Emotion Inferences in the Workplace and Healthcare: Workers' and Patients' Emotional Privacy Judgments and the Relative Influence of Contextual, Socio-demographic, and Individual Privacy Belief Factors

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The increasing use of emotion AI in workplaces and healthcare has raised ethical and privacy concerns. We conducted a factorial vignette survey with a U.S. nationally representative sample (n = 300) and a sample representing minoritized groups (n = 385) to investigate workers' and patients' privacy judgments concerning their emotions inferred by these technologies. Participants judged 56 scenarios involving emotion inferences across workplace and healthcare settings that varied by data input (image/video, speech/text) and purpose (e.g., diagnostics, harm prevention), and reported their socio-demographic information and privacy beliefs. Findings surface the relative importance of contextual, socio-demographic, and individual privacy belief factors on workers' and patients' generally unfavorable emotional privacy judgments, with notable sample-level differences. Our research underscores the significance of purpose and minoritized populations to privacy theory, research, and policy; and demonstrates the need for policies that recognize emotional information as a sensitive data category and advocate inference minimization principles.

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

Additional Key Words and Phrases: AI, emotion AI, emotion recognition, affective computing, workplace

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1 INTRODUCTION

Increasingly, technologies that algorithmically infer and/or interact with human emotion are emerging across a range of public and corporate sectors [47]. Known commercially as "emotion AI" [144], artificial emotional intelligence and its affective computing, digital phenotyping, and passive sensing predecessors aim to automatically infer human emotion and related affective phenomena by analyzing a wide variety of data, including online behaviors, text communications, bio-sensors, voice recordings, and video surveillance [47, 76, 128, 163, 225]. More advanced emotion AI technologies may include additional architectural layers (e.g., goals, planning, reasoning) that synthesize emotion inferences in order to then automatically respond with emotional sensitivity in a given situation – augmenting emotions in the humans with whom it interacts [218].

Two key application areas for emotion AI are the workplace [39, 47, 76, 106, 128, 163, 225] and healthcare [126, 168]. Alongside the transformative promises emotion AI makes to the workplace [39] and healthcare [127] are substantial privacy and ethical trade-offs. In these contexts marked by power imbalances, the collection and use of inferred personal emotional data can carry adverse consequences for workers and patients, yet existing applications frequently overlook adequate personal privacy considerations [183, 248, 269]. These concerns are compounded by the technology's limitations – notably, the manifestation of demographic and identity-laden biases [71, 77, 109, 113, 124, 132, 182, 200, 263]; suboptimal levels of accuracy [78, 264]; and limited scientific reliability, specificity, generalizability, and validity [24] – which are often acknowledged in academia but neglected in emotion AI's rapid commercialization [50]. In spite of calls to regulate real-world adoption of emotion AI [65] and ban its use in high-risk contexts [61, 66], the emotion AI market remains a booming industry with global reach [47, 147] that flourishes with minimal oversight, especially in the US [22]. As a result, potential harms from emotion AI's automatic emotion inferences (and consequent interactions) include unchecked threats to workers' and patients' health, wellbeing, and livelihoods that perpetuate discriminatory or otherwise unjust employment and healthcare outcomes [168, 173, 182, 240], widen existing power imbalances [190, 211], and facilitate exploitative surveillance methods [168, 212, 272] that invade privacy over deeply intimate and sensitive emotional information [13, 164, 212]. Despite these risks, industry and academic discourses often portray workers and patients as beneficiaries of automatic emotion inferences and interactions [47, 127]. Yet, research on the perceptions of emotion data subjects (i.e., individuals subject to automatic emotion inferences and interactions) suggests that such uncritically optimistic positions do not align with the perspectives held by those targeted and directly impacted by the technology. On the contrary, prior interview studies reveal that emotion data subjects view emotion inferences as a distinct type of information that, akin to mental health information [212], is highly sensitive and prone to misuse [13], and desire enhanced protections for their inferred emotional information accordingly [208, 212]. Further, research has uncovered deep privacy concerns held by workers [144, 212] and patients [35, 220] about the unregulated intrusive collection and use of their inferred emotion data in these high-stakes contexts, finding that they perceive automatic inferences of and interactions with human emotion as a violation of personal *emotional privacy* – privacy over one's emotional information and ability to remain free from emotional manipulation [212].

Technology practice and design involving emotion inferences remains challenged to align with privacy concerns, we suggest, in part due to a lack of knowledge specifically concerning their impact to *emotional privacy*. While some scholarship has raised the need to consider privacy in technologies that interface with emotion more explicitly [164, 183, 248, 269], an understanding of what "privacy" means and how it is implicated by these technologies remains vague. Though privacy is often broadly construed as an umbrella term, it is a varied and contextual construct [175] that is mediated by dynamic and ever-shifting internal and external conditions [11, 146, 169, 191, 254], and spans multiple academic disciplines (e.g., behavioral economics [3], law and philosophy [48, 149, 187], and Human-Computer Interaction (HCI) [23, 259]) and myriad theoretical frameworks (e.g., justice theories [16, 69], social contract theory [68, 143], contextual integrity [176], bounded rationality [4], and differential intersectional vulnerability [160, 193]). In particular, most privacy scholarship in HCI draws on the theory of contextual integrity to acknowledge that privacy is context-dependent, violated when the norms governing the flow of information in a specific context are transgressed [175], and strives to promote the ethical and responsible collection and use of personal information driven by a human-centered understanding of the human values (e.g., privacy perceptions) held by people who are or would be impacted by emerging technologies and related data practices. Thus, timely empirical research on privacy perceptions of emerging technologies like emotion AI that specifically interface with *emotional* information types within distinct social contexts is key to developing effective designs and regulatory frameworks that attenuate harms stemming from its technology-enabled privacy violations and that respect existing social norms [54, 154, 165]. Indeed, failing to define these more specific privacy concepts more precisely can dangerously obscure and perpetuate privacy intrusions [202], and limit possibilities to mitigate them [54, 226]. What's at stake when technologies implicate our emotional privacy by inferring and interacting with our private emotions?

Emotions play a crucial foundational role in human life. At an individual level, emotions mediate what we attend to [99], how we think and form ideas [28, 70], what motivates us [166], the identities we form [267] and, more fundamentally, our potential to grow and prosper [105, 252]. Socially, emotions shape our social interactions and relationships [150, 265], the norms we follow and accept [7, 231], how our structures and institutions are formed [21], and our capacity to thrive as a society [21, 184]. The social construct of privacy similarly operates at individual and collective levels in ways that mediate our ability to flourish [145, 191, 255, 256]. Privacy serves as a means to achieve self-realization and wellbeing [11, 12, 45, 256] by enabling us to control whether, how, with whom, and to what extent our information is shared [12, 256] via dynamic processes through which we manage privacy boundaries over our actual levels of privacy to achieve the privacy we desire [12]. Concerning *emotional privacy*, then, it allows us to open ourselves up emotionally when we desire more social connection, and close ourselves off emotionally when we desire more privacy. Drawing on Westin's four states of privacy [256], emotional privacy also means that we can keep emotions in *solitude*, protected from the gaze of others; we can keep emotions *intimate*, within the bounds of our close relationships — a state that strengthens those intimate relationships; we can keep our emotions *anonymous*, allowing our emotions to be free from identification and surveillance by others; and we can *reserve* our emotions by placing limits or boundaries around what is known about our emotions to others – boundaries that should be recognized and respected by others. Thus, as one manifestation of privacy, emotional privacy crucially helps us to achieve self-realization and individual and relational wellbeing by granting personal autonomy over our socio-emotional interactions: emotional privacy allows us to remain free from emotional manipulation [256], protects our emotional lives from unwanted emotional interferences by others [45], and minimizes our social vulnerabilities [145] – all through the ability to exercise privacy over our emotions. Yet, control over our emotional privacy is threatened by the emergence of technologies and data practices that collect, store, and disseminate automatic inferences of human emotion. Recognizing and safeguarding emotional privacy not only respects our basic human right to privacy, but, as we have argued, is essential to promote our very ability to flourish.

Given the significance of emotional privacy to our lives and the substantial risks to emotional privacy introduced by emotion AI, there is a need for research to more thoroughly understand emotional privacy judgments concerning emotion inferences, and to identify the key factors that shape these perceptions (and relative importance thereof) – particularly in the high-stakes contexts of the workplace and healthcare. Addressing this gap, as we do in this work, can enhance our understanding of the privacy impacts of emotion AI technologies and related data practices that automatically infer and interact with human emotion, providing crucial knowledge to advance a more comprehensive evaluation of integrating these controversial technologies in employment and healthcare. In particular, this knowledge can contribute to the development and deployment of more human-centered and privacy-aware systems that generate and handle emotion inferences, and advance holistic approaches to regulation and policy that consider the emotional privacy judgments, needs, and concerns of the situated workers and patients who stand to be most impacted by automatic emotion inferences and interactions in these contexts – including people of color, minority genders, and people with mental illness who are under-represented in research and may be disproportionately exposed to technological harms facilitated by these emerging technologies and data practices [168, 201, 208, 233, 249, 273].

To this end, we designed a mixed-methods factorial vignette survey to systematically measure and analyze workers' and patients' emotional privacy judgments concerning automatic emotion inferences. We conducted this study with US adults from two distinct samples: (1) a nationally representative sample (n = 300) by sex, age, and race and (2) a sample representing minoritized identities of minority genders, people of color, and/or people with mental illness (n = 385). We designed our survey to elicit participants' normative privacy judgments regarding the collection and use of emotion inferences by employers and healthcare providers, respectively. It featured various scenarios, systematically varied by two types of data inputs (image/video, speech/text) and 14 purposes (e.g., diagnostics, harm prevention) for which emotion inferences may be collected and used in these contexts. [1] Theoretically and empirically grounded in the understanding that privacy norms are interdependently bound by contextual variables [153, 154], vary by socio-demographic and individual privacy belief factors [29, 32, 125, 136, 143], and may differ between dominant (i.e., nationally representative) and minoritized perspectives [160], this study contributes a deeper understanding of emotional privacy judgments and the factors that shape them by answering the following research question: **What is the relative influence of contextual, socio-demographic, and individual privacy belief factors on workers' and patients' emotional privacy judgments concerning emotion inferences?**

Our findings reveal insightful trends in how emotional privacy is perceived in workplace and healthcare settings using emotion inferences. We highlight four key insights that yield significant implications for privacy theory, research, and policy:

- **Contextually Reinforcing vs. Straining Purposes** Our analysis reveals that the purpose of inferring workers' and patients' emotions is a variable that interdependently shapes their emotional privacy judgments. In general, emotion inference purposes that aligned with contextual goals or were bound within contextual integrity's theoretical parameters were judged more positively. In the workplace, this included purposes of group-level mental health support, enhancing organizational mental health resources, and promoting workplace safety. Meanwhile, emotion inference purposes such as medical diagnostics challenged the expected dynamics of the workplace environment, and were judged more negatively. In healthcare, automatic emotion inferences inherently transgress conventional bounds of information disclosure and confidentiality between patients and providers; we found that even for purposes that supported the overall goals of healthcare the healthcare context, all but one were judged more negatively. Illustrating the critical influence of purpose in shaping emotional privacy judgments within specific contexts, these findings highlight the need for policies that extend data minimization principles to minimize inferences, and furthermore, enriches contextual integrity privacy theory by demonstrating that purpose is a relevant contextual variable that interdependently constitutes contextualized privacy norms.
- **General Discomfort with Facial Emotion Recognition** Echoing growing public concern about facial recognition technologies, speech and text-based emotion inferences were consistently judged more negatively than inferences derived from facial emotion recognition. This finding should not be misconstrued as a normative endorsement of speech or text-based emotion recognition, but rather understood as a normative judgment against facial emotion recognition. These insights contribute to ongoing discussions about public trust and acceptance of different AI technologies, and raise the need for more rigorous regulation where they implicate privacy-sensitive areas like emotional information.
- **Nuanced Socio-Demographic Influences** Our findings uncover nuanced socio-demographic influences on emotional privacy judgments, through both sample-level differences and at the level of distinct socio-demographic factors. Demonstrating that emotional privacy judgments vary by demographics, these findings underscore the need for demographic sensitivity when designing, applying, and regulating technologies that

[1] Our prior work contributed qualitative insights from open-ended questions included in this study, finding that while participants, from their perspectives as workers and patients, acknowledged the potential benefits promised by emotion AI, they raised concerns indicating that the technology could ultimately enable or worsen harms for the very same application areas its implementation is intended to benefit. Though these findings about data subjects' perceptions of emotion AI's impacts to the workplace [63] and healthcare [210] are outside the present article's scope investigating emotional privacy judgments and the factors that shape them, we encourage readers to review for a comprehensive understanding of this topic.

generate emotion inferences, and call for privacy research to investigate the diverse experiences and perceptions of under-represented groups more intently.

- **Contextual Relevance in Privacy Predictors** Our findings identify independent privacy beliefs – specifically institutional trust in employers' and healthcare providers' handling of sensitive information, and perceived sensitivity of emotional information when handled by these entities – as factors that significantly influence emotional privacy judgments. These findings highlight the need for policy interventions to recognize the heightened sensitivity of emotion inferences and to enact contextually-sensitive protections for it in workplace and healthcare environments.

Contributing to a more nuanced understanding of emotional privacy in the age of AI, our research motivates the need for technology policy and practice interventions to institution stronger emotional privacy protections for the contextually-situated workers and patients impacted by automatic emotion inferences in the workplace and in healthcare. Reinforcing the explanatory power of contextual integrity in understanding privacy norms, our analysis provides empirical evidence for the relevance of purpose in shaping emotional privacy norms, extending contextual integrity privacy theory and motivating the need to adopt inference minimization principles; for the nuanced differences in emotional privacy judgments between demographic groups, motivating demographic sensitivity in future privacy research, policy, and practice; and for the heightened sensitivity of emotion inferences, calling for emotional information – including emotion inferences – to be recognized as a sensitive data category.

2 BACKGROUND

How people choose to communicate their emotions has been a subject of scholarship across fields including psychology, human-computer interaction, and computer-mediated communication (among others). An inter-disciplinary understanding of emotional information flows suggests that the ways in which people share information about their emotions and their decisions to do so or not may vary by individual factors such as age, gender, and culture [204–206]. As emotions' qualities themselves [96] and the social norms that govern the appropriateness of sharing information about them are culturally [140, 144] and contextually [175, 176] dependent, we can expect that privacy perceptions concerning emotional information may vary by individual and contextual factors.

Yet, the commercial emergence of emotion AI and related data practices that infer human emotion removes individual agency over whether, how, and to what extent one's emotional information is shared – concentrating the power to set, enforce, and challenge norms surrounding the flow of emotional information largely in the hands of privileged actors (e.g., employers and healthcare systems that deploy technologies that generate emotion inferences) [114, 158, 160] that facilitate personal emotion data sharing by circumventing individuals' ability to intentionally initiate (or withhold) emotional disclosures [52, 212]. In power asymmetric relationships such as that between employer and worker or healthcare provider and patient, collecting and sharing automatic emotion inferences may result in adverse, rather than beneficial, impacts to the data subjects' wellbeing, safety, and personal autonomy [63, 212]. Yet, the actors (e.g., healthcare providers, employers) engaging in data practices involving emotion inferences may not easily recognize these risks, as they often have a poor understanding of the norms of the particular communities of individuals over whom they hold power [157] on account of the actors' privileged positions [75], which in turn can both mask and perpetuate harmful privacy violations [158, 160]. It is therefore crucial to identify where, whether, how, and for whom automatic emotion inferences violate (or preserve) emotional privacy by centering the perspectives of those disproportionately subject to the impact of collecting and using emotion inferences, as this knowledge is key to preserving the human values of privacy and social justice, and can guide our decisions regarding whether and how emotion AI and related data practices that infer human emotion ought to be accepted or resisted [176].

The following literature review motivates the present study's investigation of the contextual, socio-demographic, and individual privacy belief factors associated with emotional privacy judgments concerning automatic emotion inferences in the workplace and healthcare – important factors that can directly and interdependently affect peoples' privacy perceptions about technology [29, 136, 154, 197].

2.1 Contextual Influence on Privacy Perceptions

Generally, privacy norms consist of closely linked attributes that govern how socially acceptable it is to share information. These include, notably, contextual factors that dictate the appropriate exchange of information within specific social contexts; privacy violations occur when these contextual norms are breached [176]. Certainly, we cannot reasonably expect that what contributes to the acceptability of information sharing within the patient-healthcare provider context will generalize to that of worker-employer: interactions with technologies that facilitate the flow of personal information affect contextually-situated groups differentially, positioned in distinct contexts "not only of place but of politics, convention, and cultural convention" that are themselves partly constituted by norms [175]. Attending to the unique social contexts of the workplace and healthcare when understanding emotional privacy judgments then allows us to understand whether and the extent to which privacy is preserved or violated when emotional information flows within said contexts, facilitating the possibility for technology practice and policy to more closely align with the preferences of individuals who are the subjects of emotion inferences.

2.1.1 Data Input. Within contextual bounds, additional contextual factors – how information is collected [154] and the purpose for which it is collected and used [176] – further influence privacy judgments. Regarding how information is collected, a wide body of research demonstrates variations in privacy perceptions by data input, identifying source-specific privacy concerns across a variety of technologies including camera surveillance and related facial recognition technologies [20, 230, 268, 271], speech data collected by continuous microphones such as those used in smart speakers [133], and monitored text communications like email [253]. Concerning emotion inferences, personal emotional information is not transmitted directly, but rather, collected indirectly through data processing and then subsequently automatically shared. Under the theory of contextual integrity, data sources for emotion inference can be considered as part of the larger "sender" of emotional information [176]. A considerable array of data inputs can be analyzed to infer emotion, including but not limited to the content of text communications; speech pattern and tone data recorded by microphones; facial expressions, body gestures and gait, and eye movements recorded by cameras; bio-physiological signals such as skin temperature, EEG, and heart rate recorded by bio-sensors; and combinations thereof [56, 76, 98, 121, 225]. Prior work investigating commercial uses of automatic emotion recognition via patent analysis found that the most commonly cited data inputs for emotion recognition intended for workplace contexts were text records, followed by speech records and facial images; additional data inputs included non-facial biometrics, physical activity, video, computing behavior, and contextual information [39]. The literature indicates a similar range of data inputs for emotion inferences intended for healthcare contexts [18, 19, 74, 117, 131, 198, 236]. Recent work investigating privacy perceptions with mobile applications that infer emotion and related affective phenomena supports this assertion. For example, Lee et al. investigated perceptions of sensor data collected and used in mobile affective computing applications and the sharing of that information in open datasets; their qualitative investigation found sensor-specific privacy concerns regarding the potential for sensor data to reveal their personal traits and subsequently expose them to risks of profiling and surveillance [135]. Regarding perceptions of mobile applications that infer mental health status, Zhang et al. found that contextual variables including data type used for said inferences affected peoples' privacy concerns [269]. Thus, the source of data from which emotion inferences are generated may directly affect workers' and patients' emotional privacy judgments.

2.1.2 Purpose. Privacy perceptions are also known to be influenced by the purpose of information exchanges, with acceptable privacy judgments toward purposes that contribute to contextual ends, purposes, or goals [177] – especially so if said purpose implies an associated personal or collective benefit [72, 81, 120, 161, 171, 209, 214, 260]. For instance, past work shows that individuals are more willing to share their sensitive (e.g., health) information if it is claimed to be used for a beneficial purpose, providing benefits to oneself [32] and/or society [110, 135, 242]. These findings conveying the importance of purpose to privacy perceptions should be critically interpreted within their broader social context, however, as data collectors and processors – especially in power asymmetric contexts like the workplace and healthcare – can exploit these privacy judgments. For instance, workplace surveillance scholarship has documented how employers increasingly leverage positive framing of the purpose for implementing worker surveillance data practices in ways that simultaneously encourage worker participation while effectively suppressing worker dissent [8]. Similarly, positive rhetoric regarding digital technologies in the healthcare context can promote enthusiasm that obfuscate problematic privacy implications that underlie its use [30]. Despite the potential for framing effects about the potentially beneficial applications of emotion AI (e.g., improve mental health management and emotional wellbeing [134]) to mask privacy concerns, prior work suggests that people nonetheless remain concerned about their personal privacy when interacting with technologies that infer human emotion [269]. Indeed, our prior work qualitatively investigating workers' and patients' perceptions of emotion AI's potential benefits and risks (collected from open-ended questions in the present article's study, as further described in Section 3.2.2) indicates that workers and patients remain deeply concerned about emotion AI's potential to inflict harm, even after considering its potential benefits to the workplace and healthcare. Specifically, participants expressed concern that emotion AI deployed in workplace environments might harm (rather than improve) their wellbeing, impair (rather than enhance) individual work performance and shared work environments, and perpetuate (rather than mitigate) identity-related biases and stigmas [63]. Regarding patients' perceived impacts of emotion AI to healthcare, participants acknowledged emotion AI's potential to improve mental healthcare provisions, promote mental health information disclosures, prevent harm, and lead to increased understanding about patients' mental health, yet cited considerable concerns for emotion AI to promote inaccurate mental health diagnoses and inappropriate mental health assessments and treatments, remove patient voices from mental healthcare interactions and processes, negatively impair their wellbeing, and facilitate privacy abuses [210]. This line of research clearly demonstrates the contextually-specific relevance of purpose to privacy perceptions – a concept that is underscored by precision around data use in U.S. privacy regulations for sensitive information such as the Health Insurance Portability and Accountability Act (HIPAA) [[5, 90]. Yet, the contextual integrity framework does not include purpose as one of its five critical parameters [176].

Considering that automatic emotion inferences can be generated by analyzing a wide variety of input data and for a range of purposes, this body of work supports our expectation that emotional privacy judgments, nested within each workplace and healthcare context, would vary by the source of the data analyzed to generate emotion inferences and the purpose for which emotion inferences are used. The present study's analysis of workers' and patients' contextually-bound emotional privacy judgments extends our knowledge of the relevant contextual parameters that constitute privacy norms by empirically demonstrating that, in addition to the contextual parameters specified in Section 3.1.1

to define an emotional privacy norm (within which we include data input under the existing contextual integrity framework), that the purpose for which emotion inferences are collected and used interdependently influences emotional privacy judgments concerning emotion inferences in the workplace and healthcare.

2.2 Socio-Demographic Influence on Privacy Perceptions

While the influence of context on privacy perceptions is significant [177], it is also important to attend to personal characteristics that may shape individual perceptions in order to promote more effective privacy practices and policies that are sensitive to individual differences. Though the relationship between privacy perceptions and socio-demographics is relatively understudied [125], past scholarship indicates that individual privacy perceptions can also vary by socio-demographic statuses including education [32], race/ethnicity [32], and gender [29, 136]. Relatedly, recent Pew polling indicates that Americans' perceptions of AI also varies by socio-demographic characteristics including education, gender, and race/ethnicity [197].

2.2.1 Education. Recent Pew research found that public concern with various applications of AI differed by educational attainment: those with postgraduate education were more concerned with facial recognition use by police than those with a high school degree or less, while those with lesser educational attainment were more highly concerned with applications involving AI-enabled misinformation detection on social media and automatic vehicles [197]. Educational attainment is known to influence privacy perceptions as well. For instance, in a study of factors that influence privacy risk perceptions, Bhatia and Breaux found, among other socio-demographic factors, that people with a doctorate degree were less concerned with sharing personal information than those with a high school diploma or less [32].

2.2.2 Race/Ethnicity. Prior research demonstrates that Black and Latine racial and ethnic minorities are afforded less privacy in US society due in part to racialized surveillance [43] that has been normalized [57], which may lead to privacy resignation and associated underestimation of privacy risks among these populations that is disproportionate to their population's level of privacy vulnerability [97]. Indeed, past work suggests that people of color may be at heightened risk with emotion AI technologies, including from biased emotion recognition algorithms using automatic speech detection, facial recognition, and natural language processing methods which may be less accurate for these groups [107, 200, 263].

2.2.3 Gender. Similar results indicating heightened and/or unique privacy concerns are also prevalent for other minority socio-demographic statuses that are disproportionately surveilled, for example gender [167, 222, 230]. Women, who face higher exposure to gender-based harassment [122, 222] and workplace surveillance [230] compared to men, have been found to hold more prominent privacy concerns in this context [15, 25, 86, 104, 245]. Though research on the privacy perceptions of minority genders (i.e., trans and/or non-binary people) is more scant, the available scholarship nonetheless indicates minority genders may have unique privacy concerns and needs related to autonomic systems [102, 138] in part due to gender-based vulnerability to a wide range of threats of harm enabled by technology [217], as well as heightened needs for safe and supportive technology-mediated interactions [100].

2.2.4 Mental Health Status. The privacy perceptions of individuals with mental illness about emotion inferences warrants special consideration due to this population's potentially higher susceptibility to the impacts of automatic emotion inferences' collection and use. People with mental illness may stand to especially benefit from some applications involving emotion inferences [126]; however, they may also be exposed to greater risks from their emotions being inferred as a result of increased stigmatization, disability discrimination, and inaccurate inferences [168]. Of particular concern, research centering the privacy perceptions of individuals with mental illness indicates that though they may acknowledge personal risks associated with the collection and sharing of their emotional and related mental health information, the limited control and protection individuals have over their personal information presents them with a limited choice architecture that requires trading personal privacy to receive the potential benefits mental health technologies, including those using emotion inferences, may provide [35, 64]. Additionally, research suggests that people with mental illness hold unique workplace and healthcare privacy concerns. For example, workers with mental illness tend to be reluctant to disclose their condition to employers, and engage in complex decision-making processes that balance the potential benefits of mental health disclosures (i.e., workplace accommodations) against its wide range of risks [238], among them mental health-based employment discrimination and stigmatization [42, 80] and damaged professional reputation [80]. Research investigating the privacy perceptions of patients with mental illness about health information exchanges similarly indicates that patients with mental illness hold unique privacy concerns related to the sharing of their health-related information even within healthcare contexts, citing privacy concerns informed by experiences with mental health-related mistreatment in healthcare settings [220]. Furthermore, prior work investigating mental health patients' perceptions of mobile mental health applications found that they are particularly concerned with the transmission and sharing of their data, and hold unique privacy concerns about some types of information such as social interaction data, potentially owing to experiences with social isolation that may render this information especially sensitive for this population [269].

The unique privacy challenges that people with mental illness face in increasingly digitized workplace and healthcare environments may be compounded by the emergence of emotion AI and related data practices that automatically infer emotion and related affective phenomena in these settings. This is partially due to the technology's problematic developmental history that stigmatized differences in emotional expression and regulation (i.e., in individuals with autism), giving rise to current data economies that surveil human emotion [172]. These economies leverage emotion AI as a normative technology that prioritizes the tractability and commodifiability of inferred emotional information, while overlooking its limited ontological and epistemological grounds and its reification of medical models of disability that conceptualize differences in emotional expression and regulation as deficits in need of correction [119, 229]. And yet despite these limitations and concerns, which may be heightened for individuals with mental illness and other disorders that are characterized by differences in emotional expression and regulation, the use of emotion inferences includes predictions of mental illness in individuals [73, 94] using computational methods that can bypass individual mental health disclosure decisions.

The work reviewed here indicates that emotional privacy judgments may vary by socio-demographic differences including education, race/ethnicity, gender, and mental health status, and suggests that an individual's vulnerability to technology-mediated risk can be associated with these factors. Complementing this body of knowledge, our work surfaces the relationship between socio-demographics and emotional privacy judgments concerning the use of emotion inferences in the workplace and healthcare in both a US nationally representative sample by sex, age, and race, and a minoritized sample of people of color, minority genders, and/or individuals with lived experience with mental illness. We provide further detail about our recruitment and sampling approach in Section 3.3.

2.3 Individual Privacy Beliefs Influence Privacy Perceptions

Individual beliefs about privacy can impact one's privacy perceptions about a technology, including general privacy concerns, perceived information sensitivity, risk perceptions, and individual levels of trust [143, 165, 219, 250].

2.3.1 General Privacy Concerns. When measuring privacy, many scholars rely on the concept of privacy concern, in part due to ongoing disparities in how privacy is conceptualized and defined [41, 180]. Though the earliest privacy concern scales aimed to measure privacy concerns at a generic level [143, 224, 243, 257], a growing body of work has shown that privacy concerns are malleable to contextual influences [2, 6, 170], and indicate that general privacy concerns have limited utility in explaining contextually-bound privacy preferences and related privacy outcomes [156]. Nonetheless, research continues to leverage general privacy concern scales such as the Internet User's Information Privacy Concerns (IUIPC) scale as a control measure when investigating privacy perceptions [143] as well as an independent variable when investigating related privacy constructs like decision-making [123] and expectations [155].

2.3.2 Perceived Risk. Privacy concern is closely related to perceived privacy risk [32, 130]. While perceived privacy risk is sometimes operationalized as a global construct [91, 223], it can also be conceptualized at more specific levels such as likelihood of specific hypothetical harms [32]. Perceived privacy risk can impact privacy perceptions on an affective level: the more positive an association with a technology or data practice, the less risky it is perceived and the more likely it is to be associated with benefits [84, 188], reducing overall privacy concerns [32]. Risk perceptions are also known to mediate privacy perceptions. For instance, regarding use of emerging technologies in healthcare settings, Alraja et al. found that privacy, security, and trust were major factors in shaping attitudes toward the technology, mediated by individual risk perceptions [10]. This line of research highlights the need to control for perceived risk when measuring privacy perceptions.

2.3.3 Trust. Privacy and trust are mutually reinforcing constructs [152, 250]: institutional trust in a specific entity is known to influence, and be influenced by, both general and contextually-specific privacy perceptions [152]. Institutional trust [213, 262] can lower privacy concerns, for example, by lowering perceived risks associated with information misuse [213]. At the same time, individual privacy dispositions are known to precede individual levels of trust [123, 152]. In both workplace and healthcare contexts, trust plays a key role in shaping individual privacy beliefs. For example, Tolsdorf et al. found that privacy perceptions in digitized workplaces were highly influenced by individual levels of trust in employers' processing of one's personal information [237]. Relatedly, Shen et al. found that patients' privacy perceptions of health information sharing was influenced in part by individuals' trust in healthcare organizations [220]. These works demonstrate that levels of institutional trust can influence privacy perceptions in work and healthcare environments.

2.3.4 Data Sensitivity. Data sensitivity is best conceptualized not as a fixed construct, but rather as an individual belief that varies by both situational contexts and individual traits [148, 165]. Data sensitivity is closely related to the concept of privacy risk; as sensitive information is viewed as riskier [143], it renders individuals more vulnerable, and as such requires heightened protection and oversight [27]. Perceived sensitivity of emotion inferences may also be a relevant factor that influences emotional privacy, as prior work has indicated that people perceive information about their emotions [13, 208] and related data like mental illness [244] as sensitive and do not want it shared for commercial purposes [64]. The distinction between the information collected and inferred is crucial here, as it may help resolve contrasting findings that show people associate low sensitivity with certain data types (e.g., sensor) that can be processed to infer emotional information. Investigating peoples' perceptions of mobile affective computing applications, Lee et al. found that the perceived sensitivity of sensor data itself was generally low, as participants had difficulty associating the ways in which their collected sensor data could be processed to generate inferences about their emotions; indeed, as described in Section 2.1, participants expressed concern *if* data could be used to reveal their personal traits. These findings indicate that people may underestimate privacy risks associated with the collection and use of their personal information for affective computing purposes broadly, and their privacy concerns may be better surfaced when the ways in which their information may be processed (e.g., from what data inputs, for what purpose) to infer their personal states and traits (e.g., emotions, mental health) is made more explicit. We emphasize the implications for specifying these parameters in privacy research further in Section 3.2.

Our work contributes an understanding of the relationship between emotional privacy judgments and individual privacy beliefs – specifically, general privacy concerns, institutional trust, and perceived sensitivity of emotional data – with a focused investigation of workers' and patients' perceptions concerning the flow of their inferred emotional information in the workplace and in healthcare, allowing for policy and design remedies to develop interventions that more closely align with emotional privacy judgments in these contexts.

3 METHODS

A useful method to uncover individuals' privacy perceptions about a technology which may otherwise be difficult to examine [116, 175, 181, 261], we designed a factorial vignette survey to elicit workers' and patients' emotional privacy judgments concerning automatic emotion inferences, and allow us to investigate how their emotional privacy judgments vary by individual and situational factors. From their perspectives as workers and patients, participants rated their level of comfort to a series of vignettes in which their employers and healthcare providers processed data already collected about them to automatically infer their emotions. We varied the vignettes by contextual factors, and issued a post-test for participants to report their socio-demographic information and privacy beliefs. Our analysis contributes an understanding of whether and to what extent workers' and patients' emotional privacy judgments concerning automatic emotion inferences vary by contextual, socio-demographic, and individual privacy belief factors. In this section, we describe our survey's theoretical underpinnings, design, recruitment and data collection efforts, and data analysis procedure, followed by a reflection on our research's limitations and opportunities for future work.

3.1 Contextual Integrity and Privacy Vulnerability as Theoretical Frameworks to Measure Emotional Privacy Judgments

Two theoretical frameworks for privacy underlie our study design: (1) Nissenbaum's *contextual integrity* [175, 176], which defines privacy "as respecting the appropriate norms of information flow for a given context" [153]; and (2) McDonald and Forte's *privacy vulnerability*, a theoretical perspective to surface the privacy risks vulnerable people face in the operation of privacy norms [160].

3.1.1 Contextual Integrity. Under contextual integrity, privacy violations occur when information flows transgress contextually specific privacy norms. To establish a privacy norm, five specifications are necessary: (1) information type (about what); (2) subject (about whom); (3) sender (by whom); 4) recipient (to whom); and (5) transmission principle (flow under what conditions) [153]. Together, these parameters "predict a complex dependency between privacy judgments on the one hand, and the values for all five parameters on the other" [154]. As such, it was important that our study recognized the combined interdependency of these contextual parameters (in addition to individual differences) when investigating workers' and patients' emotional privacy judgments by using this framework to establish emotional privacy norms in the workplace in healthcare.

Methodologically, factorial vignette surveys are well-suited to account for a set of interdependent contextual parameters to surface privacy perceptions, enabling researchers to study the effect of factors *in combination* on privacy perceptions by asking participants to report their perceptions to various scenarios that are bound within contextual specifications and vary by a researcher's factors of interest. Informed by prior work specifying contextual, socio-demographic, and individual privacy belief parameters in factorial vignettes to study privacy perceptions [32, 154, 175], our vignette design uses contextual integrity principles to measure emotional privacy judgments by defining contextual specifications that govern norms surrounding emotional information sharing in the workplace and healthcare as follows in Table 1.

Contextual Parameter	Emotional Privacy Norms
Information Type	emotional state (e.g., emotions, moods, emotional states including but not limited to stress, anxiety, depression, boredom, calmness, fear, fatigue, attentiveness, happiness, sadness, disgust, surprise, and/or anger)
Subject*	employees/patients
Sender	emotion AI technologies and related data practices that automatically infer emotion after processing various sources of data input
Recipient*	employer/healthcare provider(s)
Transmission Principles	-recipient retains subject's emotional information indefinitely, as allowed by law -recipient will not share subjects' emotional information, unless otherwise noted -subject consented to monitoring by recipient

Table 1. Emotional Privacy Norms Specified in Vignettes, Adapted from Martin and Nissenbaum, 2016 [153] **Factorial Vignette Condition*

3.1.2 Privacy Vulnerabilities. Though contextual integrity is a leading theoretical framework for privacy scholarship in Human-Computer Interaction (HCI), McDonald and Forte draw upon intersectional [58–60, 67, 103, 199] and Queer-Marxist [139] theories to compellingly argue that privacy scholarship in HCI must move beyond privacy norms (i.e., contextual integrity) to approach privacy from the perspective of minoritized and vulnerable groups, which can expose the unequal and compounded challenges people face in their interactions with socio-technical systems on account of their identities and social positions [14, 89, 129, 196, 199, 234, 258], and the ways in which norms can operate to exclude and oppress them [87, 88, 139, 158], in order to develop a socially just understanding of privacy that accounts for all [160].

Aligning with McDonald and Forte's call to center privacy vulnerabilities in our study of emotional privacy, our study design involved 1) attending to socio-demographic differences that could potentially influence workers' and patients' emotional privacy judgments of automatic emotion inferences (described further in Section 2.2) and 2) oversampling for participants of color, with mental illness, and minority genders that may be subject to disproportionate harm from emotion inferences in the workplace and healthcare [168, 201, 208, 233, 249**?**] (described further in Section 3.3).

3.2 Survey Design

Privacy skeptics often point to what is commonly referred to as the *privacy paradox*: though people say they have privacy concerns, behaviors implicating their privacy suggest otherwise [227]. One way to explain the privacy paradox relates to how we measure privacy in the first place, with privacy research often failing to specify and account for the variables upon which privacy judgments so crucially depend [153]. Other explanations include an individual's lack of awareness regarding the extent to which data is collected and repurposed, and how said collection and use may impact them [4, 137, 151]. Certainly, how we measure privacy also has important societal implications, as public policy often relies upon conceptualizations of privacy as employed in research [130, 153] to inform privacy regulation, and it is therefore important to attend to factors that can influence privacy perceptions and norms when conceptualizing, operationalizing, and measuring privacy [153].

3.2.1 Factorial Vignettes. Conventional survey instruments measuring privacy sometimes ignore contextual and individual specifications that can offer powerful and nuanced explanatory power to understand privacy concerns, for instance, whether privacy expectations have been met, what constitutes a privacy violation [153], and for whom [160]. Grounded in the theory of contextual integrity to establish emotional privacy norms as explained in Section 3.1.1, our factorial vignette design attended to these variables to investigate workers' and patients' emotional privacy judgments in several ways.

First, we fixed contextual parameters concerning consent, data retention, and data sharing practices as defined in 1 along with a definition of automatic emotion inferences with a statement at the beginning of each vignette set to ensure these specifications were readily available for participants to reference when answering the survey as follows:

> "Emotional state" refers to your emotions and moods, including but not limited to stress, anxiety, depression, boredom, calmness, fear, fatigue, attentiveness, happiness, sadness, disgust, surprise, and/or anger.
>
> Unless otherwise noted, please assume that:
> 1) your employer/healthcare provider won't share your information with anyone else;
> 2) your information is kept by your employer/healthcare provider indefinitely, to the extent allowed by law;
> 3) you have consented to your employer/healthcare provider recording this information about you, such as through an employee/patient consent form.
>
> We will ask you to please consider your willingness to be a subject of the described technology, considering the type of information used, purpose of using the software, and context as noted in the scenarios.

Within each of the two vignette sets organized by context (i.e., workplace, healthcare) ($C), we then presented participants with a series of vignettes that were further split into two additional sets by the independent variable of data input ($I), under which participants were presented with fourteen various purposes ($P) for which employers/healthcare provider(s) may collect and use workers'/patients' emotion inferences. As a 2x2x14 within-subjects design, all participants responded to each of the 56 scenarios. We asked participants to rate their level of comfort with each scenario, responding from their position as an employee ($C1) and patient ($C2) as appropriate to ensure we captured both workers' and patients' perspectives. Participants indicated their comfort level using a Visual Analog Scale (VAS) ranging from 0 = "very uncomfortable" to 100 = "very comfortable." Used in past work to elicit privacy judgments, comfort is a suitable variable to measure privacy perceptions as it is strongly correlated to perceived privacy risk [32, 186]. By using a VAS, our design allowed for participants to think of the variable as purely continuous rather than ordinal, and for us to measure participants' emotional privacy judgments at a high level of granularity, while overcoming methodological limitations that may adversely affect results when using ordinal variables such as Likert scales, most notably clustering and data loss [9, 34, 51, 53, 115, 239]. We constructed the vignettes as follows:

As a $C1, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable) with your $C2 using a computer program to automatically detect your emotional states using records of $I recorded from your daily activities and device use, for the purpose of $P

Vignette Variables	Levels
Contextual Position	(1) employee* ($C1), employer** ($C2), work performance ($C3) (2) patient* ($C1), healthcare provider(s)** ($C2), overall health ($C3)
Data Input ($I)	(1) what you say (either verbally or written/typed) and how you say it (such as your speed or tone when saying it) (2) images or video of what you look like, based on your facial expressions
Purpose ($P)	(1) giving ($C2) data-driven insights into ($C1) wellbeing (2) sharing that information with academic researchers to help them learn more about mental health, as part of a research partnership (3) diagnosing mental illness in ($C1) earlier than otherwise possible (4) diagnosing neurological disorders, such as dementia or ADHD, in ($C1) earlier than otherwise possible (5) avoiding subjectivity in other methods your ($C2) may use to learn about your emotional state, like a survey or your ($C2)'s observation (6) inferring the mental health state of ($C1) individually (7) inferring the mental health state of ($C1). Inferences of an individual's mental health will not be made; only at a group level (8) identifying ($C1) in need of mental health support, to better plan organizational mental health resources (9) inferring whether ($C1) are at risk of harming others (10) inferring whether ($C1) are at risk of harming themselves (11) developing an intelligent computer program, such as a chat bot, that can conduct mental health therapy with ($C1), including you (12) inferring moments ($C1) may be in need of emotional support, and responding with an intelligent computer program designed to help ($C1) improve their wellbeing, such as offering wellbeing tips (13) automatically alerting your ($C2) when ($C1)s may need support, including you (14) assessing the ($C3) of individual ($C1)

Table 2. Vignette Variables by Contextual Factor **Contextual Integrity Parameter: Subject; **Contextual Integrity Parameter: Recipient*

Participants only saw the text relevant to the specific vignette set, either employment (i.e. *as an employee...*) or healthcare (i.e., *as a patient...*). We provide values for each of the vignette variables in Table 2. Illustrating the presentation of vignettes that vary by context, data input, and purpose, the following is a partial example of a vignette for emotion inferences derived from speech/text data inputs ($I) in the employment context ($C), with a slider scale for each of the 14 purposes ($P):

To avoid negatively influencing or confusing respondents, we chose the phrase "computer program to automatically detect [their] emotional state" compared to alternative terms describing the technology (e.g. emotion AI, automatic emotion recognition) and the specific inference or proxy (e.g., mental health state, affective state) for its relative neutrality and simplicity. To avoid ordering effects, we randomized the order in which participants were presented with vignettes at each of the three nested sets by (1) context, (2) data input, and (3) purpose. The purposes by which the

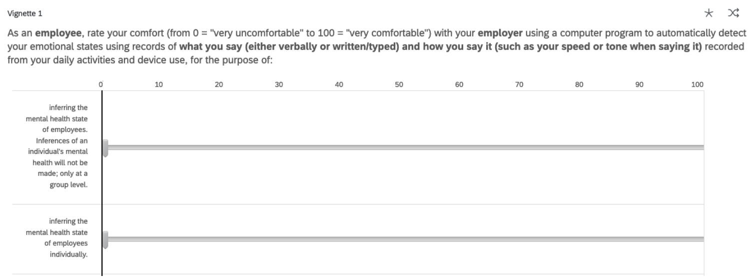

Fig. 1. Presentation of Vignettes for the Employment Context, Partial Example

vignettes varied were informed by related work analyzing patent applications concerning emotion AI [39] in addition to scholarship identifying potentially beneficial applications of emotion AI for workers and patients, included facilitating early detection of mental and neurological illnesses [73, 94], providing timely and potentially more accurate automated mental health and well-being insights and interventions [127, 162, 208, 235], equipping data collectors with increased understanding about people at either individual or group levels [49, 127], detecting or preventing potential self-harm or harm to others [73, 208, 215, 235], and supporting academic research [127, 208].

Our institution's IRB determined our study was exempt from oversight.

3.2.2 Open-ended questions. After answering each of the two vignette sets specific to employment and healthcare contexts, participants answered three open-ended questions: (1) what benefits they associate with emotion AI in the workplace/healthcare, if any; what (2) concerns they have or risks they anticipate with emotion AI in the workplace/healthcare, if any; and (3) what aspects of their identity (broadly construed) may have influenced their responses, if any.

The rich data collected in these open-ended questions exceeded the scope of the present article's research questions and merited separate in-depth analysis [63, 210] from the quantitative results presented here. However, where relevant, we briefly reference these qualitative insights when presenting our findings.

3.2.3 Post-test. After responding to the survey vignettes and open-ended questions, participants completed a post-test that obtained additional information about individual respondent characteristics. Following best practices for inclusivity in survey data collection [46, 85, 93, 228], the post-test collected the following socio-demographic information about participants: race/ethnicity, gender, age, subjective socio-economic status, mental health status, employment status, and educational attainment.

In addition, the post-test collected information about participants' individual privacy beliefs. Specifically, participants responded to questions regarding their general information privacy concerns, perceived risk associated with employer and healthcare provider access to their sensitive personal information, institutional trust beliefs regarding employer and healthcare provider handling of their sensitive information, and perceived sensitivity of emotional information (along with other types of information already categorized as "sensitive" in existing regulation and scholarship [1, 55]) by adapting the Internet Users' Information Privacy Concerns (IUIPC) [143] to our contexts of interest (employment and healthcare). We provide post-test socio-demographic and individual privacy belief questions in Appendixes B and C, respectively.

Participants used the same VAS ranging from 1-100 to report individual privacy beliefs as they did to rate their comfort to each vignette. We intentionally collected participants' socio-demographics and individual privacy beliefs *after* they finished rating the factorial vignettes to avoid biasing our results. The post-test information enabled us to analyze whether and how the socio-demographic and individual privacy belief factors reported in the post-test directly and interdependently influenced emotional privacy judgments regarding emotion inferences used in employment and healthcare [29, 136, 197] in addition to the contextual factors by which survey vignettes varied.

All together, participants' responses to the factorial vignette survey and post-test enabled us to measure workers' and patients' emotional privacy judgments concerning automatic emotion inferences in the workplace and healthcare, and how they vary by contextual, socio-demographic, and individual privacy belief factors.

3.2.4 Pilot Study. To ensure our survey design consistently measured what we intended, we first ran a pilot survey (*n*=25) of the survey vignettes and asked participants to explain anything they found confusing. Our analysis of the pilot surveys indicated that our design did not require further changes. For example, participants' responses indicating their answers to the vignettes were specific to their perceptions of employer use of computational inferences of their emotion, indicating that we elicited respondents' comfort to emotion inferences specifically, rather than employee or patient monitoring generally, confirming construct validity. The pilot survey also served to assess participant fatigue. We included attention check questions and paid particular attention to length of completion time. Of note, factorial vignettes are known to suffer more from a steep learning curve due to the novelty of the study design rather than respondent fatigue [157]; although participants responded to a considerable 56 vignettes, they were able to complete the survey relatively quickly once respondents familiarized themselves with the questions and the factors by which they varied. The average time to complete was 24 minutes; as only two participants failed the attention check, we determined the survey was an appropriate length for its contributions.

3.3 Recruitment and Data Collection

3.3.1 Sampling. As described in Section 3.1, our study draws from both contextual integrity and privacy vulnerabilities as theoretical frameworks, which also informed our sampling strategy.

Specifically, we collected two samples. Following *contextual integrity's* conceptualization of privacy as a social norm [177], we elicited emotional privacy judgments concerning emotion inferences in the workplace from a US nationally representative sample by age, sex, and race (n=300), a sampling strategy used in past scholarship to define privacy norms and whether and how contextual conditions surrounding the use of information can violate them [154].

However, minoritized perspectives have been historically excluded from technology research sampling designs [160]. Relying on nationally representative samples alone to study workers' and patients' emotional privacy judgments may perpetuate contextual integrity's "unique set of norms of justice" [175], as privacy perceptions are shaped and enforced by powerful actors [2] and influenced by prior experience with privacy abuses [266]. Particularly in power-asymmetric contexts marked by social inequality like the workplace and healthcare, a failure to represent the perspectives of minoritized groups whom do not enjoy the same level privacy [40, 97, 159, 160, 222] when studying workers' and patients' privacy perceptions may obscure the inequalities and unmet privacy needs they may face in these contexts [160], and misrepresent the norms and underlying values of groups most vulnerable to algorithmic harms [33] by suppressing the perspectives of those less privileged [95, 160, 195, 247].

As such, our recruitment efforts also followed the principles of *privacy vulnerability* [160] in our assessment of workers' and patients' emotional privacy judgments by collecting a separate minoritized sample of people of color, people with mental illness, and/or minority genders (n=385). These minoritized groups may be disproportionately harmed by emotion AI technologies and related data practices that infer and/or interact with human emotion [168, 201, 208, 233, 249, 273]. Therefore, our choice to separately sample these minoritized perspectives allowed us to surface and center the privacy perceptions of groups who may be particularly vulnerable to harms associated with emotion inferences in the workplace and healthcare, aligning with related oversampling methods used in HCI scholarship to surface perceptions from minoritized perspectives [101], and gain insight into how they may differ from US nationally representative perspectives.

3.3.2 Recruitment. We recruited participants via Prolific, an online recruitment platform for research surveys that allows for recruitment of specific populations for which Prolific members have already been pre-screened. Interested and eligible participants were directed to a Qualtrics survey link, which contained detailed study information that we asked participants to review before consenting to proceed. Participants that completed the survey were issued an incentive of $3.80, following recommendation from Prolific's compensation suggestion tool.

We ran two separate recruitment efforts on Prolific for each of the two samples. The US representative sample by sex, age, and race (n=300) was collected in October 2021 using Prolific's automatic representative sampling feature. To sample for people with at least one of the minoritized identities of interest – person of color, current or past mental illness (no formal diagnosis necessary), and/or gender minority (n=385) – we used Prolific's pre-screened attributes to target our sample accordingly. The minoritized sample was collected between December 2021-February 2022.

We additionally collected information about participants' socio-economic status (using MacArthur's scale of 1-10 for subjective social status [93]) and educational attainment in the post-test for both samples, as described in 3.2.3. Descriptive statistics for each of the samples are provided in Table 3.

Of note, levels for two of the variables by which Prolific balances participants for US representativeness, sex and race, excluded certain gender and ethnic minorities (i.e., trans and/or non-binary people; Latine) by grouping them into less descriptive and inclusive categories (i.e., mapped ethnic minority groups into "white" or "other" races). We report summary statistics that include our analysis' gender and race/ethnicity categories rather than Prolific's. Despite our efforts to recruit for a range of under-represented ethnic minorities including Indigenous and Middle Eastern/North African participants, our samples did not have adequate representation to study these groups separately; we aggregated results from these participants under the race/ethnicity level "additional races/ethnicities."

3.4 Data Analysis

3.4.1 Pre-processing. We prepared our dataset for analysis by removing 49 respondents that did not complete both sets of vignettes, 13 respondents that did not provide any demographic information, and one respondent that failed the attention check. We additionally removed one low quality (i.e., same answer for every question without justification in the open-ended questions) submissions and 12 duplicate submissions. For those that had one incomplete and one complete submission, we preserved the complete submission and discarded the incomplete one; for those that had two complete submissions, we preserved the first submission and discarded the second. We imputed missing responses (i.e., randomly skipped questions) using the mice package in R, a common method in social science research to handle missing data [79, 241].

Due to the size of our sample, it was necessary to condense groupings of the socio-demographic levels collected in the post-test (provided in Appendix B). We provide final socio-demographic groupings in Table 3. Due to race/ethnicity mapping and value differences between our pre-screener and Prolific's categories described in Section 3.3.2, participants reporting mixed or multiple race/ethnicities were grouped according to either their non-white race/ethnicity or primary

Factor	Level	Rep. Sample	Minoritized Sample
Race/Ethnicity	additional ethnicities	11	26
	Asian	26	47
	Black	51	104
	Latine	15	42
	white	197	194
Gender	trans and/or non-binary	6	44
	woman	148	232
	man	146	139
Mental Health Status	under treatment for 1+ mental illness	67	115
	untreated/resolved mental illness	50	101
	no mental illness	183	140
	did not report	0	57
Age Group	18-27	55	170
	28-37	55	120
	38-47	49	42
	48-57	52	30
	58+	89	36
	Did Not Report	0	15
Education	Bachelor's degree or higher	170	167
	No Bachelor's degree	130	190
	Did Not Report	0	56

Table 3. Descriptive Sample Statistics by Socio-demographic Level

ethnicity in order to preserve the most data integrity. For example, participants identifying as white and Latine in the prescreener had inconsistent race/ethnicity values reported by Prolific (e.g., some "white", some "mixed", some "other"); to ensure data consistency and in acknowledgement of historical controversies in US reporting of Latine racial categories as white [207], we coded these participants' race/ethnicity as Latine. Participants reporting multiple non-white ethnicities in our pre-screener were grouped according to the primary race/ethnicity reported in their Prolific profile, as data in these cases did not have the same inconsistencies.

3.4.2 Factors. For both our representative and minoritized samples, we regressed the contextual, socio-demographic, and individual privacy belief variables of interest on participants' reported comfort level to each scenario. Table 4 lists the factors used in our analysis:

For the socio-demographic categorical variables, we re-leveled the reference categories so that the results would compare levels to the most socially dominant group in each category, which we defined as white race/ethnicity, male gender, age 58+, no mental illness experience, and educational attainment of Bachelor's degree or higher. For the contextual categorical variable of purpose, we defined the reference category as "giving employers/healthcare providers data-driven understanding into employee/patient wellbeing" given the prevalence of organizational initiatives to drive employment and healthcare decisions with data, including those providing insights into workers' [174] and patients' [141] emotional state.

For individual privacy beliefs reported in the post-test, we averaged participants' reported value (ranging from 0-100) across each construct: general privacy concerns, trust in employer/healthcare provider handling of sensitive

Factors	Levels
Contextual	Context (Employment v. Healthcare)
	Data Input
	Purpose
Socio-demographic	Race/Ethnicity
	Gender
	Mental Health Status
	Educational Attainment
Individual Privacy Belief	General Privacy Concerns
	Trust in Employer/Healthcare Provider Handling Sensitive Info
	Perceived Sensitivity of Emotional Information in Employment/Healthcare

Table 4. Analysis Factors and Levels

information, and perceived sensitivity of emotional information handled by employer/healthcare provider. Responses to some questions were first reverse-coded as necessary (e.g., if the higher value for the question indicated the opposite direction of the belief measured).

3.4.3 Mixed Effect Modeling. Our analysis takes a comprehensive approach to understanding how each of the contextual, socio-demographic, and individual privacy belief factors interdependently influence emotional privacy judgments. We conducted the quantitative analysis in R using multi-level modeling techniques with the lme4 package. As our factorial vignette design obtained multiple observations from each participant, the multi-level modeling approach clusters the analysis by participant, which allowed our analysis to account for individual variation within participant responses and avoid violating the independence assumption in traditional linear regression approaches [83]. This structure specifies individual participants as a random effect to account for subject to subject variability, thus limiting biased covariance estimates for each participant, and specifies our independent variables of interest as fixed effects [83, 92].

We fitted four multivariable linear mixed-effects models: one for responses to each employment and healthcare vignette sets, for both the representative and minoritized samples. To facilitate comparisons between samples, and because our individual privacy belief variables collected responses that were specific to and varied by either the employment or healthcare context, it was necessary to run separate models for both samples and vignette contexts.

To assess the best model fit for each dataset [26], we used Anova to compare various model combinations that specified individual participants as a random effect, included fixed effects for our contextual variables of interest (purpose and data input), and additionally included fixed effects combinations that varied by what socio-demographic and individual privacy belief variables were included. The Anova function conducts likelihood ratio tests (LRTs) to compare the likelihoods of multiple models and assess whether including or excluding certain fixed effects significantly improve model fit. We used LRTs along with Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values for each model to select models based on fit [26, 194]. We fit our models using maximum likelihood (ML), which means that estimates for the specified random and fixed effect parameters were generated by maximizing the likelihood of the observed data; fitting models with ML rather than lmer's default restricted maximum likelihood (REML) criterion is necessary to meaningfully compare models with varying fixed effects structures [194].

To facilitate model comparisons to investigate our research questions, we chose to employ a model with the same fixed effects across all four models. We included a variable as a fixed effect if our ANOVA analysis showed it was a significant predictor in at least one of the four datasets and a variable that contributed to the best model fit, with the exception of respondents' general privacy concerns. Respondents' general privacy concerns were not a predictor in any of the four models, but we chose to include given our interest in privacy perceptions. During this process we opted to exclude the socio-demographic variables for age group, perceived socio-economic status, and employment status as fixed effects in our models. We conducted t-tests using the Satterthwaite's method to assess statistical significance [216], as it is generally inappropriate to use traditional p-values to assess the significance of fixed effects in mixed effect models [142].

We additionally used Anova to compare our chosen model to each of the four datasets' respective null models (containing no predictors), confirming our final models' fitness. To assess the proportion of variance explained by the model's structure, we computed the intra-class correlation (ICC) for the null models of both datasets [112]; the ICC for the representative and minoritized models was .72 and .67 respectively, indicating fair to good reliability [221]. For all models, we plotted the residuals to the quantiles of the standard normal distribution to confirm that the normality assumption was met [246]; although not all variables were normally distributed, the linear mixed effect analysis we employed is suitable for both normal and non-normal variables [17, 111].

We ultimately selected (and report on) a random slope mixed effects model for all datasets. This model provides a nuanced understanding of how our study's contextual, socio-demographic, and individual privacy belief variables of interest influence workers' and patients' emotional privacy judgments by recognizing that individuals may have unique responses to the explanatory variables, and that the relationship between the independent variables and participants' reported comfort can differ from person to person, by assigning distinct baseline values for each participant and allowing the effects of the independent variables to have a different effect for each participant. Specifically, our chosen model treats individual participants as random effects, and as described in Table 4, includes the following explanatory variables as fixed effects: contextual variables of data input and purpose; socio-demographic variables of gender, race/ethnicity, mental health status, and educational attainment; and individual privacy beliefs concerning general privacy, trust toward employer/healthcare provider handling of sensitive information, and perceived sensitivity of emotion data use in employment/healthcare. Participants' individual privacy beliefs regarding the riskiness of their employer/healthcare provider handling of sensitive information was found to be a predictor, but removed from the analysis due to multicollinearity with individual trust beliefs.

For each factor, we compare the relative magnitude and strength of the relationship between samples using Z-tests; a positive Z-score indicates the factor effect is greater in the U.S. representative group compared to the minoritized sample, while a negative Z-score indicates the factor effect is relatively greater in the minoritized group. We identify significantly different variable effects between U.S. representative and minoritized samples where the absolute value of the Z-score is greater than the critical value (e.g., 1.96 for a 5% significance level). The variation between samples reveals meaningful differences in how distinct contextual, socio-demographic, and individual privacy belief factors influence U.S. representative and minoritized perspectives differently, even where the variation is not significantly different between samples or where the effect of some predictors is not strong enough within each sample to be significant on its own.

3.5 Reflections, Limitations, and Opportunities

3.5.1 Survey Responses. Our survey design uses workers' and patients' self-reported comfort with being subject to various applications of automatic emotion inferences in the workplace and healthcare as the dependent variable to measure their associated emotional privacy judgments. In line with related work [32, 186], comfort level offers insight into individual privacy judgments and the perceived privacy risks associated with a technology and its related data practices. However, measuring privacy perceptions is difficult and lacks consensus on the dependent variable to measure [116, 175, 181, 261]; other measures include a focus on normative beliefs (e.g., appropriateness [175]) and behaviors (e.g., willingness to use [32]) as proxies for privacy perceptions about a technology. Though we considered using these variables, in recognition of the "malleability" of individuals' privacy perceptions to corporate influence [4] and the choice constraints workers and patients may experience in consenting to emotion inferences in workplace and healthcare contexts, we decided "comfort" was the most suitable dependent variable for our study. Future work could use other dependent variables to investigate whether and how emotional privacy judgments may differ from those in our findings.

We attempted to frame vignettes as neutral as possible by wording vignettes so as to avoid indicating potential harms, thus avoiding negatively biasing participants' responses. However, many of the purposes by which the vignettes varied nevertheless implied a benefit to participants (e.g., physical safety, improved mental health resources and support). As such, our vignettes may have had positive framing effects on participant responses. In presenting our findings on the effect of purpose on participants' comfort with emotion inferences, we include mention of possible ways in which the potential benefits (and risks) participants associated with each purpose may have influenced participant responses. Future work could test the effect of framing on privacy perceptions of emotion inferences.

Of note, we treated comfort as a continuous variable, which can overcome some of the limitations including data loss and clustering found in more traditional ordinal (i.e., Likert) scales [51, 239] (the merits of which are described in Section 3.2.1).

The standard limitations of self-reported survey data apply, including respondent bias. However, presenting factorial vignettes that vary by multiple factors can reduce respondent bias, as participants may find it difficult to adjust their answers (i.e., to appear more concerned) when the factors are constantly changing [153], as was the case in our design. As such, our factorial vignette design may have mitigated respondent bias.

3.5.2 Selected Independent Variables. As described in 3.2, while we follow contextual integrity principles to define our emotional privacy norm within the parameters specified in Table 1, deviations from these specifications would likely impact workers' and patients' perceptions of emotional privacy. For example, our data transmission parameters specified to participants that each vignette involved consenting to their employers' and healthcare providers' monitoring of their daily activities and device usage to infer their emotional state, and that the inferred emotional information would be retained indefinitely (to the extent allowed by law) by their employer or healthcare provider and would not be shared (unless otherwise noted in the vignettes, such as in the case of sharing with academic researchers). In practice, obtaining meaningful consent to the generation and use of emotion inferences in power imbalanced contexts is challenging [52] and potentially coercive [212], and as such this dynamic may have contributed to participants' poor emotional privacy judgments surfaced in this study. emotional privacy judgments may also be impacted if data practices were more restrictive than those presented in this study, for instance if the collected and inferred data were deleted rather than indefinitely stored and potentially reused and shared. We encourage future work to examine how emotional privacy judgments may differ by consent and data handling variables not considered in this study.

Moreover, we recognize that our findings as they relate to purpose may have been influenced by framing effects not tested in this study. While we did our best to frame these purposes neutrally, some nevertheless implied a benefit that may have positively biased participants' responses, as benefit perceptions can lessen privacy risk perceptions [32] (which we directly address when interpreting results). Future work could further investigate the influence of framing on peoples' emotional privacy judgments.

Our results may be further limited by the potential effect of variables our study design did not include, such as individual characteristics like privacy awareness and technological literacy, expertise, and familiarity. Though our study included related variables like general privacy concerns and educational attainment that may be considered as proxies for privacy awareness and technological literacy, we acknowledge that there are individual factors for which we did not test that may have influenced our results. Future work could investigate how additional individual and contextual factors affect peoples' privacy perceptions of emotion inferences.

3.5.3 Representativeness and Generalizability. Relatedly, we highlight the limitations of this study's generalizability to contextual variables for which we did not test. For example, while we assessed the effect of input data type on emotional privacy judgments (i.e., speech/text records and image/video records), other data inputs (e.g., sensor data) not considered in this study may surface differing privacy judgments. Moreover, our choice to combine data input types, which helped to reduce the size of the survey and consequently mitigate participant fatigue, limits our study's ability to understand how peoples' emotional privacy judgments vary between the combined inputs of speech/text and image/video records. Nonetheless, our study's design specifying the purpose for which differing data sources are analyzed to infer human emotion, and analysis of the combined effects of data input and purpose (among other variables) on peoples' comfort, surfaced distinct privacy perceptions that highlight the inter-dependency of multiple contextual parameters (i.e., data input and purpose) on workers' and patients' emotional privacy judgments. As we further discuss in Section 2.3, we hope future research is encouraged to more explicitly address data purpose when investigating the effect of data type on privacy perceptions.

Our study examined emotional privacy judgments broadly construed, without consideration for the *type* of emotion inference. The privacy risk profile for emotional information flows may vary between emotion types (e.g., anger, happiness, sadness), and thus we expect that peoples' perceptions about emotional information sharing may vary by the emotional state that is inferred. We encourage future work to explore if and how emotional privacy judgments vary by emotion type.

Lastly, it is important to note that our findings are limited to the parameters we define within workplace and healthcare contexts, and may not generalize to other contexts and contextual parameters. Furthermore, our sample of people with at least one minoritized identity may not be representative of the broader population of people with mental illness, people of color, and minority genders, and as such our findings from this sample may not generalize to these groups as a whole. It should also be noted that although we aimed for representativeness in our US nationally representative sample, the participant pool from which we recruited participants – Prolific – is comprised of click workers who are already over-represented in research and whose perceptions may differ from the general population; that said, recent scholarship indicates that Prolific is generally representative for studies about privacy perceptions and beliefs [232] and we thus remain confident in the representativeness of our US representative sample's findings. Relatedly, we highlight that our sample of minoritized perspectives from people of color, people with mental illness, and/or minoritized genders does not, and is not intended to, represent the perspectives of all minoritized perspectives. Rather, our choice to separate the two samples is to center the perspectives of groups who may be more vulnerable to harm from emotion inferences in the workplace and healthcare and to illustrate that, at an aggregate level, their privacy perceptions can and do differ from the more socially dominant. In either sample, we did not stratify along dimensions by which workers' and patients' perspectives may vary (e.g., occupation, industry, diagnostic condition), and look forward to additional research investigating emotional privacy judgments at these sub-population levels.

3.5.4 A Note on Statistically Insignificant Results. We note that our decision to use the same mixed-effects structure across our four datasets means that we report on several statistically insignificant results. Though mixed effect models are well-suited to detect nuanced relationships within the data by accounting for variability within a cluster (i.e., within an individual respondent), this flexibility can result in greater estimate variability and standard errors than simpler regression models (e.g., more estimates that are close to zero), which in turn may result in more statistically insignificant findings [36, 194]. As such, researchers employing mixed effect models often focus on the patterns and relationships within the data to surface their theoretical and practical significance rather than evaluating statistically significant findings alone [36, 142] – including in the present study's field of interest, privacy perceptions [32, 152, 154]. In addition to observing potential trends for which we did not have statistical power to confirm, we report confidence intervals for our findings to avoid dichotomous interpretations of our results [31]. The relationships for statistically insignificant fixed effects on our dependent variable may indicate potential trends that could be confirmed with larger-powered samples [36, 44, 142]. We also note that traditional effect size measures such as Cohen's d or eta-squared do not apply well to multilevel analysis, and instead use the independent variable's coefficient direction, magnitude, and statistical significance – the extent to which it affects the dependent variable [62] – to interpret effect sizes [192]. We highlight these methodological differences to better contextualize our study's results, which include both statistically significant and statistically non-significant findings. Although we may briefly report on the potential trends statistically non-significant findings provide, we emphasize that we are unable to conclude that the relationship for statistically insignificant results in our analysis is not due to chance, and therefore encourage readers to exercise caution when interpreting any reported statistically insignificant results.

4 FINDINGS

Our study systematically dissects the complex interplay of factors influencing emotional privacy judgments in the context of automatic emotion inferences within workplace and healthcare settings. Our comprehensive analysis, grounded in mixed effect modeling, reveals nuanced insights into the *relative* influence that contextual, socio-demographic, and individual privacy belief factors have in differentially shaping workers' and patients' emotional privacy judgments. Our findings contribute substantially to the fields of privacy theory, human-computer interaction, and technology policy, offering a multi-faceted view that deepens our understanding of emotional privacy in an era increasingly dominated by AI and data-driven practices.

In exploring these relationships, we remain sensitive to the diversity of workers' and patients' perspectives, acknowledging that privacy perceptions can vary between dominant (i.e., U.S. representative) and minoritized groups [160], as well as across different contexts [176]. Such variation underscores the need for a nuanced approach to privacy, recognizing the multi-factorial influences that shape individuals' emotional privacy judgments. Our theoretical underpinning and methodological rigor, detailed in Sections 3.1 and 3.4.3 respectively, allows us to draw meaningful comparisons and highlight theoretically relevant trends or significant differences where they exist.

The regression results, detailed in Tables 5 (employment context) and 6 (healthcare context), offer a comprehensive view of the estimated coefficients, standard errors, and statistical significance of various factors influencing workers' and patients' comfort with emotion inferences. These tables, complemented by the coefficient plot in Figure 8 (Appendix A), provide a visual representation of the relationships between these factors and emotional privacy judgments across both U.S. representative and minoritized samples in the employment and healthcare contexts.

Regression Results for Employment Context

	Representative (n=300)	Minoritized (n=385)	Z-Test (Sample Comparison)
(Intercept)	$36.64\ (6.44)^{***}$	$34.24\ (6.08)^{***}$	0.27
<u>Contextual Factors</u>			
Data Input *(baseline: image/video)*			
speech/text	$2.69\ (0.35)^{***}$	$4.25\ (0.34)^{***}$	**-3.21**
Purpose *(baseline: (1) data-driven wellbeing insights)*			
(2) academic research	$4.18\ (0.93)^{***}$	$1.26\ (0.89)$	**2.28**
(3) early diagnosis - mental illness	$-1.32\ (0.93)$	$-2.49\ (0.89)^{**}$	0.91
(4) early diagnosis - neurological disorder	$0.55\ (0.93)$	$-1.70\ (0.89)^{\cdot}$	1.75
(5) avoid human subjectivity	$0.57\ (0.93)$	$-1.39\ (0.89)$	1.52
(6) individual level mental health inference	$-3.48\ (0.93)^{***}$	$-3.70\ (0.89)^{***}$	0.17
(7) group level mental health inference	$2.63\ (0.93)^{**}$	$2.16\ (0.89)^{*}$	0.36
(8) identify individuals in need of support	$2.15\ (0.93)^{*}$	$3.78\ (0.89)^{***}$	−1.27
(9) infer risk of harm toward others	$6.39\ (0.93)^{***}$	$7.03\ (0.89)^{***}$	−0.50
(10) infer risk of self-harm	$3.20\ (0.93)^{***}$	$2.60\ (0.89)^{**}$	0.47
(11) develop auto. intervention - therapy	$1.68\ (0.93)^{\cdot}$	$1.92\ (0.87)^{*}$	−0.19
(12) receive auto. intervention - acute support	$1.66\ (0.93)^{\cdot}$	$1.85\ (0.89)^{*}$	−0.14
(13) alert employer when in need of support	$0.28\ (0.93)$	$-0.05\ (0.89)$	0.26
(14) assess overall performance	$-0.88\ (0.93)$	$-2.55\ (0.89)^{**}$	1.30
<u>Socio-demographic Factors</u>			
Race/Ethnicity *(baseline: white)*			
Asian	$-3.15\ (4.31)$	$-8.05\ (3.55)^{*}$	0.88
Black	$5.64\ (3.19)^{\cdot}$	$7.38\ (2.79)^{**}$	−0.41
Latine	$8.27\ (5.44)$	$4.45\ (3.84)$	0.57
additional races/ethnicities	$6.78\ (6.27)$	$3.53\ (4.69)$	0.41
Gender *(baseline: male)*			
trans and/or non-binary	$-0.63\ (8.71)$	$-4.63\ (4.08)$	0.42
woman	$-2.99\ (2.41)$	$-0.06\ (2.45)$	−0.85
Mental Health *(baseline: no mental illness)*			
under treatment for 1 or more mental illnesses	$6.47\ (3.13)^{*}$	$-0.79\ (3.06)$	1.66
used to have/not treated for mental illness	$-3.67\ (3.36)$	$2.17\ (2.97)$	−1.30
Education *(baseline: Bachelor's or higher)*			
no Bachelor's degree or less	$0.14\ (2.46)$	$6.16\ (2.37)^{**}$	−1.76
<u>Individual Privacy Beliefs</u>			

	Representative (n=300)	Minoritized (n=385)	Z-Test (Sample Comparison)
general privacy concerns	−0.04 (0.07)	−0.07 (0.07)	0.34
sensitivity toward emotion data in employment	−0.30 (0.05)***	−0.25 (0.05)***	−0.71
trust beliefs re: employer sensitive info	0.54 (0.05)***	0.40 (0.05)***	**2.09**
Akaike Information Criterion (AIC)	71657.54	93685.87	
Bayesian Information Criterion (BIC)	71861.58	93911.72	
Log Likelihood	−35799.77	−46811.94	
Number of observations	8400	10780	
Number of groups: Individual participants	300	385	
Var: Individual participant (Intercept)	394.19	417.98	
Var: Residual	257.45	303.61	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; · $p < 0.1$; **Bold** Z-scores indicate statistical significance between samples at p<0.05

Table 5. Regression results: Effect of Independent Variables on Comfort with Emotion Inferences in Employment

Regression Results for Healthcare Context

	Representative (n=300)	Minoritized (n=385)	Z-Test (Sample Comparison)
(Intercept)	28.91 (8.21)***	26.96 (6.72)***	0.18
<u>Contextual Factors</u>			
Data Input *(baseline: image/video)*			
speech/text	4.13 (0.37)***	5.35 (0.36)***	**-2.37**
Purpose *(baseline: (1) data-driven wellbeing insights)*			
(2) academic research	−2.61 (0.98)**	−2.43 (0.95)*	−0.13
(3) early diagnosis - mental illness	−1.98 (0.98)*	−0.55 (0.95)	−1.05
(4) early diagnosis - neurological disorder	2.19 (0.98)*	3.47 (0.95)***	−0.94
(5) avoid human subjectivity	−3.73 (0.98)***	−2.44 (0.95)**	−0.94
(6) individual level mental health inference	−5.52 (0.98)***	−4.72 (0.95)***	−0.59
(7) group level mental health inference	−4.32 (0.93)***	−4.74 (0.95)***	0.31
(8) identify individuals in need of support	−1.17 (0.98)	1.34 (0.95)	**-1.84**
(9) infer risk of harm toward others	−0.26 (0.98)	−0.56 (0.95)	0.22
(10) infer risk of self-harm	−0.27 (0.98)	−1.10 (0.95)	0.61
(11) develop auto. intervention - therapy	−7.91 (0.98)***	−7.88 (0.95)***	−0.02
(12) receive auto. intervention - acute support	−3.49 (0.98)***	−3.18 (0.95)***	−0.23
(13) alert provider when in need of support	−3.89 (0.98)***	−2.09 (0.95)*	−1.32

	Representative (n=300)	Minoritized (n=385)	Z-Test (Sample Comparison)
(14) assess overall health	−1.91 (0.98)$^{\cdot}$	0.23 (0.95)	−1.57
Socio-demographic Factors			
Race/Ethnicity *(baseline: white)*			
Asian	3.33 (5.44)	−3.90 (3.92)	1.08
Black	10.65 (4.02)**	6.66 (3.05)*	0.79
Latine	4.60 (6.87)	5.47 (4.29)	−0.11
additional races/ethnicities	3.01 (7.93)	0.95 (5.18)	0.22
Gender *(baseline: male)*			
trans and/or non-binary	−6.26 (10.99)	−15.32 (4.55)***	0.76
woman	−1.52 (3.03)	−0.07 (2.71)	−0.36
Mental Health *(baseline: no mental illness)*			
under treatment for 1 or more mental illnesses	3.69 (3.94)	1.70 (3.33)	0.39
used to have/not treated for mental illness	−0.12 (4.23)	3.32 (3.31)	−0.64
Education *(baseline: Bachelor's or higher)*			
no Bachelor's degree or less	2.06 (3.06)	2.12 (2.63)	−0.01
Individual Privacy Beliefs			
general privacy concerns	−0.04 (0.08)	−0.08 (0.07)	0.35
sensitivity toward emotion data in healthcare	−0.10 (0.05)$^{\cdot}$	−0.11 (0.04)**	0.15
trust beliefs re: healthcare sensitive info	0.44 (0.06)***	0.53 (0.05)***	−1.07
Akaike Information Criterion (AIC)	72732.10	94520.25	
Bayesian Information Criterion (BIC)	72936.15	94745.93	
Log Likelihood	−36337.05	−47229.12	
Number of observations	8400	10724	
Number of groups: Individual participants	300	385	
Var: Individual participant (Intercept)	632.11	511.98	
Var: Residual	288.95	342.41	

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$; **Bold** Z-scores indicate statistical significance between samples at p<0.05

Table 6. Regression results: Effect of Independent Variables on Comfort with Emotion Inferences in Healthcare

As we delve deeper into the results in the following sections, we integrate findings from both samples and contexts within the same narrative framework. This approach not only facilitates comparison across variables and contexts, but also provides a holistic understanding of the complex dynamics at play in shaping workers' and patients' emotional privacy judgments in an age where emerging technologies like emotion AI implicate unique threats to privacy over personal emotional information.

4.1 Influence of Contextual Factors on Emotional Privacy Judgments of Emotion Inferences in the Workplace and Healthcare

In our examination of emotional privacy judgments concerning emotion inferences, we draw upon contextual integrity privacy theory [176]. This framework helps us to define and understand emotional privacy norms specific to workplace and healthcare settings, as detailed in Table 1 (Section 3.1.1). Building on this foundation, our analysis, as outlined in Table 4 (Section 3.4.2) centers around three key contextual variables: context ($C), data input ($I), and purpose ($P). We engaged participants through tailored vignettes that varied by each of these three contextual variables as follows:

As a $C1, rate your comfort (from 0 = "very uncomfortable" to 100 = "very comfortable) with your $C2 using a computer program to automatically detect your emotional states using records of $I recorded from your daily activities and device use, for the purpose of $P

Our analysis dissects emotional privacy norms by examining the relative impact of data input ($I) and purpose ($P) on workers' and patients' perceptions about emotion inferences within each context.

4.1.1 *Context: Emotional Privacy Judgments More Susceptible to Factor Influences in Healthcare than in Employment.*

Grounded in contextual integrity privacy theory [176], our analysis recognizes that privacy perceptions are inherently context-dependent. This is reflected in differences in participants' reported levels of comfort with emotion inferences between employment and healthcare contexts.

Context	Sample	Mean	Mean StdDev	Regression Intercept
employment	representative	32.50	32.59	36.64
employment	minoritized	32.55	32.11	34.24
healthcare	representative	49.70	32.45	28.91
healthcare	minoritized	50.02	32.54	26.96

Table 7. Summary Statistics - Mean and Estimated Comfort Levels by Context and Sample

As Table 7 illustrates, there is a clear disparity in the mean reported comfort levels between the contexts. Rated on a scale between 0-100, the mean comfort with emotion inferences in the workplace is markedly lower (32.50 and 32.55) compared to healthcare (49.70 and 50.02). However, the regression intercepts – indicating baseline comfort levels when controlling for all other variables – paint a more complex picture. In healthcare, the intercepts are substantially lower (28.91 and 26.96) than the mean comfort levels, suggesting that factors in our mixed effect model have a greater impact on comfort levels in healthcare to the employment context, where the intercepts are closer to the mean comfort levels.

This difference in baseline comfort levels can be understood through the lens of distinct power dynamics and privacy expectations characteristic of each context. The healthcare context is traditionally anchored in trust and confidentiality in healthcare providers, with a heightened focus on patient autonomy and voice, particularly in mental healthcare. The reliance on subjective emotional disclosures in this setting may amplify privacy sensitivities, especially among minoritized groups who have historically lacked equitable access to healthcare, and thus may view automatic emotion inferences as greater potential threats to their autonomy and access to quality healthcare. This interpretation aligns with qualitative findings from our related study [210], which indicate heightened concerns among patients, particularly those with marginalized identities, about the impact of emotion AI on patient autonomy, healthcare access, and the integrity of the patient-provider relationship. In contrast, the employment context presents differing power dynamics and privacy expectations. Here, the norm of invasive surveillance and limited worker autonomy is reflected in workers' baseline discomfort with emotion inferences. As our qualitative insights show, workers perceive emotion inferences to potentially exacerbate existing workplace challenges related to worker privacy and autonomy [63]. This perception was particularly acute among workers from marginalized backgrounds, who may already feel disproportionately impacted by surveillance and control measures in the workplace.

These differences underscore the contextual variability in emotional privacy judgments, and highlight the necessity of mixed effect modeling to uncover the intricate relationships between emotional privacy judgments and the various factors that may shape them. The lower regression intercepts in healthcare suggest a context where the influence of contextual, socio-demographic, and independent privacy belief factors is more pronounced, potentially rendering some applications of emotion inferences in healthcare more acceptable under certain conditions. Conversely, in the employment context, where invasive surveillance practices are more normalized and worker autonomy is typically limited, the introduction of emotion inferences may be seen as less of a departure from existing practices, albeit still concerning given the highly-consequential potential for employers to misuse and abuse workers' inferred emotional information. Overall, these results highlight that while there is an overall discomfort with emotion inferences in both contexts, it is critical to use methods such as mixed effect modeling, as we do in this analysis, to disentangle the complex interplay of factors that shape emotional privacy judgments in different contexts.

4.1.2 Data Input: Workers and Patients Favor Speech/Text Emotion Recognition Over Facial Emotion Recognition, though Emotional Privacy Judgments Remain Low with All Modalities. We were interested to know whether and how participants' comfort with employers' and healthcare providers' collection and use of their emotion inferences varied by the type of data input to the emotion recognition algorithm. From their perspectives as employees and patients, participants rated their comfort (from 0 = "very uncomfortable" to 100 = "very comfortable) with their employers and healthcare providers, respectively, using a computer program to automatically detect their emotional states using records recorded from their daily activities and device use, either (1) what they say (either verbally or written/typed) and how they say it (such as their speed or tone when saying it) (e.g., speech/text records) or (2) images or video of what they look like, based on their facial expressions, for various purposes.

Our regression results show that both workers and patients are significantly more comfortable with speech and/or text-based emotion inferences than facial recognition-based emotion inferences. Compared to the baseline category of image/video records of one's facial expressions, comfort levels were significantly higher with emotion inferences generated from employers' analysis of speech/text records of what workers said and/or how they said it (representative: $\beta = 2.69$, $SE = 0.35$, $p < 0.001$; minoritized: ($\beta = 4.25$, $SE = 0.34$, $p < 0.001$). Similarly, comfort levels with emotion inferences were significantly higher when generated by healthcare providers' analysis of patients' speech/text records than image/video records of their facial expressions (representative: $\beta = 4.13$, $SE = 0.37$, $p < 0.001$; minoritized: ($\beta = 4.34$, $SE = 0.33$, $p < 0.001$). We suggest this finding may reflect the public's particular discomfort with facial recognition technologies and their attendant accuracy and privacy concerns [271]. Of note, although our findings demonstrate a general discomfort toward emotion inferences in both healthcare and employment across both samples, the more pronounced positive effect speech and/or text-based emotion inferences had on participant comfort was statistically significant in both employment and healthcare samples, with Z-scores of -3.21 and 2.37, respectively.

With regard to a specific manifestation of facial recognition used in employment and healthcare – facial *emotion* recognition – our results support a growing understanding that people in general are uncomfortable with being subjected to facial recognition technologies. Furthermore, our findings show that data type is a relevant and statistically significant

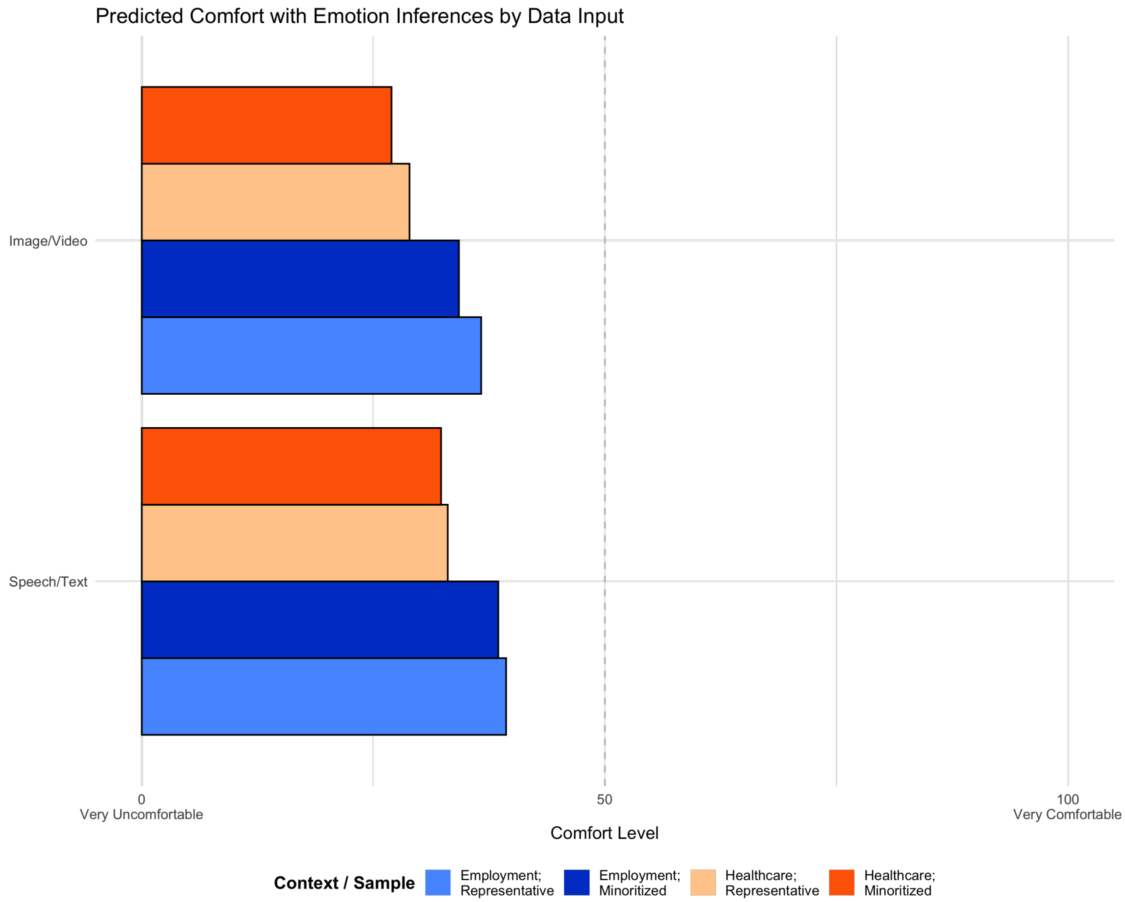

Fig. 2. Predicted Comfort Levels by Data Input Type. This figure illustrates the predicted comfort levels by combining the data type variable coefficients to each mixed-effects regression model intercept, derived by analyzing respondent comfort on a scale from 1 (very uncomfortable) to 100 (very comfortable). Bars with black borders indicate statistically significant results.

contextual factor that affects workers' and patients' emotional privacy judgments, influenced by a parameter for how their emotional information is collected in the first place: the type of data input to the emotion recognition algorithm. That is not to suggest, however, that emotional privacy can be preserved on the basis of specific (i.e., non-facial) emotion recognition data inputs: as Figure 2 shows, workers' and patients' predicted comfort with emotion inferences by data input remains low across modalities, contexts, and samples, with comfort estimates only ranging from 32.31-39.33 on a scale of 0-100. Moreover, we observe that the effect of data input on both workers' and patients' perceptions is more pronounced for participants in the minoritized sample than in the representative sample, and that both workers' and patients' predicted comfort with emotion inferences by data input is consistently lower in the minoritized sample compared to the US representative sample. All together, these results show that while workers and patients are relatively more comfortable with speech/text-based emotion inferences than facial recognition-based emotion inferences, they are still uncomfortable with either application, and indicate that there are greater emotional privacy concerns at all levels of emotion recognition data input – speech, text and facial emotion recognition – among people of color, people with mental illness, and/or minority genders than in the US representative population.

4.1.3 Purposes for Which Employers and Healthcare Providers Use Emotion Inferences Shape Emotional Privacy Judgments.

To understand the influence of purpose on emotional privacy judgments, we examined whether and how the purpose for which employers and healthcare providers may use emotion inferences affected participants' comfort with their emotions being inferred. Participants rated their comfort (from 0 = "very uncomfortable" to 100 = "very comfortable) with their employers and healthcare providers using various data inputs to infer their emotions for fourteen distinct purposes (defined earlier in Table 2). Our analysis compared all 14 purposes to the same baseline category: giving employers/healthcare providers data-driven understanding into employee/patient wellbeing. To aid theoretical interpretation of our regression results, we grouped purposes into higher level themes post-analysis as outlined in Table 8.

Purpose Grouping	Purpose Levels
early diagnosis of mental illness and neurological disorders	(3) diagnose mental illness in ($C1) earlier than otherwise possible (4) diagnose neurological disorders (e.g., dementia or ADHD) in ($C1)
augment employee and patient assessments	(5) avoiding subjectivity in other methods your ($C2) may use to learn about your emotional state, like a survey or your ($C2)'s observation (14) assessing the ($C3) of individual ($C1)
individual and group-level mental health inferences	(6) inferring the mental health state of ($C1) individually (7) inferring the mental health state of ($C1). inferences of an individual's mental health will not be made; only at a group level
societal benefit	(2) sharing that information with academic researchers to help them learn more about mental health, as part of a research partnership (8) identifying ($C1) in need of mental health support, to better plan organizational mental health resources
harm prevention	(9) inferring whether ($C1) are at risk of harming others (10) inferring whether ($C1) are at risk of harming themselves
supportive interventions	(11) developing an intelligent computer program, such as a chat bot, that can conduct mental health therapy with ($C1), including you (12) inferring moments ($C1) may be in need of emotional support and responding with an intelligent computer program designed to help ($C1) improve their wellbeing, such as offering wellbeing tips (13) automatically alerting your ($C2) when ($C1)s may need support, including you
baseline purpose	(1) giving ($C2) data-driven insights into ($C1) wellbeing

Table 8. We examined the impact of 14 purposes for which employers and healthcare providers may use emotion inferences, as shown in Table 2, and grouped into higher level themes described here to help interpret results.

As we explicate below, our findings demonstrate that the purpose for which employers and healthcare providers may use inferences of workers' and patients' emotions is a contextual factor that can significantly influence emotional privacy judgments, to varying degrees that differ by the specific purpose, contextual application and sampling stratification. Overall, purposes that reinforced the overall contextual goals of each employment and healthcare context or were otherwise bound by contextual integrity's parameters (see Section 3.1.1) were often judged more positively, while those that strained these contextualized qualities were often judged more negatively. As perceived technological benefits and risks can both influence privacy perceptions [32], in this section we situate our quantitative results within our adjacent analyses that qualitatively examine the perceived benefits and risks emotion AI data subjects anticipate with its use in employment [63] and healthcare [210], analyzed from participants' responses to open-ended questions included in this same study (see Section 3.2.2). To aid interpretation of our results, we include Figure 3 to visualize workers' and patients' predicted levels of comfort with emotion inferences by purpose.

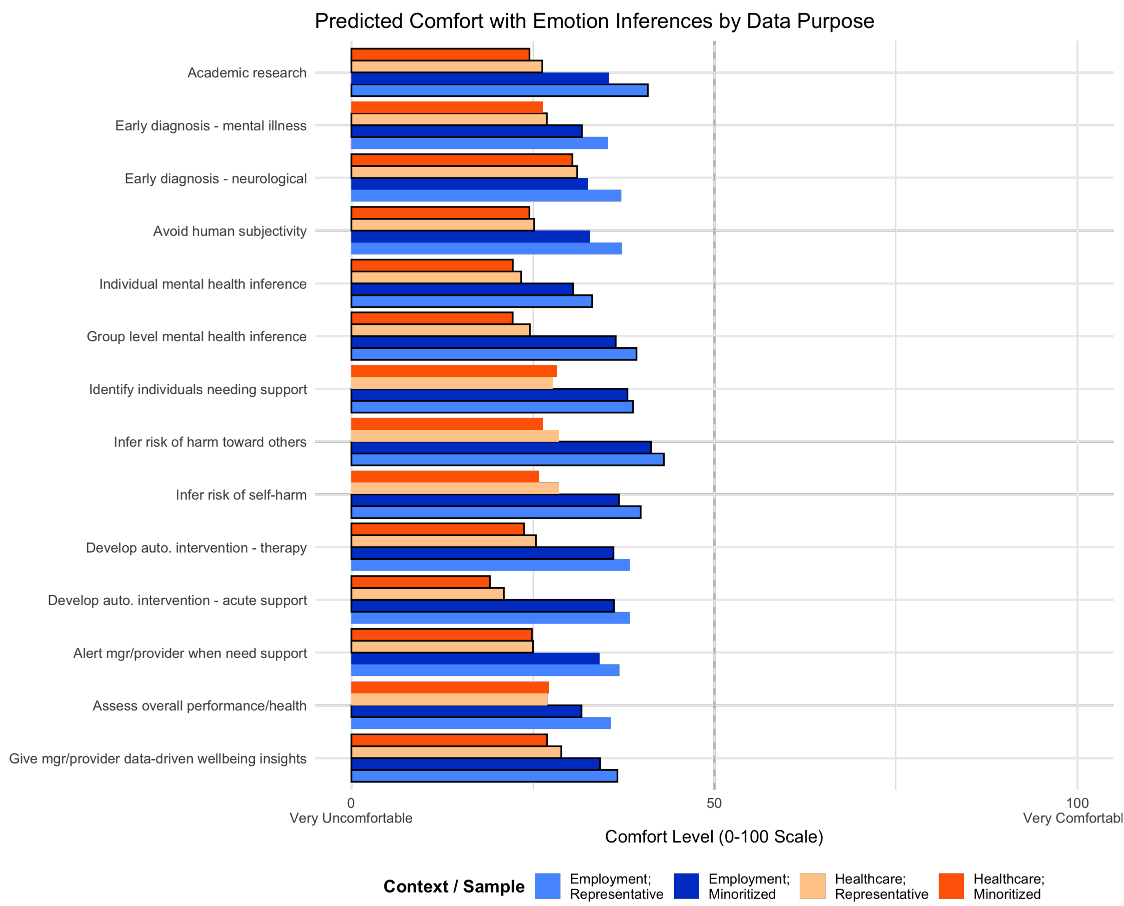

Fig. 3. Predicted Comfort Levels by Purpose. This figure illustrates the predicted comfort levels by combining the purpose variable coefficients to each mixed-effects regression model intercept, derived by analyzing respondent comfort on a scale from 1 (very uncomfortable) to 100 (very comfortable). Bars with black borders indicate statistically significant results.

Facilitating Earlier Diagnosis of Neurological Disorders and Mental Illness. One use case for emotion inferences involves its potential to diagnose certain medical conditions earlier than otherwise possible. In addition to the obvious application of this use case to healthcare contexts, the possibility of using emotion inferences for earlier medical diagnostics has been proposed for the workplace context given the significant amount of time people spend at work, monitored by pre-existing workplace surveillance infrastructures that already collect personal data containing emotion-laden features that can be extracted and processed to predict an individual's health status [47, 128, 189]. From their perspective as workers and patients, we examined how employers and healthcare providers using emotion inferences for the purpose of detecting mental illnesses and neurological disorders earlier than otherwise possible affected participants' comfort with their emotions being inferred. Participants were asked to rate their comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with their employers/healthcare providers inferring their emotions using various data inputs for the purposes of:

(3) diagnosing neurological disorders, such as dementia or ADHD, in employees/patients earlier than otherwise possible; and

(4) diagnosing mental illness in employees/patients earlier than otherwise possible.

Predicted comfort levels with emotion inferences for medical diagnostics remained low across contexts and samples, with estimated worker comfort ranging from 31.75-37.19 and patient comfort ranging from 26.41-31.1, on a scale of 0-100. Figure 3 illustrates the relatively higher predicted level of worker comfort in both samples with employers' use of automatic emotion inferences to facilitate both earlier diagnosis of mental illness and earlier diagnosis of neurological disorders, compared to patients' comfort with their healthcare providers using emotion inferences for the same purposes, reflecting consistently lower emotional privacy judgments of emotion inferences in healthcare than in employment.

As we explore further in the next sections, the influence of employers' and healthcare providers' use of emotion inferences for medical diagnostics on participants' comfort with emotion inferences varied by the type of medical diagnosis, context, and sample.

Earlier diagnosis of mental illness. Across both employment and healthcare contexts, emotion inferences for the purpose of detecting *mental illness* early had a negative effect on comfort levels in both representative and minoritized samples, compared to the baseline purpose of giving employers/healthcare providers data-driven understanding into employee/patient wellbeing. Although trends from these results show that both workers and patients are discomforted by employers and healthcare providers using emotion inferences to detect mental illnesses early, indicating a negative impact of this purpose on the emotional privacy of workers and patients alike, our analysis reveals interesting differences at the levels of context and sample.

The negative effect of employers using emotion inferences to aid the earlier detection of mental illness in workers was larger and only had statistical significance in the minoritized sample (representative: $\beta = -1.32$, $SE = 0.93$, insignificant; minoritized: ($\beta = -2.49$, $SE = 0.89$, $p < 0.01$). Our qualitative findings suggest this sample-level difference may be attributed to heightened privacy concerns with employer access to employees' mental health information, particularly from participants with marginalized identities [63]. Meanwhile, the negative effect on patient comfort with healthcare providers using emotion inferences for the purpose of earlier mental illness diagnosis was more pronounced and only statistically significant in the U.S. representative sample (representative: $\beta = -1.98$, $SE = 0.98$, $p < 0.05$; minoritized: ($\beta = -0.55$, $SE = 0.95$, insignificant). The attenuated effect in the minoritized sample, our qualitative findings indicate, may relate to disparities in mental healthcare quality, as participants – the majority of whom held minoritized identities – highlighted challenges they experienced with getting healthcare providers to listen to their mental healthcare concerns, and emphasized the unique potential for emotion inferences to legitimate their concerns that may otherwise remain neglected [210]. As Figure 3 illustrates, however, predicted levels of patient comfort with emotion inferences for the purpose of healthcare providers diagnosing mental illness in patients earlier than otherwise possible ultimately remains lower in the marginalized sample (26.41) than in the US representative sample (26.93), although the difference is marginal.

Notably, although aiding mental health diagnoses is a purpose that reinforces the overall goal of the healthcare context, this emotion inference purpose negatively impacted patients' emotional privacy perceptions in both samples. Together, these results show that despite its potential benefits, people of color, with mental illness, and/or minority genders associate greater invasions of emotional privacy with both employers and healthcare providers using emotion inferences for earlier detection of mental illness than the US representative sample.

Earlier diagnosis of neurological disorders. The effect of employers and healthcare providers using emotion inferences for the purpose of facilitating earlier detection of *neurological* disorders had a notably different effect on participant comfort than that for facilitating earlier diagnosis of mental illness.

In both representative and minoritized samples, emotion inferences to detect neurological conditions earlier than otherwise possible had a significantly positive effect on patient comfort when used by healthcare providers than the baseline purpose (representative: $\beta = 2.19$, $SE = 0.98$, $p < 0.05$; minoritized: ($\beta = 3.47$, $SE = 0.95$, $p < 0.001$). Of note, out of all fourteen purposes, this use case for emotion inferences was the only purpose in our analysis with a significantly positive effect on patient comfort in either sample, suggesting that while patients are generally discomforted by healthcare providers using emotion inferences for most purposes, their use in neurological care is a limited exception. Thus, under the same parameters defined in Table 1, this finding suggests that although patient comfort with healthcare providers using emotion inferences is low on average regardless of the use case, doing so for the specific purpose of detecting neurological conditions earlier may be an exception that respects patients' emotional privacy. While our qualitative analysis did not offer insights that help to explain this finding, we suggest it may be linked to the higher availability of objective measures in neurological diagnostics (e.g., imaging and neurological exams), which could lessen the perceived risk to patient autonomy and voice compared to mental healthcare, where diagnoses and treatments rely more heavily on subjective assessments. Hence, we suggest that patients' more favorable views of emotion inferences for neurological diagnostics compared to mental health diagnostics may reflect varied power dynamics and risk perceptions in neurological versus mental healthcare settings, and indicate that patients may view the use of emotion inferences for neurological diagnoses as less threatening to their autonomy and emotional privacy – a contrast underscored by the negative impact of emotion inferences for mental health diagnostics on patient perceptions. In addition, we observe the larger and more significant positive effect that healthcare providers using emotion inferences for earlier neurological diagnoses had on patient comfort levels in our minoritized sample, indicating that people of color, with mental illness, and/or minority genders may attribute a greater benefit and/or associate less risk with healthcare providers inferring patient emotions to detect neurological disorders early compared to the US representative population. It is important to keep in mind, however, that patients' estimated comfort with this purpose ultimately remains lower in the marginalized sample (30.43) than in the US representative sample (31.1), as illustrated in Figure 3.

The effect of employers using emotion inferences for earlier detection of neurological disorders had mixed results. Both the direction and statistical significance of this purpose's effect differed between samples: compared to the same baseline, this purpose had a weakly significant negative effect (at the .1 level) on worker comfort in the minoritized sample, with a smaller, statistically insignificant effect on worker comfort in the US representative sample (representative: $\beta = 0.55$, $SE = 0.93$, insignificant; minoritized: ($\beta = -1.70$, $SE = 0.89$, $p < 0.1$). The greater and more significant effect this purpose had on comfort levels in the minoritized sample indicates workers from minoritized backgrounds may attribute lesser benefit and/or higher risk to employers using emotion inferences to detect neurological illnesses than the US representative population. The coefficient plot in Table **??** shows that within a 95% interval, the estimated coefficient range for worker comfort with this purpose crosses zero in the US representative sample and does not cross zero in the marginalized sample, indicating that while a representative understanding of the direction of this purpose's effect on workers' emotional privacy judgments is unclear, we can say with greater confidence that it has a negative effect on minoritized workers' perceptions of emotional privacy. Qualitative insights from our adjacent study suggest that the greater perceived negative impact to emotional privacy in the minoritized sample from employers using emotion inferences to infer neurological disorders relates to historical health and employment inequities, as participants, the majority of whom held a marginalized identity, cited fear of negative personal and professional consequences associated with revealing health diagnoses to employers [63].

Employee and Patient Assessments. Scholars and technologists alike have proposed automatic emotion inferences as a potentially objective method to reduce bias in both employee [211] and patient [270] assessments. Rather than relying on self-reports or human observations of how workers and patients feel, incorporating presumably objective emotion inferences into work performance evaluations and health assessments promises to minimize human subjectivity and associated biases involved in understanding individuals' emotional states and their relation to overall work performance and health. We examined the influence that purposes pertaining to employers and healthcare providers using emotion inferences to augment employee and patient assessments had on participants' comfort with emotion inferences. Participants were asked to rate their comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with their employers/healthcare providers inferring their emotions using various data inputs for the purposes of:

> *(5) avoiding subjectivity in other methods of your employer/healthcare provider learning about your emotional state, like a survey or your employer/healthcare provider's observations*; and
> *(14) assessing the work performance/overall health of individual employees/patients*

Predicted comfort levels for these purposes were generally low. On a scale of 0-100, worker predicted comfort levels ranged from 31.69-37.21 and patient predicted comfort levels ranged from 24.52-27.19, as shown in Figure 3.

Employment context. With regard to employee assessments, the effect of employers using emotion inferences to assess workers' overall performance had a negative effect on worker comfort in both samples compared to the baseline category, with statistical significance observed in the minoritized sample only (representative: $\beta = -0.88$, $SE = 0.93$, insignificant; minoritized: ($\beta = -2.55$, $SE = 0.89$, $p < 0.001$). We expect that in addition to the trend we observe across our results that the minoritized sample associates a greater invasion to emotional privacy with emotion inferences than the US representative sample, greater statistical power from the minoritized sample's larger size may also contribute to this result. Regarding this purpose in particular, qualitative insights from our adjacent studies indicate that the minoritized sample's more pronounced discomfort may additionally be explained by shared concerns, particularly prevalent among participants with minoritized identities, that being subject to emotional surveillance could impair their work performance and consequently result in negative employment outcomes [63]. The impact of employers using emotion inferences for the purpose of reducing subjectivity involved in understanding workers' emotional state on worker comfort did not yield statistically significant results in either sample. Overall, these findings show that workers are uncomfortable with employers inferring their emotions for the purpose of assessing their work performance, and that this use case has a negative impact to workers' emotional privacy.

Healthcare context. With regard to patient assessments, healthcare providers using emotion inferences to avoid human subjectivity in traditional ways in which they understand patients' emotional state (e.g., self-reports or human observation) had a significant negative effect on patient comfort in both samples, compared to the baseline category (representative: $\beta = -3.73$, $SE = 0.98$, $p < 0.001$; minoritized: ($\beta = -2.44$, $SE = 0.95$, $p < 0.01$). This finding indicates that patients are discomforted by healthcare providers using emotion inferences to avoid human subjectivity in their understanding of patients' emotional state. That said, although the estimated level of patient comfort for this purpose in the minoritized sample (24.52) remains lower than the US representative sample 25.18 as Figure 3 shows, the smaller and less significant negative effect of this purpose observed in the minoritized sample suggests that people of color, with mental illness, and/or minoritized genders may associate higher benefit and/or less risk with healthcare providers using emotion inferences for this purpose. As qualitative insights from our related study suggests, this observation reflects minoritized patients' unmet need for more objective and less biased evaluations of their emotional and mental health, and the desire they expressed for objective interventions to mitigate provider biases in mental healthcare on the one hand, and concern that algorithmic inferences would in practice exacerbate provider biases on the other hand [210]. Our analysis did not find a statistically significant effect (at a .05 threshold) on participant comfort in either sample in the case of healthcare providers inferring patient emotions to assess patients' overall health had a weakly significant (at the .1 level) negative impact in the U.S. representative sample.

In summary, these results show that employers inferring worker emotions to assess work performance has a significant negative effect on workers' emotional privacy, while healthcare providers inferring patient emotions for the purpose of avoiding human subjectivity in their understanding of patients' emotional state has a significant negative effect on patients' emotional privacy.

Inferring Mental Health at Individual and Group Levels. We examined how participant comfort was affected by employers and healthcare providers using emotion inferences for the purpose of inferring workers' and patients' mental health at both individual and group levels. Participants were asked to rate their comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with their employers/healthcare providers inferring their emotions using various data inputs for the purposes of:

> *(6) inferring the mental health state of employees/patients individually*; and
>
> *(7) inferring the mental health state of employees/patients. Inferences of an individual's mental health will not be made; only at a group level.*

As Figure 3 illustrates, predicted comfort levels for both purposes were low across contexts and samples, with levels of worker comfort on a scale of 0-100 ranging from 30.54-39.27, and relatively lower levels of patient comfort ranging from 22.22-24.59. In both contexts, predicted comfort levels were lower in the marginalized sample than the US representative sample.

Employment context. Employers using emotion inferences to infer individual workers' mental health had a significant negative effect on worker comfort in both samples, compared to the baseline purpose (representative: $\beta = -3.48$, $SE = 0.93$, $p < 0.001$; minoritized: ($\beta = -3.70$, $SE = 0.89$, $p < 0.001$), with a slightly more pronounced negative effect in the marginalized sample than in the US representative sample. Yet, employers using emotion inferences to infer workers' mental health at a group level had a significantly positive impact to worker comfort in both samples, compared to the same baseline (representative: $\beta = 2.63$, $SE = 0.93$, $p < 0.01$; minoritized: ($\beta = 2.16$, $SE = 0.89$, $p < 0.05$), with a slightly less pronounced positive effect in the marginalized sample than in the US representative sample. Together, these findings indicate that employers' generation and use of individual level inferences of mental health are discomforting to workers and perceived as privacy invasive, but that group-level inferences of workers' mental health may be welcomed and more privacy-preserving. Indeed, as we find in our related qualitative analysis, participants expressed enthusiasm for emotion inferences generated by emotion AI to potentially improve their mental and emotional wellbeing by enabling (or potentially, compelling) employers to identify opportunities to provide enhanced supports and work environments that would improve workers' mental health, tempered by deep concern that employers would misuse the sensitive emotional information about individual employees to their detriment (e.g., firing or denying employment opportunities to employees) [63]. As our regression results here suggest, however, aggregated emotion inferences may mitigate individual-level risks linked to worker identifiability, preserving workers' emotional privacy and the potential benefits of supplying employers with aggregated information about worker' mental health.

Healthcare context. In contrast, our findings for the healthcare context show that healthcare providers using emotion inferences to infer patients' mental health at either individual (representative: $\beta = -5.52$, $SE = 0.98$, $p < 0.001$; minoritized: ($\beta = -4.72$, $SE = 0.95$, $p < 0.001$) or group (representative: $\beta = -4.32$, $SE = 0.98$, $p < 0.001$; minoritized: ($\beta = -4.74$, $SE = 0.95$, $p < 0.001$) levels has a significantly negative impact to patient emotional privacy in both samples, compared to the same baseline. The size of the negative effect of individual inferences on patient comfort was noticeably smaller in the minoritized sample than in the US representative sample; effect sizes were similar between samples in the case of group level inferences. These findings demonstrate that patients are significantly discomforted by healthcare providers using emotion inferences to infer their mental health, regardless of the inference's level of identifiability. Our adjacent qualitative study offers explanatory insights regarding patients' considerable discomfort with emotion inferences to infer patient mental health, finding that patients expressed concern that harmful mental healthcare provisions (e.g., mental health assessments, diagnoses, and treatments) could be facilitated – or worsened – by the integration of automatic emotion inferences generated by emotion AI into mental healthcare. Namely, patients cited concern that technologically-mediated understandings of patient mental health could result in diminished patient voice, impaired patient-provider interactions, and misuse of patients' health information at both individual and collective levels [210]. Although our qualitative study did not offer insight as to why the positive impact to emotional privacy from group level inferences we observed in the employment context was not present in the healthcare context, we suggest that the inherently individual relationship between patient and healthcare provider may help to explain why participants did not attribute any benefit to group-level patient mental health inferences that could have alleviated their discomfort.

Societal and Collective Benefit. We examined how employers and healthcare providers using emotion inferences for purposes of societal or collective benefit – specifically, to the benefit of society by supporting academic research, and to the collective benefit of workers and patients by identifying individuals requiring additional support in order to improve organizational/institutional mental healthcare resource planning – affected participants' comfort with emotion inferences in both employment and healthcare contexts. Participants were asked to rate their comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with their employers/healthcare providers inferring their emotions using various data inputs for the purposes of:

> *(2) sharing that information with academic researchers to help them learn more about mental health, as part of a research partnership*; and
>
> *(8) identifying employees/patients in need of mental health support, to better plan organizational mental health resources*

Predicted comfort levels (on a scale of 0-100) with these purposes remained low overall, and as shown in Figure 3, demonstrate that patient comfort (ranging from 24.53-28.3) was consistently lower for these use cases than worker comfort (ranging from 35.5-40.82).

Employment context. Employers using emotion inferences to support academic research had a positive impact on worker comfort compared to the baseline purpose category, with larger and statistically significant results in the US representative sample only (representative: $\beta = 4.18$, $SE = 0.93$, $p < 0.001$; minoritized: ($\beta = 1.26$, $SE = 0.89$, insignificant). Although our adjacent study [63] did not surface relevant insights for this result, this finding echoes prior qualitative work suggesting that although people hold predominantly negative views toward automatic emotion recognition, their attitudes are less negative in specific use cases involving benefits to society such as supporting academic research [13, 208]. This purpose exhibited a statistically significant differential impact between samples, with a more pronounced influence on the U.S. representative sample compared to a relatively attenuated effect in the minoritized sample, as evidenced by a Z-score of 2.38. This divergence potentially reflects a heightened level of mistrust towards academic research within minoritized communities, a sentiment rooted in historical patterns of exclusion and mistreatment in research practices [37].

In the case of employers using emotion inferences to identify individuals in need of support in order to improve organizational mental healthcare resource planning, this purpose had a significantly positive impact on worker comfort compared to the baseline in both samples, with a larger and more significant positive effect in the minoritized sample (representative: $\beta = 2.15$, $SE = 0.93$, $p < 0.05$; minoritized: ($\beta = 3.78$, $SE = 0.89$, $p < 0.001$). In contrast to our finding in Section 4.1.3 that individual emotion inferences had a negative impact to worker comfort, this result suggests that workers' discomfort with individual emotion inferences may be alleviated if they are not used to infer an individual workers' mental health state, and/or if emotion inferences are specifically used by employers for a purpose that is beneficial to workers (i.e., improving mental healthcare resources). Indeed, our related study's qualitative results found that nearly one third of participants, the majority of whom held a marginalized identity, acknowledged benefits to the potential for emotion inferences to provide organizations with information necessary to improve their mental health resources and accommodations [63].

All told, these results demonstrate that inferences of worker emotion, when restricted to use for societal and collective worker benefit, may be an acceptable use case that respects workers' emotional privacy. However, given the sample-level differences observed, these results also underscore the need for nuanced and personalized approaches to collecting, using, and sharing workers' emotion inferences that respect individual workers' emotional privacy needs and preferences.

Healthcare context. On the other hand, our findings for these same purposes in the healthcare context indicate that healthcare providers using emotion inferences for societal benefit does not preserve patient emotional privacy. Healthcare providers inferring patient emotions to support academic research had a significantly negative effect to patient comfort, with a similar effect size across samples (representative: $\beta = -2.61$, $SE = 0.98$, $p < 0.01$; minoritized: ($\beta = -2.43$, $SE = 0.95$, $p < 0.05$). Our analysis did not yield a statistically significant result for the case of healthcare providers identifying individuals in need of support to better plan organizational/institutional mental healthcare resources; however, sample comparisons show that the negative effect that this purpose had in the representative sample and differentially positive effect in the marginalized sample was statistically significant, with a Z-score of -1.84. Offering qualitative insights for these results, our adjacent study found that although participants acknowledge the potential for emotion AI to advance mental health research with emotion inferences that can enhance clinical researchers' understandings of mental health, they remained highly concerned about patient data sharing practices. Specifically, participants expressed concern that sharing patients' emotion inferences with third parties, including academic researchers, could create barriers to accessing quality mental healthcare and intrudes patient privacy, subsequently exposing patients to myriad risks of privacy harm [210]. In addition, we suggest that higher confidentiality expectations between patients and healthcare providers may have contributed to this finding, considering the negative impact this purpose had on patient comfort compared to its positive impact to worker comfort. All considered, these results indicate that sharing patients' collected and inferred emotional information, even when intended to benefit society through supporting academic research, is a discomforting practice that violates patients' emotional privacy.

Harm Prevention. We investigated whether and how employers and healthcare providers inferring workers' and patients' emotions for the purpose of preventing self-harm and harm toward others affected workers' and patients' comfort with emotion inferences. Participants were asked to rate their comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with their employers/healthcare providers inferring their emotions using various data inputs for the purposes of:

(6) inferring whether employees/patients are at risk of harming themselves; and
(7) inferring whether employees/patients are at risk of harming others

On a scale of 0-100, predicted comfort levels for harm prevention were consistently lower in the healthcare context (ranging from 25.86-28.65) than in the employment context (ranging from 36.84-43.03), with lower estimates observed in the marginalized sample than in the US representative sample, as illustrated in Figure 3.

Employment context. Employers' use of emotion inferences for harm prevention had a significantly positive effect on worker comfort for harm prevention purposes than the baseline category. Notably, inferring risk of harm toward others had the largest positive impact on worker comfort levels among all tested purposes in both samples (representative: $\beta = 6.39$, $SE = 0.93$, $p < 0.001$; minoritized: ($\beta = 7.03$, $SE = 0.89$, $p < 0.001$). Though to a lesser extent, employers using emotion inferences to predict self-harm also had a significantly positive impact on worker comfort in both samples (representative: $\beta = 3.20$, $SE = 0.93$, $p < 0.01$; minoritized: ($\beta = 2.60$, $SE = 0.89$, $p < 0.01$). For both harm prevention purposes, positive effects to worker comfort were similar between samples, indicating that employers using emotion inferences may be appropriate for the specific purpose of preventing workplace violence toward oneself and others. Offering a nuanced take to help explain these findings, our adjacent qualitative study found that workers may welcome monitoring employee emotions as a preventive measure against workplace violence and self-harm, as they acknowledge the potentially significant boost this practice could bring to workplace safety – but only if the use of emotion inferences were restricted to this purpose, and if the inferences were accurate. Indeed, participants cited considerable concern that employers could reuse emotion inferences initially collected for harm prevention purposes in unacceptable ways, and for the potential that inaccurate and biased risk predictions would falsely flag workers at risk of harm toward oneself or others. These risks could facilitate unwarranted and unjust procedural responses by employers that could severely harm individual workers, compromising (instead of protecting) worker safety [63]. All considered, these findings underscore the need to comprehensively consider the potential risks of emotion inferences to workplace safety against its potential benefits.

Healthcare context. Somewhat surprisingly given the strong positive effect on worker comfort associated with using emotion inferences in the employment context for the purpose of preventing harm, in either sample, our analysis did not find a statistically significant impact on patient comfort with healthcare providers using emotion inferences for the same harm prevention purposes, though trends indicate negative impacts to patient comfort for purposes of both preventing self-harm (representative: $\beta = -0.27$, $SE = 0.98$, insignificant; minoritized: ($\beta = -1.10$, $SE = 0.95$, insignificant) and harm towards others (representative: $\beta = -0.26$, $SE = 0.98$, insignificant; minoritized: ($\beta = -0.56$, $SE = 0.95$, insignificant). Supporting this finding, our qualitative analysis found that most participants did not associate benefits with the potential for automatic emotion inferences to prevent healthcare patients' self-harm or harm toward others, emphasizing substantial privacy concerns that such uses would legitimate over-surveillance of already vulnerable mentally ill patients, and worry that inaccurate inferences could unjustly position patients in dangerous and coercive situations (e.g., involuntary commitment) [210].

Supportive Interventions. We examined how emotion inferences used for supportive interventions influenced participants' comfort with emotion inferences in workplace and healthcare contexts. Participants rated their comfort with employers and healthcare providers using emotion inferences to develop automatic mental health therapy (e.g., a chatbot), deliver automatic interventions that offered acute emotional support (e.g., wellbeing tips), and automatically alert one's employer or healthcare provider when in need of support. Specifically, participants were asked to rate their comfort (from 0 = "very uncomfortable" to 100 = "very comfortable") with their employers/healthcare providers inferring their emotions using various data inputs for the purposes of:

> *(11) developing an intelligent computer program, such as a chat bot, that can conduct mental health therapy with employees/patients, including you*;
> *(12) inferring moments employees/patients may be in need of emotional support, and responding with an intelligent computer program designed to help employees/patients improve their wellbeing, such as offering wellbeing tips*; and
> *(13) automatically alerting your employer/healthcare provider when employees/patients may need support, including you*

On a scale of 0-100, predicted levels of comfort for supportive interventions ranged from 34.19-38.32 for workers and 19.08-25.42 for patients. Figure 3 illustrates the markedly lower predicted levels of comfort for supportive intervention purposes in the healthcare context and in the marginalized sample, than in the employment context and the US representative sample respectively.

Employment context. Emotion inferences for supportive interventions in the workplace had a positive impact to worker comfort when used to develop (representative: $\beta = 1.68$, $SE = 0.93$, $p < 0.1$; minoritized: ($\beta = 1.92$, $SE = 0.89$, $p < 0.05$) and deliver (representative: $\beta = 1.66$, $SE = 0.93$, $p < 0.1$; minoritized: ($\beta = 1.85$, $SE = 0.89$, $p < 0.1$) automated interventions intended to provide direct intervention and support to individual workers, compared to the baseline purpose, although results were only weakly significant at the .1 level. Effects of both purposes to worker comfort were similar between samples. Our analysis did not yield statistically significant results for interventions involving a third party – alerting one's manager when in need of support. These results indicate that workers may associate benefit to using emotion inferences to develop and deliver technologies that provide wellbeing interventions directly to workers in the workplace, although this suggestion needs to be statistically confirmed. Our qualitative study did not offer insights that directly help to explain these findings, however, that workers expressed a desire for improved wellbeing support in the workplace yet were concerned that employers' access to their inferred emotional information would result in personal and professional consequences [63] suggests that workers may welcome automated wellbeing interventions that offer personalized and direct support, provided the inferences and resulting interventions remain private: not shared with third parties or employers.

Healthcare context. Conversely, healthcare providers using emotion inferences for these same purposes had a significantly negative and considerably larger impact to patient comfort for all three levels of supportive interventions. Of note, healthcare providers using emotion inferences to develop automated mental health therapy interventions had the largest negative effect on participant comfort among all tested purposes (representative: $\beta = -7.91$, $SE = 0.98$,$p < 0.001$; minoritized: ($\beta = -7.88$, $SE = 0.95$, $p < 0.001$). Though to a lesser extent, both receiving automated interventions providing acute wellbeing support, such as wellbeing tips (representative: $\beta = -3.49$, $SE = 0.98$,$p < 0.001$; minoritized: ($\beta = -3.18$, $SE = 0.95$, $p < 0.001$), and alerting one's provider when in need of support (representative: $\beta = -3.89$, $SE = 0.98$,$p < 0.001$; minoritized: ($\beta = -2.09$, $SE = 0.95$, $p < 0.05$) were also significantly associated with discomfort across both samples. As our qualitative insights suggest, participants' significant discomfort with healthcare providers using their emotion inferences to develop and deliver both direct and third-party interventions may be explained by patient concern that automated wellbeing interventions could produce or perpetuate harm to patients' mental health with inaccurate inferences and/or inadequate responses, weaken relations between patients and healthcare providers through diminished human interactions, lower the quality of mental healthcare that patients receive, and breach patients' confidentiality in a context characterized by heightened expectations for patient privacy [210].

4.2 Socio-demographic Factors Have Nuanced Influence on Emotional Privacy Judgments of Emotion Inferences in the Workplace and Healthcare

We examined the effect of socio-demographic factors on participants' comfort with emotion inferences in employment and healthcare, specifically race/ethnicity, gender, mental health status, and educational attainment as described in Section 3.2.3 for reasons we review in Section 2.2.

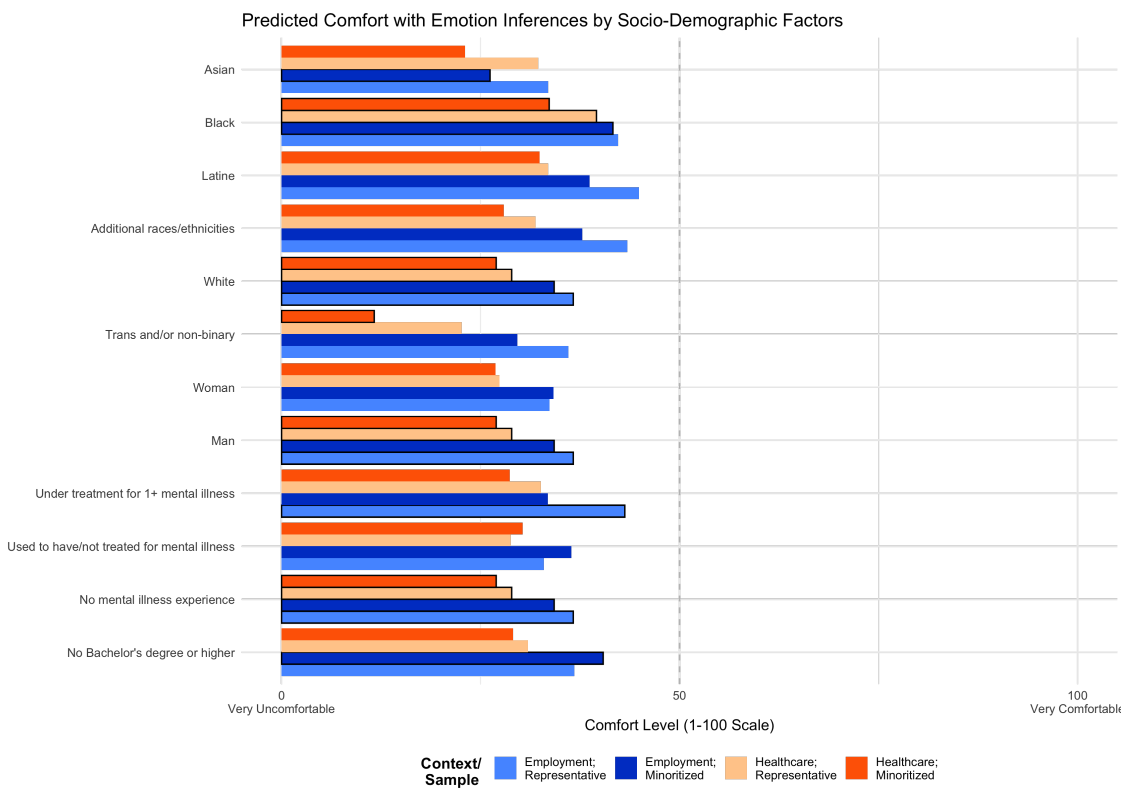

Fig. 4. Predicted Comfort Levels by Socio-demographics. This figure illustrates the predicted comfort levels by combining the socio-demographic variable coefficients to each mixed-effects regression model intercept, derived by analyzing respondent comfort on a scale from 1 (very uncomfortable) to 100 (very comfortable). Bars with black borders indicate statistically significant results.

4.2.1 Race/Ethnicity. Compared to white participants, Black participants across both samples reported higher comfort with emotion inferences in employment (representative: $\beta = 5.64$, $SE = 3.19$,$p < 0.1$; minoritized: ($\beta = 7.38$, $SE = 2.79$, $p < 0.01$), with significance confirmed in the minoritized sample. Similarly, Black participants reported significantly higher comfort with emotion inferences for the healthcare context in both samples (representative: $\beta = 3.33$, $SE = 5.44$,$p < 0.01$; minoritized: ($\beta = 6.66$, $SE = 3.05$, $p < 0.05$). We did not observe statistically significant results for Latine and additional race/ethnicity categories; higher-powered studies are needed to better understand the emotional privacy judgments of these populations.

Asian participants were the only non-white race/ethnicity category reporting less comfort on average with emotion inferences in employment contexts than white participants. On average, Asian participants in both samples reported lower comfort than white participants with employers inferring their emotions, with the higher-powered minoritized sample confirming these results (representative: $\beta = -3.15$, $SE = 4.31$, insignificant; minoritized: ($\beta = -8.05$, $SE = 3.55$, $p < 0.05$). We did not observe statistically significant results for the Asian race/ethnicity level in the healthcare context.

Among all race/ethnicity categories, our results show that Black participants reported the highest levels of comfort with emotion inferences in either employment or healthcare contexts, that Asian participants reported the lowest levels of comfort with emotion inferences in employment contexts, and that white participants reported the lowest levels of comfort with emotion inferences in healthcare contexts. Given the disproportionate risk to which Black people may be exposed with regard to emotion inferences, in part due to algorithmic racial and cultural biases present in emotion recognition training datasets that result in less accurate inferences for racial and ethnic minorities [107, 200, 263], the higher level of comfort with emotion inferences among Black participants in both contexts and samples indicates this population may underestimate risks with and/or attribute greater benefit to emotion inferences. Although, our qualitative analyses did not investigate race/ethnicity as a factor for participants' perceived risks and benefits of emotion AI technologies, we report numerous examples from Black participants indicating they associate benefits to the promise of emotion AI to combat racial discrimination and improve the level of emotional support they receive in both the workplace and healthcare, yet remain concerned about the potential for emotion AI to perpetuate racial discrimination and promote disparately adverse health and employment outcomes for Black people in these contexts [63, 210]. More work is needed to understand how Black workers' and patients' nuanced perceptions of emotion AI affect their emotional privacy judgments concerning emotion inferences.

4.2.2 Gender. In employment scenarios, we did not observe a statistically significant influence for any gender category on participants' comfort in either sample. As prior work suggests that privacy perceptions are gendered, including in one of the contexts we investigate (e.g., the workplace [230]), we suggest that future work with larger sample sizes may be needed to confirm whether or not gender has a significant effect on emotional privacy judgments with regard to emotion inferences in the workplace and healthcare.

However, regarding emotion inferences used by healthcare providers, trans and/or non-binary participants reported less comfort than men on average, with statistically significant results in the minoritized sample's larger sample size of trans and/or non-binary people, confirming this trend (representative: $\beta = -6.26$, $SE = 10.99$, insignificant; minoritized: ($\beta = -15.32$, $SE = 4.55$, $p < 0.001$). We did not observe statistically significant differences in comfort for women compared to men.

Trans and/or non-binary participants' significant discomfort with healthcare providers' use of emotion inferences, which had the largest negative effect on comfort out of any factor in our analysis, indicates considerable concern with emotion inferences in healthcare among this population.

4.2.3 *Mental Health Status.*

Regarding emotion inferences in employment, participants in only our US representative sample currently under treatment for one or more mental illnesses reported significantly higher comfort, compared to participants with no mental illness (representative: $\beta = 6.47$, $SE = 3.13$, $p < 0.01$; minoritized: ($\beta = -0.79$, $SE = 3.06$, insignificant). While participants in this same category in the minoritized sample reported less comfort on average, the result was not statistically significant, and the coefficient range in Table 8 suggests that the direction of this level's impact on the comfort with emotion inferences in employment among minoritized participants currently under treatment for one or more mental illnesses remains inconclusive. We did not observe a statistically significant difference in comfort for people with resolved or untreated mental illness.

Regarding emotion inferences in healthcare, our analysis did not yield statistically significant results at any level of mental health status.

The significantly higher comfort with emotion inferences in employment observed for participants currently under treatment for one or more mental illnesses in the US representative sample, but not in the minoritized sample (which, notably, had a comparatively higher representation of this population), indicates that more research is needed to understand the emotional privacy judgments of people with mental illness and other intersecting marginalities. Since our sampling did not differentiate participants on the basis of specific mental illness diagnosis, we recommend that future focused research further explores the perceptions of people with specific mental illnesses toward emotion inferences to better understand and address their unique perspectives.

4.2.4 *Educational Attainment.*

Compared to people with a Bachelor's degree or higher, participants without a Bachelor's degree reported, on average, higher levels of comfort with emotion inferences in both contexts and samples.

For emotion inferences used by employers, participants without a Bachelor's degree in both samples reported higher comfort with emotion inferences on average; the statistical significance of the positive relationship between education and worker comfort with emotion inferences was confirmed in the minoritized sample, with a considerably larger positive effect size, which we attribute to the minoritized samples' larger representation of participants without a Bachelor's degree (representative: $\beta = 0.14$, $SE = 2.46$,insignificant; minoritized: ($\beta = 6.16$, $SE = 2.37$, $p < 0.01$). The relationship between lower educational attainment and comfort with emotion inferences in healthcare was statistically insignificant in both samples, although trends similarly suggest a positive relationship.

That participants with lower educational attainment reported higher comfort with emotion inferences in employment compared to participants with a Bachelor's degree indicates that this population may be less likely to recognize risks associated with emotion inferences and/or may associate higher benefits with their use. More research is needed to better understand the relationship between educational attainment and emotional privacy judgments.

4.3 Individual Privacy Belief Factors Affect Emotional Privacy Judgments When Contextualized

We investigated whether and how the individual privacy beliefs of general privacy concerns, trust in employers' and healthcare providers' handling of sensitive information, and perceived sensitivity of emotional information handled by employers and healthcare providers each affected participants' comfort with emotion inferences.

4.3.1 *General Privacy Concerns.*

Participants' level of general privacy concerns did not have a significant effect on their comfort with emotion inferences in either context or sample.

4.3.2 *Trust in Employers' and Healthcare Providers' Handling of Sensitive Information.*

The level of trust participants attributed to their employers' and healthcare providers' handling of their sensitive information significantly and

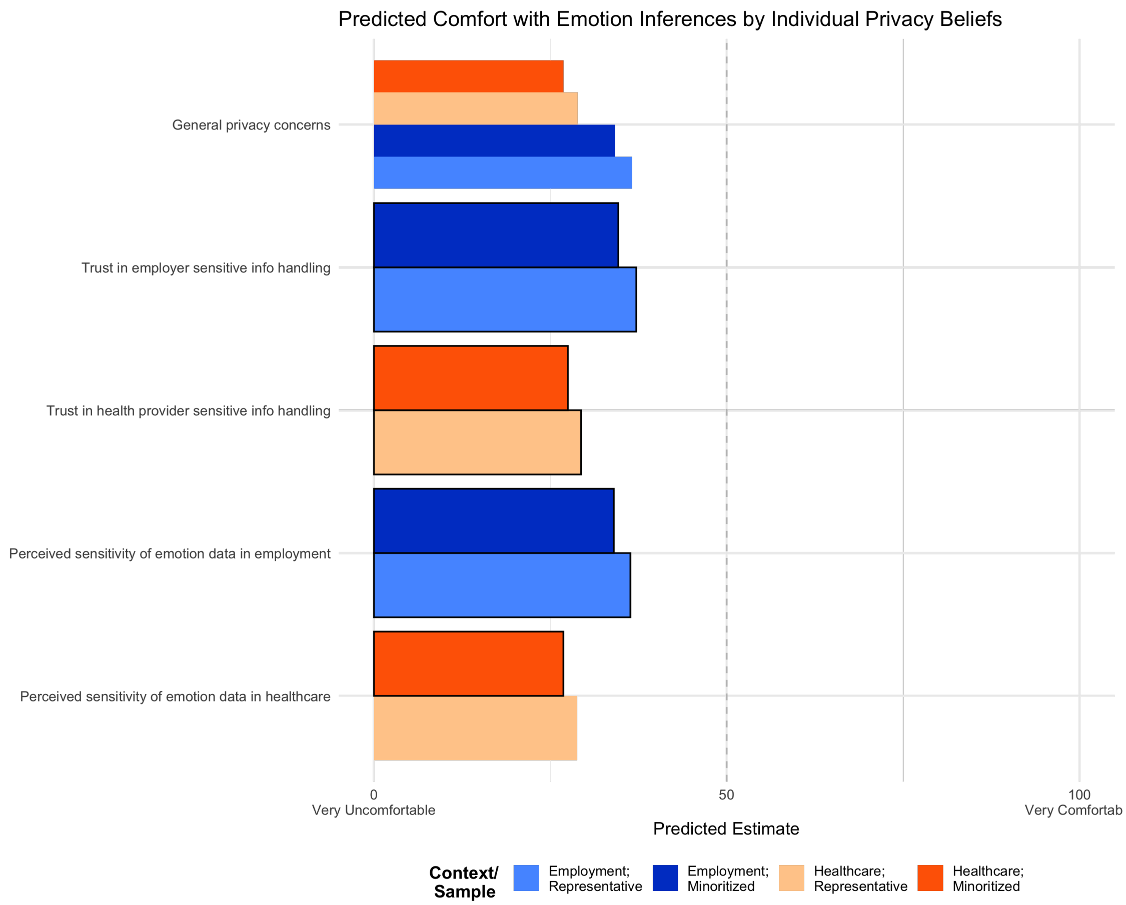

Fig. 5. Predicted Comfort Levels by Individual Privacy Beliefs. This figure illustrates the predicted comfort levels by combining the individual privacy belief variable coefficients to each mixed-effects regression model intercept, derived by analyzing respondent comfort on a scale from 1 (very uncomfortable) to 100 (very comfortable). Bars with black borders indicate statistically significant results.

positively influenced their comfort with emotion inferences in both contexts. Participants reporting higher levels of trust reported significantly higher comfort with emotion inferences in both employment (representative: $\beta = 0.54$, $SE = 0.05$, $p < 0.001$; minoritized: ($\beta = 0.40$, $SE = 0.05$, $p < 0.001$) and healthcare (representative: $\beta = 0.44$, $SE = 0.08$, $p < 0.001$; minoritized: ($\beta = 0.53$, $SE = 0.05$, $p < 0.001$) contexts. Of note, this effect was significantly different between samples for the healthcare context; the Z-score of 2.09 indicates a greater influence of positive trust beliefs in employers' handling of sensitive information among the U.S. representative sample than in the minoritized sample.

4.3.3 Perceived Sensitivity of Emotional Information. Participants rated the level of sensitivity they associated with emotional information along with other information types already categorized in law and literature as sensitive – political opinions, religious beliefs, biometric data, health information, sex life/sexual orientation, genetic information, and union membership [1, 55] – when handled by one's employer and healthcare provider. As participants answered this question in a post-test after responding to vignettes that described various uses of their emotion inferences, we expect that responses are indicative of participants' perceptions of emotion inferences.

Employment context. As the box plot in Figure 6 illustrates, participants rated the sensitivity of emotional information handled by one's employer similar to data types already recognized as sensitive. The median level of perceived sensitivity of emotional information handled by employers for participants in the representative sample ranks higher than that for genetic information, health information, and union membership. The median sensitivity rating for emotional information handled by employers in the minoritized sample ranked the lowest of all data types, with a similar sensitivity to political opinions.

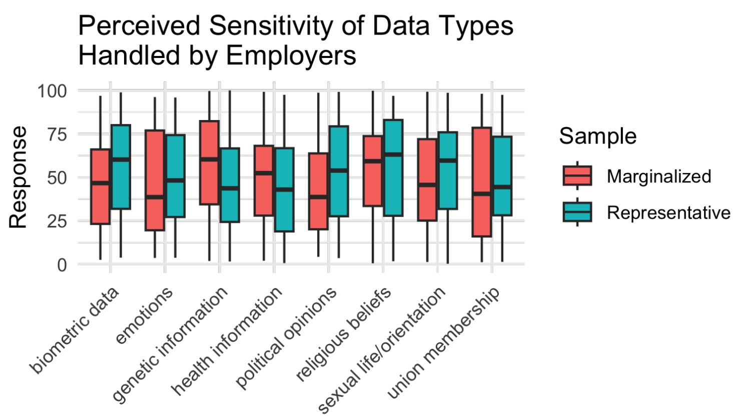

Fig. 6

Healthcare context. Participants rated the sensitivity of emotional information handled by healthcare providers higher than when handled by employers, as shown in Figure 7. Participants in the representative sample perceived the sensitivity of emotional information handled by healthcare providers higher than biometric data, health information, political opinions, religious beliefs, and union membership. In contrast to their relatively lower perceived sensitivity of emotion data information handled by employers compared to other data types, participants in the minoritized sample rated emotion data information's sensitivity higher when handled by healthcare providers than all other sensitive information types.

In addition, our analysis examined whether and how participants' perceived sensitivity of emotional information when handled by employers and healthcare providers affected their comfort with emotion inferences. We found that participants' perceived sensitivity of emotion data had a significant effect on their comfort with emotion inferences in both contexts. Participants associating emotional information with higher sensitivity reported significantly less comfort with emotion inferences in the employment context (representative: $\beta = -0.30$, $SE = 0.05$, $p < 0.001$; minoritized: ($\beta = -0.25$, $SE = 0.05$, $p < 0.001$). Participants similarly reported less comfort with emotion inferences in healthcare (representative: $\beta = -0.10$, $SE = 0.05$, $p < 0.1$; minoritized: ($\beta = -0.11$, $SE = 0.04$, $p < 0.01$) contexts, with a significant effect confirmed in the minoritized sample.

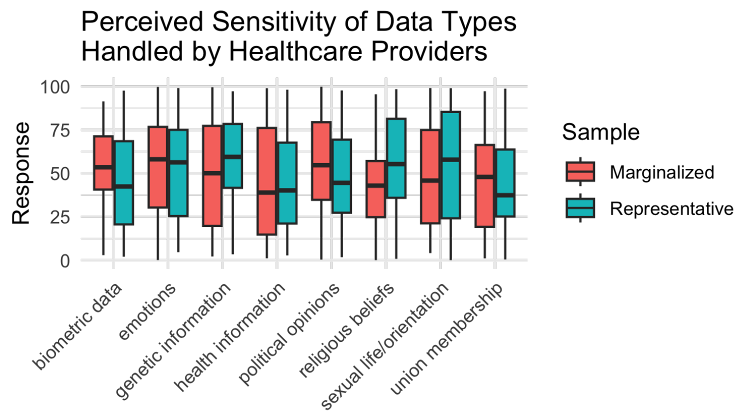

Fig. 7

In light of these findings, we bring attention to the fact that personal emotional information is not currently recognized in existing literature or legal/regulatory frameworks as a special category of data that requires heightened protections and safeguards – an issue we elaborate on in the discussion.

5 DISCUSSION

Workers' and patients' ability to manage their emotional privacy is threatened by the emergence of technologies and data practices that collect, store, and disseminate inferences of human emotion. Certainly, emotion AI and similar data practices involving emotion inferences promise to confer benefits to our lives. Assuming algorithmic predictions infer the human emotions or other affective phenomena they claim to, such technologies hold potential to aid in the diagnosis of medical conditions, identify when people are in need of support and intervene accordingly, prevent harm, and promote a greater understanding about human emotions – including to powerful actors like employers and healthcare providers that are socially positioned to shape the course of our wellbeing. Yet, the beneficial outcomes to personal wellbeing promised by automatic emotion inferences by and large have yet to be scientifically validated, and the storage, use, and dissemination thereof necessarily carries threats to personal privacy over individuals' deeply sensitive emotional information with which emotion-adjacent technology research, practice, and policy must contend. As discourse continues about the appropriate development, design, and regulation of still-nascent emotion AI and the emotional information it infers, the privacy perceptions held by those subject to powerful actors inferring their emotional information can, and should, help guide the creation of the privacy "rules" people want to more ethically and responsibly respect individuals' emotional privacy – helping to preserve the potential benefits of emotion inferences while mitigating risks associated with their collection and use. Thus, we argue that emotional privacy is about more than simply the disclosure of our emotional information – it is about the contextually-dependent rules [175, 203] governing how and why emotional information is collected and used, and is a matter of degree [203]: just because our emotions may be discernable to others (e.g., through our facial expressions, text-based communications, or speech patterns), it does not follow that it is acceptable for automatic inferences of those emotions to be collected and used in whatever ways deemed appropriate by third-party organizations and institutions in ways that are largely invisible to and outside the control of the individuals about whom emotion inferences are generated. People ought to have a say in whether, how, and to what degree their emotional information is inferred, collected, and used.

Protecting emotional privacy not only respects our human right to privacy, but, we argue, can also serve to enhance our wellbeing. In the context of technologies and data practices that infer human emotion, preserving emotional privacy then may even enhance the potential benefits promised by technologies that infer human emotion by promoting trust that encourages individuals' emotional reflections and disclosures without fear that engaging with the technology means losing complete privacy over one's emotional information. For scholarship concerned with promoting justice and human values in socio-technical systems, it is important to develop an understanding of how to protect and preserve peoples' emotional privacy implicated by emotion inferences that attends to the factors that shape their privacy judgments [153], and centers the perspectives of those most vulnerable to privacy harms [33, 160], rather than simply as a shared understanding of social norms (i.e., contextual integrity [176]) among the socially dominant [160]. Indeed, relying upon socially dominant "internal standards of justice" [185] to define local and culturally dependent privacy norms and the privacy violations that exceed them [38, 175, 251] can in effect uphold social injustices that prevail within their social systems and silence dissenting views from minoritized groups [160, 185]. As our findings show, the factors that influence workers' and patients' emotional privacy judgments consistently had differential impact in the minoritized sample, underscoring the need to center the needs and concerns of those most vulnerable to technology-enabled emotional privacy harms when assessing and mitigating the impact of automatic emotion inferences and interactions. By aligning practice and design with the needs of those most vulnerable to harm, everyone benefits.

Our findings reinforce an urgent need to recognize and protect emotional privacy, and we suggest that policy and design can best do that by governing the type of information involved – emotional information – rather than attempting to regulate or bright-line ban use of the technology alone (e.g., through automatic emotion recognition moratoriums or bans). While such efforts are noble and well-intentioned, their narrow focus could allow organizations and institutions to skirt legal requirements by overlooking indirect methods that infer emotion from proxies (e.g., verbal and written language patterns, bio-physiological data, and behavioral patterns) that are not explicitly emotional expressions but may still correlate to emotional states – including those examined in our study – which would not fall under an explicit distinction of automatic emotion recognition that aims to directly measure one's emotions through observable emotional expressions. Whether the practice of inferring and interacting with human emotion at a technical level falls more closely under a definition for affective computing, digital phenotyping, passive sensing, or emotion AI, based on our findings, we would not expect that technical distinction to matter to a degree that would exclude any of these technologies and data practices from implicating data subjects' emotional privacy. As such, our findings suggest that a narrow focus on regulating and governing the technology used for emotion recognition alone may lead to legal loopholes, as many data practices involving emotion inferences fall outside this scope. Instead, we suggest, by broadly regulating the collection and use of all types of emotional *information*, governance efforts can be made more comprehensive and future-proof, effectively safeguarding emotional privacy against both direct and indirect intrusions. This privacy-based approach would better ensure that any threat to the privacy of personal emotional information is subject to regulation and scrutiny.

In the following sections, we further discuss the implications our findings have for technology practice, policy, and research to protect and preserve emotional privacy through (1) limiting the purpose for which inferred emotional information is collected or used through inference minimization policies; (2) recognizing emotional information – including inferred emotional information – as a special category of sensitive data; (3) both contextual and demographic sensitivity in the design, application, and regulation of technologies that use emotion inferences.

5.1 Limiting Purpose through Inference Minimization Principles

Currently, the contextual integrity framework accommodates data purpose through limits inherently bound by the combined contextual parameters and/or the overall goal of the context itself. For instance, appropriate data flows between patients and their healthcare provider are not only determined by their respective roles in this context, but also the type of information, conditions under which it was collected, and whether the information serves the overall goal of the healthcare context. For the emotional privacy norms our study established, these specifications do indeed restrict workers' and patients' judgments concerning their inferred emotional information. As our findings show, employers' already normalized invasive surveillance practices is reflected in patients' baseline discomfort with emotion inferences. Several purposes that had positive effects on workers' emotional privacy judgments, even if workers' overall predicted comfort levels remained low, indicate that workplace surveillance practices that require emotional information flows are received more positively when they extend a benefit to workers in a way that reinforces overall expectations of the workplace context's purposes or goals – improving worker safety, for example, or improving the availability of organizational mental healthcare support workers receive. Likewise, employers' use of emotion inferences for purposes that strained the expected goals of the workplace – for medical diagnostics, for instance – were often judged more negatively.

Results for some purposes, however, test the limits of the five contextual parameters and the overall contextual goal to bound emotional privacy norms. For example, employers using workers' emotional information to assess their overall work performance aligns with expectations for which an employer may monitor employees: employers tend to accept monitoring practices primarily to assess worker performance [20], managing one's emotions is a performance expected in many professional environments [108], and use of technologies like emotion AI are used by employers to enforce compliance with those expectations [212]. Though the purpose of emotion inferences to assess workers' overall performance serves the overall goal of employer monitoring practices to assess workers' performance, however, this purpose had a negative effect on worker comfort. Conversely, employers using emotion inferences for the purpose of sharing that information with academic researchers had a positive impact on worker comfort, despite its irrelevance to the workplace context. The limits of the five contextual parameters to constitute emotional privacy norms are even more salient in our results for the healthcare context, where the same emotion inference purposes had very different effects on emotional privacy judgments than in the workplace. While the overall goal of information sharing between patients and healthcare providers is to provision healthcare, emotion inference purposes that directly serve this goal were judged more negatively, including to avoid human subjectivity in conventional ways in which healthcare providers collect or observe patients' emotional information, to develop and deliver automated healthcare interventions, to alert providers when patients need support, to diagnose mental illness, and to assess a patient's overall health. Our interpretation suggests that these results can be explained because *automatic* emotion inferences and interactions transgress conventional bounds in which patients initiate disclosures of their emotional information and expectations that such disclosures remain confidential between patient and healthcare provider; however, this distinction is already accommodated in our specified contextual parameters for an emotional privacy norm, with the sender of emotional information being mediated by technologies like emotion AI that generate emotion inferences (see Section 3.1.1. Following contextual integrity principles through, if we were to conclude based on our results that inferred emotional information sharing between patients and healthcare providers is privacy intrusive because it violates healthcare norms around patient confidentiality and information disclosure, the theory would then say that the emotional privacy norm is bound not solely by the overall goal of information exchanges in healthcare to provision healthcare but also the transmission principles therein. However, this explanation would be challenged to explain our finding for the one purpose that did have a positive impact on patients' emotional privacy judgments: diagnosing neurological disorders. As emotion inferences to diagnose mental illness conversely had a negative impact to emotional privacy judgments, the two contextual constraints (the interplay of contextual integrity's five parameters and the overall contextual purpose) would fail to explain this difference. What distinguishes neurological disorders from mental illness in the healthcare setting is neither a contextual goal nor one of the five contextual integrity parameters: it is the very purpose itself. Our examination of emotional privacy norms concerning emotion inferences for various purposes in the workplace and healthcare exposes the limitations of contextual goals and the five contextual integrity parameters to sufficiently explain the role of contextual purpose in shaping emotional privacy norms. The contextual integrity framework would say that purpose is bound within contextual emotional privacy norms, but, as our findings demonstrate, purpose also plays a role in constituting them.

Thus, our findings empirically demonstrate the need to extend contextual integrity parameters to adopt data purpose as a separate variable – an extension that would have implications for both privacy theory and privacy policy. As Nissenbaum has acknowledged, the importance of contextual data purpose was not as clearly important at the time contextual integrity theory was developed; however, its relevance continues to surface alongside developments in modern technologies and data practices [179], to which extending contextual integrity parameters to include the purpose for which information is used may be a "necessary [policy] antitode" [178]. One of the greatest strengths of contextual integrity theoretical framework is that it allows for more nuanced and effective privacy regulation that is precisely tailored around each of its parameters [178]. Extending contextual integrity parameters to include data purpose, we argue, would then bolster its strength by allowing for targeted regulatory approaches that limit data purposes – including for inferences. Furthermore, our findings show that emotional privacy judgments not only vary by the specific purpose for which employers and healthcare providers use emotion inferences but also, in many cases, between US representative and minoritized perspectives. While many purposes reflect more pronounced privacy concern in the minoritized sample than in the U.S. representative sample, others reflect a more pronounced desire for certain benefits implied by a particular purpose – for instance, improved access to healthcare support. A commitment to ethically and responsibly developing technologies that infer human emotion, and governing emotion inferences, requires both that we center the privacy risks to which those most vulnerable to harm may be exposed [160], as well as the technological benefits they wish to receive. Even if the use of emotion inferences were restricted to purposes that result in a net benefit, however, does not mean that we ought to ignore harms that may occur along the way.

Specifically, our findings could be operationalized to develop policies that limit the development and application of technologies and data practices that infer and/or interact with human emotion outside of a limited set of purposes. Allowable purposes could be empirically evaluated before implementation to validate its promised benefit, ensuring the data subjects of emotion inferences are reasonably informed about the potential impact of the technology before making consent decisions. At a minimum, policies could require more granular consent options that allow individuals to consent (and withdraw consent) to purposes that specify purposes of collecting and using both their raw *and inferred* data, prohibit the collection or use of both raw and inferred data outside of the specific purposes to which individuals consented, and limit retention of raw and inferred data beyond that required to fulfill its limited purposes. These policies could be complemented by data handling procedures that further limit the potential for data reuse (e.g., strong access controls, data encryption, anonymization) and data governance frameworks that include oversight over emotion inferences to ensure compliance with these restrictions. By adopting these inference minimization principles, technologies and data practices involving emotion inferences would better respect individuals' emotional privacy judgments with choices that allow them to yield its potential benefits and shield against its harms as their perceptions and needs change over time.

5.2 Recognizing the Sensitivity of Emotional Data

As our findings show, workers and patients perceive emotion inferences as highly sensitive, rating emotions' sensitivity to a higher degree than several other established sensitive information types when handled by both employers and healthcare providers. Yet, to our knowledge, emotion data is not recognized as a special category of sensitive data in existing regulatory or privacy frameworks [22].

As we have explored throughout this paper, there are significant risks associated with the misuse of this sensitive information type, especially so in the high stakes contexts of the workplace and healthcare. For example, an employer may use emotion inferences to discriminate on the basis of one's mental disability, even if that person did not directly disclose their illness. In healthcare, an inaccurate emotion inference can lead to misdiagnosis. And if emotional inferences collected within these contexts are then later shared in another context (e.g., the sale of emotion inferences to data brokers), inferred emotional information may then be used in additional harmful ways, such as rendering individuals more vulnerable to exploitative ad practices. The grim consequences associated with the potential misuse and abuse of emotion inferences is reflected in the heightened degree of sensitivity that participants attributed to emotional information and contributed to their general discomfort with emotion inferences. Indeed, people are more privacy-concerned about sensitive information [143, 213], which we show emotion data also is, as it renders them more vulnerable to harm [153].

An effective way to mitigate the myriad risks implicated by emotion inferences, and better align emotion inference policy with peoples' emotional privacy judgments surfaced in our study, would be to classify emotion inferences as *sensitive*, requiring data collectors to place heightened safeguards around the collection and use of this information [82]. Such protections could enshrine the policy and governance recommendations we have noted above in Section 5.1, and crucially, overcome concerns that self-regulated institutions would not voluntary institute these practices. Moreover, classifying emotion data as sensitive would assist regulators in identifying privacy risks associated with emotion AI and related emotion inferences, acknowledging that emotion data is a high-risk information type that demands special consideration when assessing privacy risks. It may also encourage industry and academic practitioners to specify data practices related to both emotion AI input data and emotion inferences broadly, and take additional data management actions to minimize risks associated with their collection and use.

Classifying emotional data as sensitive would also strengthen protections around certain controversial technologies like facial emotion recognition. As our findings show the use of facial recognition heightens discomfort with emotion inferences, reflecting public concern with facial recognition technologies [271]. While our findings suggest that this discomfort extends to all types of facial recognition technologies, current regulation over facial recognition is typically limited to that which uses biometrics to uniquely identify an individual [118]. Recognizing emotional data as a special category of data would overcome limitations this limitation by requiring special protections over both the raw and inferred data involved in facial emotion recognition with policy that more closely aligns to the emotional privacy norms we surface in this study.

5.3 Advancing Contextual and Demographic Sensitivity in Emotional Privacy Research, Design, and Regulation

Notably, our findings surface differences between the minoritized sample and U.S. representative sample that suggest heightened discomfort with emotion inferences among minoritized groups overall. At the level of interdependent socio-demographic variables, although we did not have adequate statistical power to confirm the significance of all relationships, we observe trends that nevertheless complicate this insight. Trans and/or non-binary participants generally reported heightened discomfort, with significantly more negative judgments toward emotion inferences in healthcare in particular. Participants currently under treatment for mental illness in both samples tended to judge emotion inferences more positively in healthcare; however, in the workplace, this trend was restricted to the U.S. representative sample where the only statistically significant effect for mental health status was observed. Conversely, participants with resolved or untreated mental illness tended to judge emotion inferences more negatively in the U.S. representative sample but more positively in the minoritized sample. Asian participants tended to judge emotion inferences more negatively, with more pronounced discomfort in the marginalized sample that was statistically significant for the workplace context. Black participants, on the other hand, tended to judge emotion inferences more positively, with significantly higher levels of comfort with emotion inferences in both employment and healthcare contexts. Participants without a Bachelor's degree also tended to view emotion inferences more positively, significantly so concerning their use in employment.

Furthermore, sample-level differences were observed with regard to individual privacy beliefs. Adapting the Internet Users' Information Privacy Concern (IUIPC) scale to measure individual privacy beliefs, our analysis did not yield a significant influence of general privacy beliefs on emotional privacy judgments. On the contrary, context-specific privacy beliefs – perceived sensitivity of emotional data when handled by employers and healthcare providers, and levels of trust when these entities act as data handlers of sensitive personal information – emerged as significant predictors of emotional privacy judgments. These findings challenge the predictive capacity of general privacy concern frameworks like IUIPC in the context of emotion inferences, and emphasize the importance of contextually relevant factors in understanding and predicting privacy perceptions.

By identifying differential impacts of contextual, socio-demographic, and individual privacy belief factors on emotional privacy judgments between samples and socio-demographic categories, these findings prompt the need for demographic sensitivity in addition to contextual sensitivity when designing, applying, and regulating technologies that infer and interact with human emotion, and furthermore, call for privacy research to more closely attend to the unique privacy needs and preferences of diverse populations.

6 CONCLUSION

The results of this study uncover workers' and patients' generally unfavorable emotional privacy judgments of emotion inferences, and shed light on the relative influence of contextual, socio-demographic, and individual privacy belief factors in shaping their emotional privacy judgments in the workplace and in healthcare. Our findings surface four key insights: (1) the importance of *purpose* to emotional privacy judgments, with more positive emotional privacy judgments for emotion inference purposes that are contextually reinforcing, more negative emotional privacy judgments for purposes that strain contextual goals, and purposes that have an effect on emotional privacy judgments that can only be explained by the purpose itself, rather than the context in which the purposes is embedded; (2) general discomfort with facial emotional recognition, with consistently negative privacy judgments of emotion inferences derived from analyzing facial expressions in image or video records; (3) nuanced socio-demographic influences on emotional privacy judgments; and (4) the importance of contextually-specific, rather than generalized, individual privacy beliefs, in shaping emotional privacy judgments. Our findings prompt the need for contextual integrity privacy theory to accommodate the relevance of purpose in shaping emotional privacy norms by adopting purpose as a distinct parameter that inter-dependently shapes contextualized privacy norms; for demographic sensitivity in privacy research; and for privacy policy to adopt *purpose minimization* principles and recognize emotional information as a significant data category.

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7 APPENDICES

A PLOTTED COEFFICIENTS WITH ERROR BARS

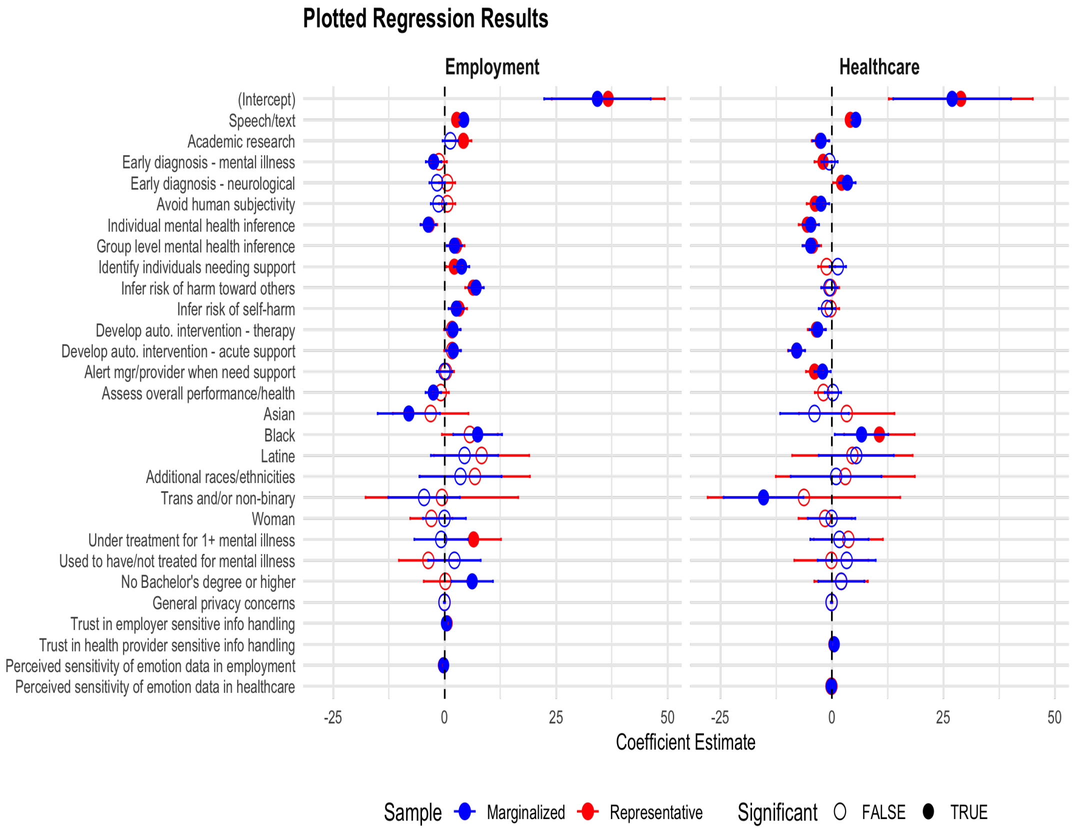

Fig. 8. Coefficient Plot with Error Bars Each point represents the tested independent variable; its position on the x-axis indicates the estimated effect size on reported comfort. Filled circles signify statistically significant relationships; open circles represent non-significant relationships; the color red represents estimated negative relationships; the color blue represents estimated positive relationships. Vertical dashed lines mark the zero line. Error bars display 95% confidence intervals around coefficient estimates. The plot offers insights into the direction, significance, and uncertainty of variable effects.

B POST-TEST SOCIO-DEMOGRAPHIC QUESTIONS

1. Please indicate your current employment status. Select all that apply.

- Employed Full-Time
- Employed Part-Time

- Looking for work
- Not in the paid workforce (retired, full-time caregiving, full-time student, etc.)
- Other

2, What is the highest level of school you have completed or the highest degree you have received?

- No formal schooling
- Some grade school
- High school graduate (high school diploma or equivalent including GED)
- Some college
- Technical, vocational, or trade school
- Associate degree in college (2-year)
- Bachelor's degree in college (4-year)
- Master's degree
- Professional degree (JD, MD)
- Doctoral degree

3. What is your year of birth? <text box>

4. Please describe your race/ethnicity. Select all that apply.

- African
- African-American or Black
- Asian-American
- East Asian
- Hispanic or Latino/a/x
- Indigenous American or First Nations
- Middle Eastern
- South Asian
- Southeast Asian
- White
- Not listed, please specify <text box>
- Prefer not to answer

5. Please describe your mental health status. Select all that apply.

- I have a mental health condition and it has not been formally diagnosed
- I have a mental health condition that has been formally diagnosed
- I am being treated for a mental health condition, and that treatment includes medication
- I am being treated for a mental health condition, not with medication
- I do not have a mental health condition
- I used to have a mental health condition and I no longer do
- I have multiple mental health conditions. Some are diagnosed, some are not
- I have multiple mental health conditions. I take medication for some, and do not for others

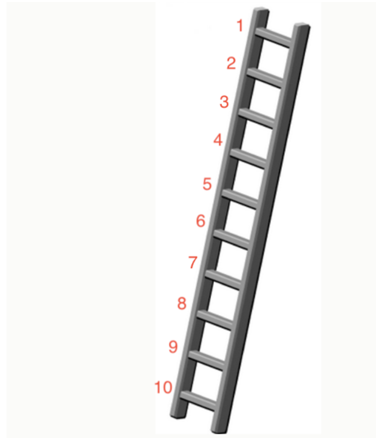

Fig. 9. MacArthur Scale of Subjective Social Status)

6. At the top of the ladder are the people who are the best off, those who have the most money, most education, and best jobs. At the bottom are the people who are the worst off, those who have the least money, least education, worst jobs, or no job. Select the number next to the rung that best represents where you think you stand on the ladder.

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10
- Prefer not to answer

C POST-TEST INDIVIDUAL BELIEF QUESTIONS

C.1 General Privacy Concerns

Rate your agreement, from 0= "strongly disagree" to 100 = "strongly agree," with the following:

- All things considered, the internet causes serious privacy problems.
- Compared to others, I am more sensitive about the way my personal information is handled.
- To me, it is the most important thing to keep my privacy intact from companies and institutions.
- I believe other people are too much concerned with online privacy issues.
- Compared with other subjects on my mind, personal privacy is very important.
- I am concerned about threats to my personal privacy today.

C.2 Risk Beliefs Regarding Employers' and Healthcare Providers' Handling of Sensitive Information

Rate your agreement, from 0= "strongly disagree" to 100 = "strongly agree," with the following:

- In general, it is risky to give sensitive information to **employers**.
- In general, it is risky to give sensitive information to **healthcare providers**.
- There is a high potential for loss associated with **employers** handling sensitive data about me.
- There is a high potential for loss associated with **healthcare providers** handling sensitive data about me.
- There is too much uncertainty associated with giving sensitive information to **employers**.
- There is too much uncertainty associated with giving sensitive information to **healthcare providers**.
- Providing **employers** with sensitive information would involve many unexpected problems.
- Providing **healthcare providers** with sensitive information would involve many unexpected problems.
- I feel safe giving sensitive information to **employers**.
- I feel safe giving sensitive information to **healthcare providers**.

C.3 Trust Beliefs Regarding Employers' and Healthcare Providers' Handling of Sensitive Information

Rate your agreement, from 0= "strongly disagree" to 100 = "strongly agree," with the following:

- **Employers** are trustworthy in handling sensitive information about me.
- **Healthcare providers** are trustworthy in handling sensitive information about me.
- **Employers** would tell the truth and fulfill promises related to how they use sensitive information about me.
- **Healthcare providers** would tell the truth and fulfill promises related to how they use sensitive information about me.
- I trust that **employers** would keep my best interests in mind when dealing with sensitive information about me.
- I trust that **healthcare providers** would keep my best interests in mind when dealing with sensitive information about me.
- **Employers** are in general predictable and consistent regarding the usage of **employees'** sensitive information.
- **Healthcare providers** are in general predictable and consistent regarding the usage of **patients'** sensitive information.
- **Employers** are always honest with **employees** when it comes to using their sensitive information about **employees**.
- **Healthcare providers** are always honest with **patients** when it comes to using their sensitive information about **patients**.

C.4 Perceived Sensitivity of Emotional Information and Other Sensitive Data Types when Handled by Employers and Healthcare Providers

Rate your agreement, from 0= "strongly disagree" to 100 = "strongly agree," with the following:

- When an **employer** has access to information about your **emotional states** (states of feeling like emotion or mood, including but not limited to stress, anxiety, depression, boredom, calm, fear, fatigue, attentiveness, happiness, sadness, disgust, surprise, and/or anger), how SENSITIVE do you consider this information?
- When a **healthcare provider** has access to information about your **emotional states** (states of feeling like emotion or mood, including but not limited to stress, anxiety, depression, boredom, calm, fear, fatigue,

attentiveness, happiness, sadness, disgust, surprise, and/or anger), how SENSITIVE do you consider this information?

- When an **employer** has access to information about your **political opinions**, how SENSITIVE do you consider this information?
- When an **healthcare provider** has access to information about your **political opinions**, how SENSITIVE do you consider this information?
- When an **employer** has access to information about your **religious beliefs**, how SENSITIVE do you consider this information?
- When a **healthcare provider** has access to information about your **religious beliefs**, how SENSITIVE do you consider this information?
- When an **employer** has access to information about your **biometric data**, such as your fingerprints, how SENSITIVE do you consider this information?
- When a **healthcare provider** has access to information about your **biometric data**, such as your fingerprints, how SENSITIVE do you consider this information?
- When an **employer** has access to information about your **health**, how SENSITIVE do you consider this information?
- When a **healthcare provider** has access to information about your **health**, how SENSITIVE do you consider this information?
- When an **employer** has access to information about your **sex life or sexual orientation**, how SENSITIVE do you consider this information?
- When a **healthcare provider** has access to information about your **sex life or sexual orientation**, how SENSITIVE do you consider this information?
- When an **employer** has access to information about your **genetic information**, how SENSITIVE do you consider this information?
- When a **healthcare provider** has access to information about your **genetic information**, how SENSITIVE do you consider this information?
- When an **employer** has access to information about your **current or past union membership**, how SENSITIVE do you consider this information?
- When a **healthcare provider** has access to information about your **current or past union membership**, how SENSITIVE do you consider this information?