability to preserve the privacy of their emotions –– what we refer to as their *emotional privacy* – restricting whether and to what extent people can manage what is known about their emotions to others by transgressing human boundaries between expressed and felt emotion. We define emotional privacy as privacy over one's emotions, and show throughout this paper how emotion AI use can disrupt this desired quality for many workers, how workers attempt to manage their emotional privacy through emotional labor, and why emotional privacy is consequential due to the harms its invasion imposes on workers. Emotional privacy has implications beyond the workplace, as emotion AI technologies and applications span many contextual use cases, including healthcare, education, marketing, and law enforcement [103]. The breadth of scholarship aiming to improve the algorithmic detection of "fake" and "genuine" emotions [52, 86, 92, 148] highlights emotion AI's threat to emotional privacy.

By exposing and manipulating human emotion, as our findings suggest, the consequences of this emerging technology's privacy harms add a new quality to the current recognition of digital privacy harms [33]. While emotion AI-enabled workplace surveillance has much in common with other surveillance infrastructures, our findings suggest that there is a different, deeper level of quality to its privacy invasiveness. Emotion AI-enabled workplace surveillance constitutes a deeper privacy intrusion into a person's interior – surveilling and manipulating humans' emotional selves and bodily interiority – than is the case with prior surveillance infrastructures that mostly monitor outward display acts. Regardless of its current technological limitations [14, 38, 110, 120], our findings show that emotion AI is perceived by those who are or may be subjected to it as a technology that reads and manipulates one's inner thoughts and emotions, and those perceptions pose real and harmful consequences to workers as we show.

Our findings demonstrate the need to study privacy of emotions or *emotional privacy* in more depth — regarding both harms to emotional privacy as well as protections of and rights to emotional privacy. As we show, emotion AI, by definition and design, erodes emotional privacy. To address its invasions of emotional privacy, we must first recognize emotional privacy as part of the human right to privacy – legally and ethically – and acknowledge that people deserve protection against technology-enabled harms from emotional privacy violations. Echoing participants' sentiments, we argue people ought to have a right to privacy over their emotional information and remain free from emotional manipulation.

Such recognition and protection of emotional privacy could take the form of a civil right and liberty, as argued by legal scholars introducing parallel forms of privacy, notably Citron's *intimate privacy* [32] and Richards' *intellectual privacy* [121], which argue that privacy over our intimate and intellectual lives – together encompassing our bodies, health, relationships, thoughts, and beliefs – are fundamental to human flourishing and thus ought to be protected. However, our theoretical understanding of emotions (and affective phenomena broadly) is complex and lacks consensus [18, 26, 135], and algorithmic inferences thereof have the potential to reveal novel insights due to emotions' fundamental integration with human behavior and cognition [115]. As such, while emotional privacy may span parallel privacy forms such as intimate and intellectual privacy, the contested and sweeping nature of human emotion raises questions about what it means and what is at stake when *emotions* are inferred using computational means. Whether and how emotional privacy involves concerns of bodily and intellectual integrity, and where it might diverge from established privacy interests, is an area requiring further research and theoretical work to which this discussion serves as a starting point.

5.2 Policy Implications: Recognizing and Protecting Emotional Privacy

Our findings have implications for policy that begins to protect emotional privacy. Law and policy can act as counterweights to limit the otherwise boundless practice of worker surveillance [3, 8]. Yet, US federal law does not currently limit or address the general surveillance of workers [3], barring public employees who enjoy constitutional privacy protection against their government employers [151]. As such, available legal avenues for workers regarding employer surveillance fall under a patchwork of state legislation and common law privacy torts [151], though both have proven woefully inadequate to protect against and remedy privacy harms workers endure in the workplace [3, 87, 151], and do not cover emotional privacy. Of note, the California Consumer Privacy Act (CCPA) mostly exempted employers from compliance under its "workforce data exemption" [88], though its successor as of 2023 – the California Privacy Rights Act (CPRA) – extends protection to all personal information, including employee data [48], which may have implications for workplace surveillance practices.

What's more, history has shown that new data practices and technologies can enable employers to evade worker privacy protections [3, 39]. In response to surveillance constraints, employers have shifted away from the discreet collection and processing of workers' personal information and other data practices that are regulated to a participatory approach that engages workers to share their information with employers under the guise of progress and well-being [35], in effect normalizing extensive and invasive employee surveillance and silencing its legal objections [3, 35]. Emotion AI-enabled workplace surveillance goes further by no longer requiring workers' participation to share their thoughts and feelings, instead circumventing worker disclosure of such information with automatic (claimed) inferences of worker emotion and affect. Absent of technological, legal, or normative constraints to restrict its use [3], emotion AI in the workplace stands to collect, process, and share deeply private and sensitive emotional information [7] about workers, leaving them without adequate and explicit protection and vulnerable to the harms we identified in this work.

Of the available employment privacy statutes in the US, most focus on remedying particular harms [125]. Exceptions include a few state statutes that limit the surveillance itself (i.e., video surveillance with audio [56]) and restrict the collection of certain types of employee data (i.e., biometric data [138]). However, because of the breadth of the information emotion AI processes and the uniqueness of the information emotion AI claims to generate (i.e., automatically reading a person's emotions and affective phenomena more broadly), it is difficult to appropriately classify it under existing regulatory schemes [12]. Open questions remain regarding whether information about human emotion and affect can be protected under existing categories, including thoughts and beliefs, biological and biometric data, sensitive information, and/or identifiable health information [12]; and whether the artificially intelligent nature of the inference's origin and its ability to "derive the intimate from the available" demands a renegotiation of conventional understandings of individual privacy to capture its potential to enable mechanisms of large-scale, "hyper-targeted control," [25] particularly at the hands of anthropomorphized, emotionally intelligent AIs [45, 81, 93]. These open questions pose significant barriers to the application of enforceable regulatory frameworks to mitigate, prevent, and remedy potential harms from emotion AI [12, 34], a matter of increasingly pressing public concern [37, 91].

Consequently, legal scholar Bard advocates for the development of a framework to prevent or mitigate emotion AI's potential harms in particular, rather than AI broadly (i.e., a general AI code of ethics). The development and enforcement of mechanisms to address emotion AI's harms, as Bard observes, necessarily begin with the task of identifying them [12]. Our identification of emotion AI's privacy harms in the workplace provides a foundational contribution to this discourse.

At a more fundamental level, regulation and policy could strengthen worker power and expand worker rights. Surely, the lack of available worker protections has enabled the adoption of exploitative and invasive emotion AI-enabled workplace surveillance [157]. Through this work, we have recognized and advocated for a right to emotional privacy in the workplace and identified the potential harms to which workers may be exposed as a result of emotion AI's erosion of emotional privacy – insights that labor rights advocates could use to take steps in protecting and preserving workers' emotional privacy.

5.3 Design Implications: Mitigating and Pre-empting Emotional Privacy Harms

There are several opportunities for industry actors to better protect emotional privacy, and mitigate or pre-empt some of emotion AI's harms within and beyond its application to the workplace.

First, for collective rather than individual monitoring applications, techniques such as differential privacy can protect privacy by introducing noise that offers plausible deniability for any identifiable individuals in emotion AI datasets [84]. For instance, after initial backlash over privacy concerns, the most recent release of Microsoft's Viva platform, which generates wellbeing-related insights about individual employees and makes that information visible to employees through an individual dashboard [132], uses differential privacy, de-identification, and aggregation [132] to ensure identifiable data is visible only to the employee, while providing "privacy-protected" wellbeing-related insights to management [132, 150]. In addition, decentralized federated learning techniques could prevent the centralized collection of individual, identifiable inferences of emotion, restricting harms from the unregulated and unconstrained flow of emotion data. However, the privacy guarantees of such techniques are limited and should not be regarded as a "silver bullet" to privacy problems [51].

Second, enterprise risk management practices that identify, categorize, assess, and prioritize privacy risks to minimize harm to consumers could recognize the harms of emotion AI and incorporate them into existing and future risk management processes, such as privacy or data protection impact assessments (PIAs/DPIAs) [153] and ethical impact assessments [97]. Given the acceleration of privacy laws and regulation, prudent organizations that handle personal data will adopt data protection and privacy risk minimization standards [63]. To mitigate harm from the collection and processing of emotion data, future work could build on this study to measure the risk of emotional privacy harm, an important component of several risk mitigation frameworks.

It is important to emphasize that emotional privacy harms may remain even if such policy and privacy interventions to mitigate emotion AI's harms were implemented. For example, efforts to improve the precision of emotion AI inferences may stem some of emotion AI's harms (i.e., reputational harms), but the perfect emotional surveillance of a highly accurate emotion AI system may perpetuate or introduce other harms (i.e., psychological and emotional labor harms). While faulty emotion AI can harm people, as we show, machine accuracy improvement is an imperfect solution, as more accurate surveillance systems can indeed exacerbate privacy concerns [66]. Certainly, many of emotion AI-enabled workplace surveillance's harms (i.e., direct psychological and autonomy harms) cannot be mitigated through either technical solutions or the governance of emotion data, but through the refusal [61] to adopt the emotion AI and prevent its emotional surveillance collecting emotional information in the first place. Surely, non-adoption decisions by organizations would pre-empt the identified emotion AI-enabled workplace surveillance harms all together.

Privacy enhancement, regulation, and risk mitigation all have limits; a failure to consider at a more fundamental level whether it is just to develop, design, and implement systems that implicate the privacy of our inner, emotional lives can expose and exacerbate social injustices for all. These are questions of ethics and justice [16, 47], and to that end we contribute *emotional privacy* to advocate for addressing the many harms posed by technologies that aim to infer emotions and other affective phenomena, and last but not least, an individual right to privacy over one's emotional information and to remain free from emotional manipulation.

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6 APPENDICES

A PRE-SCREENING SURVEY

The pre-screening survey included the following:

- Q1: Name
- Q2: Email Address
- Q3: Gender
- Q4: Race
- Q5: Ethnicity
- Q6: Occupational Industry
- Q7: Job Title
- Q8: Education Level
- Q9: Individual Income
- Q10: Household Income
- Q11: Family Size
- Q12: Which of the following types of information about you does your employer process: information about my emotions, information about my mood, information about my wellbeing, information about my attentiveness, information about my engagement, information about my fatigue, information about my stress, information about my empathy, information about my opinions, other (free text).
- Q13: The information indicated in Q12 is collected: automatically (A technological tool or device infers this information) or self-reported (I explicitly provide this information)
- Q14: Which of the following types of data or devices does your employer use to record, measure, analyze, or respond to information collected in Q13: voice (i.e., microphone, phone), video (i.e., webcam, CCTV), email, instant messaging, eye trackers, biosensors or wearables (i.e., smart helmets, smart earphones, smart watches, smart badges, fitness bands), other (free text).
- Q15: Do you have access to any of the information collected about you identified in Q12 from the tools identified in Q14?
- Q16: Do you use any of the information collected in Q12 to manage others in a supervisory capacity?
- Q17: For supervisors/managers: Do you use any of the information collected about others (i.e., direct reports) identified in Q12 from the tools identified in Q14 to manage your team?

Only those who selected at least one type of information from Q12, and indicated in Q13 and Q14 that that information is collected automatically and digitally, were invited to interview.

B INTERVIEW PROTOCOL

This protocol was designed to elicit responses for a broad range of use cases of emotion AI in the workplace. Of note, questions asked in the first phase to established context regarding the participant's familiarity with workplace monitoring practices in general. The context established in this phase was built upon to develop context-specific scenarios when eliciting speculation from respondents without cognizance use of emotion AI.

Phase 1, *Workplace environment*, was designed to warm up the conversation and grant the researcher familiarity with the participants' workplace. Phase 2, *Emotion AI in the workplace - individual* was designed to elicit participants' experiences, perceptions, and sense making about how emotion AI has affected them in the workplace. Phase 3, Emotion AI in the workplace - collective was designed to elicit participants' perceptions and sense making about how emotion AI has affected others in the workplace, as well as to elicit insight into the organizational discourse surrounding emotion AI in the workplace. Phase 4, *Privacy* was designed to understand how workers think about emotion data and information flows, and manage privacy boundaries as they relate to data collection in the workplace. Each phase was designed to start with the most broad and open questions, asking more specific and potentially sensitive questions toward the end of each phase. The order and way in which questions were asked varied dependent upon the flow of the interview.

Before beginning the interview, we asked participants if they had a chance to review the IRB consent document in their email, and ask if they had questions. Additionally, we reminded them of the study's goals to hear their experiences with technology that senses emotion at work, that the interview is recorded for purposes of data analysis, that we remove identifying information about them before analyzing the data, and asked for verbal consent to turn on the recording/enable live transcription and proceed with the interview.

Emotion AI in the Workplace Interview Protocol:

Phase 1: Workplace environment

Position, industry, workplace relationships

- Tell me about your role at <workplace where employee has experienced emotion AI>. *("Do others report to you at work?")*
- What is/was a typical day for you like?
- What kind of employee monitoring measures are you aware of in your workplace? *(Potential follow up question may include: How do you feel about them?)*
- You indicated in our survey that your employer uses some of these measures to monitor what you think or how you feel. Can you tell me more about that? *(Potential follow up questions may include, "What is the name of the tool?" and "How do you think it gets that information?")*
- Who all are you aware of that has access to the information about you from <emotion AI tool>? *(Follow up questions might include, "What do you think they use that information for?" and "What do you think/feel about that?")*
- How would you describe your relationship with your co-workers?
- How would you describe your relationship with your boss?
- How would you describe your personal views toward your employer?

Phase 2: Emotion AI in the workplace - individual

Personal experiences, impact, concerns

- How would you describe <emotion AI> tool?
- Tell me about how your employer came to tell you about <emotion AI tool>. *(Follow up questions might include, "What was your reaction like?", "What were you thinking about after you heard that?" and "How do you think they should have told you instead?")*
- Can you walk me through what it's like to work with <emotion AI tool>? *(Follow up questions might include, "What do you think/feel about that?" and "Can you describe an example of that?")*
- Can you describe a feature of or experience with <emotion AI tool> that was unexpected? *(Follow up questions might include, "What do you think/feel about that?")*
- Have you noticed an impact to the way you work or the workplace environment since your employer started using <emotion AI tool>? *Follow up questions might include, "How do you think/feel about that?" , "Tell more more about what work was like before." and "In what ways, if any, has that changed?"*
- Have you noticed a change to the way you view yourself at work since using <emotion AI tool>? *(Follow up questions might include, "Tell me more about that." and "Describe how you viewed yourself before.")*
- Can you describe a time when <emotion AI tool> identified a strong reaction to an experience you had at work? *(Follow up questions might include, "How did you feel about that?", "Did you have any thoughts about others seeing that?" and asking for an additional example (i.e., if the strong reaction was a positive one, we would ask for an additional example of a negative reaction and vice versa)*
- Can you describe a time when <emotion AI tool> made an inference that you didn't agree with? *(Follow up questions might include, "Tell me more about that.", "How did you feel about that?", and "Did you have any thoughts about others seeing that?")*

Phase 3: Emotion AI in the workplace - collective

Collective impacts and concerns, organizational discourse

- Have you noticed an impact to the way your co-workers are at work since using <emotion AI tool>? *(Follow up questions might include, "Why do you think that might be?" and "Have any of your co-workers talked with you about that?")*
- What do your co-workers say about <emotion AI tool>? *Follow up questions might include: "Why might they feel that way?" and "What was done about that?"*
- How do your managers talk to you about <emotion AI tool>? *(Follow up questions might include, "Tell me about a time that happened." and "What do you think/feel about that?")*
- Have you noticed a change in the way managers work or interact since using <emotion AI tool>? *Follow up questions might include, "Tell me more about that.", "What do the managers say about that?", "Do you think others notice that, too?" and "What was it like before?")*
- Why do you think your employers made the decision to use <Emotion AI tool>? *(Follow up questions might include, "How do you think <Emotion AI tool> helps them do that?", "What do you think/feel about that?", "What do they say about that?", and "If you were your boss, what would you have done differently?")*
- Have you noticed a change in the way you view your employer since the adoption of <emotion AI tool>? *(Follow up questions might include, "Why do you think that might be?", "Do you think your coworkers might feel the same way?", "What do they say about that?" and "What was it like before?")*

Phase 4: Privacy

Emotion data, data sharing, data access, data storage, disclosure

- What do you think about <emotion AI tool> making inferences about how you feel? *(Follow up questions might include, "Why might that be?")*
- Was use of <emotion AI tool> optional for employees? *(Follow up questions might include, "Why do you think your company made that decision?", "What did your coworkers say about that?" and "If it were, would you participate?/if it weren't, how do you think others might respond?"*)
- How does your comfort level with <emotion AI tool> compare to your comfort level with other ways your employer might observe you? *(Follow up questions might include, "Why might that be?" and "What makes it different?"*)
- In what ways do you think your data from <emotion AI tool> is used? *(Follow up questions may include, "What do you think/feel about that?" and "In what instances would you not want it to be used, and by whom?"*)
- You mentioned earlier that <X> has access to your data from <emotion AI tool>. Would you make any changes to who could see what information, if you had a say? *(Follow up questions might include, "How might that change how you feel about it?")*
- Where do you think the data <emotion AI tool> makes about your emotions might be saved or stored, and for how long? *(Follow up questions might include, "What do you think/feel about that?" and "How would you want it stored, if you had a say?")*
- Can you describe a time where <emotion AI tool> sensed an emotion that you didn't want your employer to see? *(Follow up questions might include, "Tell me more about that." and "How might you prevent that?")*
- Can you describe a time you tried to prevent <emotion AI tool> from sensing how you feel? *(Follow up questions might include, "What did you do about that?" and "Have others talked about ways to do that?"; if they have not done that, questions might include "Is that something you would like to be able to do?", "If you could, would you?", and "Why might you want to be able to do that?"*)
- Are there any ways you or your coworkers might behave differently because of <emotion AI tool>? *(Follow up questions might include, "Why might you/they do that?" and "Have you found that effective?"*)
- What, if anything, about this technology could be changed to make you feel better about it? *(Follow up questions for those that express discomfort with the technology or that they are wholly uncomfortable with it might include, "If you were able to refuse consent to its use, is that something you would want to do?")*

We ended the interview asking participants if there is anything they want to talk about before we end, and if there are any questions they have for us. We then provided participants with a claim code for their $35 incentive.