Public Perceptions About Emotion AI Use Across Contexts in the United States

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Abstract

Emotion artificial intelligence (AI) is deployed in many high-impact areas. However, we know little about people's general attitudes towards and comfort with it across application domains. We conducted a survey with a U.S. representative sample, oversampling for marginalized groups who are more likely to experience emotion AI harms (i.e., people of color, disabled people, minoritized genders) (*n*=599). We find: 1) although comfort was distinct across 11 contexts, even the most favorable context (healthcare) yielded low comfort levels; 2) participants were significantly more comfortable with inferences of happiness and surprise compared to other emotions; 3) individuals with disabilities and minoritized genders were significantly less comfortable than others across a variety of contexts; and 4) perceived accuracy explained a large proportion of the variance in comfort levels across contexts. We argue that attending to identity is key in examining emotion AI's societal and ethical impacts, and discuss implications for emotion AI deployment and regulation.

CCS Concepts

• **Human-centered computing → Empirical studies in collaborative and social computing**; *Empirical studies in HCI*.

Keywords

emotion recognition, emotion sensing, emotion inference, affect recognition, affective computing

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1 Introduction

Emotion AI (emotion artificial intelligence), rooted in affective computing [66] refers to a class of AI that promises to infer emotions and other affective phenomena (e.g., mood, mental health) based on a range of input data (e.g., language, voice, facial expressions, biometrics) [54]. [1] Emotion AI is increasingly deployed across a range of high-impact contexts such as work, education, healthcare, consumer insights, smart devices, public safety, cars, entertainment, and more [56]. Even OpenAI has demonstrated the emotion-detecting capabilities of GPT-4.0 [74], a product currently used by 200 million users globally each week [91]. The emotion AI market is expected to reach 42.9 billion USD by 2027 [52].

While proponents celebrate potential for emotion AI to improve qualities such as wellbeing, safety, efficacy, and job performance (e.g., [11, 77]), critics raise concerns about its theoretical foundations [6, 86], representativeness and validity of training data [54], accuracy [6], privacy harms [2, 20, 78], loss of mental integrity [56], imposed emotional labor [11, 78], and bias (e.g., along dimensions of gender [50], race [50, 71], and disability [59, 101]). Of note, the theoretical foundation underlying most emotion AI systems—Basic Emotion Theory (BET) [27]— is heavily contested [6, 9, 48, 86] given its central argument that there exist six universal emotions.

Despite vocal critiques emerging alongside deployment, emotion AI and associated emotion data remain unregulated across the globe, with even the European Union's (EU) AI Act overlooking emotion as sensitive personal information [26]. A key challenge of regulating emotion AI is the lack of agreement on how to regulate emotion data more broadly. While legal scholarship has considered emotion as biometric data, sensitive information, and health data, among others, a clear best path forward has yet to be identified [4]. Evidence regarding public perceptions about emotion AI across contexts will provide much needed guidance for policymakers grappling with emotion data and emotion AI regulation, which has broad relevance because *all humans have emotions*.

Given the breadth of its deployment—with each context sparking distinct norms of information flow [61]—and potential disparate impact on marginalized identity groups (e.g., along dimensions of gender, race, and disability) [20, 76], an investigation of perceptions about emotion AI should attend to its *contexts* of use, and account for *identity's* role in these perceptions. Additionally, although emotion AI systems heavily rely on detecting specific emotions per BET [27], 1) the emotions targeted often remain unknown to individuals whose emotions are inferred, and 2) people may have distinct attitudes towards making particular emotions visible to others [72]. Further, while assessing general attitudes towards a technology is valuable, people's *comfort* with emerging technologies across different contexts can signal the level of risk they associate with these innovations [49, 62, 63, 67, 73, 99]. In sum a comprehensive understanding of public comfort with emotion AI should consider how people feel about emotion AI inferring *specific emotions* and *identity*'s role across *contexts*. Against this

[1] Alternative terms describing this class of AI include emotional AI, emotion recognition, emotion detection, affect recognition, emotion sensing, affect sensing, and passive sensing, among others. We refer to **emotion AI** to capture these technologies broadly.

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background, we ask the following research questions:

RQ1. What are the general attitudes of the United States public toward emotion AI use?

RQ2. How does comfort with emotion AI use differ across a) the emotion type being inferred, b) contexts of use, and c) identity factors (i.e., race, gender, disability)?

Empirical investigation of attitudes toward and comfort with emotion AI can help us to: 1) assess emotion AI's context- and identity- dependent acceptability, 2) shed light on the implications of inferring some emotions over others, and 3) inform emotion AI regulation in the U.S. Building on prior qualitative research exploring affected individuals' perspectives on emotion AI [2, 20, 30, 36, 76, 79], and quantitative explorations of public opinions on emotion AI in the U.K. [55], this paper provides the first, and to the best of our knowledge, most comprehensive quantitative and generalizable empirical investigation of the U.S. public's attitudes towards and comfort with emotion AI across high-impact contexts and identity groups (i.e., gender, race, and disability) with attention to the role of inferred emotions.

We conducted a survey with a U.S. sample representative in terms of age, gender, race, and political orientation and an oversample for individuals with disabilities, people of color (POC), and transgender and non-binary people (n=599). We investigate 11 high-impact contexts of emotion AI use, namely: public spaces, healthcare, the workplace, job interviews, consumer research, border control, social media, children's toys, education, cars, and personal pursuits.

We find that participants have a negative attitude toward and are largely uncomfortable with the deployment of emotion AI across *all* contexts, particularly as used in the workplace, social media, job interviews, and for consumer research. Comfort levels remained low *even* in the setting where they were highest (healthcare). Additionally, participants were significantly more comfortable with emotion AI making inferences based on happiness and surprise as compared to other emotion types. In fact, comfort with happiness-based inferences—in addition to perceived accuracy of emotion AI— was consistently predictive of comfort with emotion AI use. Through our analysis, we show how simultaneously attending to *multiple* identity factors is important to gain deeper insights into people's comfort with emotion AI. For example, individuals with disabilities and gender minorities were significantly less comfortable than those without disabilities and cisgender men, respectively, across several contexts. Additionally, POC were significantly more comfortable with the use of emotion AI than white people across all contexts *except* public spaces, border control, and job interviews. We discuss the implications of our findings for emotion AI research, deployment, and regulation.

2 Relevant Work

One way to gauge risk perceptions of emerging technology is through assessing comfort. Comfort is a reliable indicator of the risks people associate with emerging technologies such as AI [53, 62, 65, 82, 99], robots [14], and social media [31]. However, it is important to reveal the implications of *emotion* AI in particular due to the perceived sensitivity of emotion data [2, 55], emotions' key roles in our lives, decision-making, and attitudes [47, 80], and existing evidence suggesting emotion AI's unique harms and implications [20, 40, 56, 70, 71, 75, 76].

Emotion AI is used or proposed to be used across high-impact contexts such as the workplace, human resources, education, healthcare, consumer insights, smart devices, public safety, cars, border control, entertainment, and more [10, 32, 51, 56]. While prior work provides preliminary (largely qualitative) insights into people's attitudes toward emotion AI in some contexts (e.g., workplace, healthcare, social media, hiring, education), [2, 11, 75–77, 96] we lack empirical and large-scale evidence that captures and compares a range of contexts.

Overall, qualitative investigation of the perceptions of potentially impacted individuals 1) identifies a range of perceived risks and harms [20, 69, 76, 78], and 2) suggests emotion AI use may in fact worsen, rather than improve, what it claims to improve (e.g., fairness in hiring, workplace well-being) [69, 77, 89]. For example, many workers do not consider emotion AI inferences to be relevant to their employers or work performance, associating it with privacy harms and imposed emotional labor [20] (e.g., needing to change their emotional displays). Similarly, job-seekers consider emotion AI's use in hiring to be unjust, concerned with the outcomes, processes, and interpersonal aspects of job interviews [69]. Meanwhile, emotion AI proponents celebrate its use to address issues of fit and bias in hiring [77], as well as performance and well-being in the workplace [20, 90]. Along the same lines, users perceive both social and individual risks of emotion AI use on social media, considering the technology privacy-invasive and potentially manipulative [2, 68]. Further, they perceive emotion AI deployment on social media to be particularly harmful if used to provide well-being interventions [75]. In the context of mental healthcare, while proponents claim emotion AI can reduce mental illness stigma, improve patient care and provider communication, and improve patient wellbeing [24, 43], people raise concerns about inaccurate and biased inferences, deterioration of communication with providers, and reduced care quality [76]. Lastly, while acknowledging potential benefits for self-regulated learning [96], students raise privacy concerns about sensing affective states in educational settings. Taken together, this work highlights a range of concerns that people subjected to emotion AI systems have about them in several contexts.

Notably, a recent survey of a representative sample in the U.K. indicated that 50% of respondents "are not OK" with any form of emotion AI while a third are "OK" only if it does not identify them [55]. Across these contexts, the accuracy of emotion AI's inferences surface as a risk factor. Qualitative evidence [36] suggests that perceptions of emotion AI accuracy shape people's attitudes towards it with mixed results: while some believe inaccurate emotion AI should not be used due to its inaccuracy, others feel more accuracy makes emotion AI more intrusive. These concerns raise questions about the role of perceived accuracy in comfort with emotion AI.

Overall, the work reviewed so far, while valuable, leaves gaps in 1) generalizability to the U.S., and 2) our understanding of the implications of emotion AI use in under-explored contexts such as in public spaces, consumer research, border control, children's toys, personal pursuits, and cars. Our study addresses these gaps.

2.1 Understanding the Role of Specific Emotion Inferences in Perceptions of Emotion AI

What's more, much of prior work assessing people's comfort with emotion AI does not specify what particular emotions may be inferred. It is possible that this shapes people's comfort with emotion AI. For example, individuals may be more comfortable if positive emotions are inferred as opposed to those which cast them in a negative light. However, empirical evidence for this relationship remains unknown. Broadly, negative emotions like sadness and anger tend to carry more stigma, making them more private and risky to share with others [72]. Additionally, despite what BET (informing the design of many emotion AI systems) suggests [27], people express emotions differently [6]. For example, neurodivergent individuals may not conform to normative forms of emotional expression [41, 101]. This background raises questions about the role that the specific emotion that emotion AI systems aim to infer may play in people's comfort, which we explore in this study.

2.2 Centering Individuals with Minoritized Race, Gender and Disability Status

Lastly, important in examining people's attitudes towards and comfort with emotion AI is their identity. A nationally representative survey in the U.K. [55] examining how "OK" people were with emotion AI across entertainment and advertising contexts found little variance across identity factors such as gender, socioeconomic status, and region. This work [55] did not account for other identity factors such as race and disability and held a binary view on gender. On disability specifically, Nagy argues that emotion AI exploits disability as a "a rhetorical, conceptual, and material resource" to further capitalism [60], which is fundamentally harmful to disabled people and raises questions around disabled people's views on emotion AI. Further, Kang argues that emotion AI use in call centers facilitates abelist workplace politics [42]. This past work motivates our exploration of disability's role in comfort with emotion AI. Additionally, there are indications of salient emotion AI-inflicted perceived harms for minoritized people such as POC, disabled people, and gender minorities in the U.S. (largely in the workplace and healthcare) [8, 16, 58, 69, 76, 78] and beyond [50] indicating that identity may play a role in people's comfort with emotion AI. These perceived harms include biased and inaccurate assessments [70], unjust outcomes (e.g., inferences used to exacerbate existing biases such as worsened healthcare experiences or employment and promotion opportunities) [69, 76, 78], and imposed emotional labor [20, 69, 78] which POC, gender minorities, and disbaled people already endure [38] and emotion AI may exacerbate [20]. This past work raises questions about the role gender, race, and disability may play in perspectives on emotion AI across contexts.

Taken together, we examine people's general attitudes towards emotion AI (RQ1) and comfort with emotion AI use across a) the emotion being inferred, b) contexts of use, and c) identity factors (i.e., race, gender, disability) (RQ2).

3 Methodology

3.1 Participants

We used Prolific to recruit participants, as this recruitment firm is deemed more reliable than alternatives [64]. To determine a sufficient sample size, we conducted a power analysis a priori using G*Power with a desired effect size of .25 [18], power of .99, error of probability <.05, and 8 covariates. The power analysis indicated a need for at least 511 participants. Given anticipated data cleaning and our desire to oversample for marginalized groups, we recruited 649 participants who were then routed to a survey hosted on Qualtrics in August 2024. The survey was representative of the U.S. population by age, sex, race, and political orientation, and oversampled for respondents with disabilities, and those of minoritized genders and races who may be more likely to experience AI-inflicted harm [20]. Prolific provides options to recruit samples that are representative of the U.S. population as well as those that fit certain criteria. We compensated participants at a rate of $12/hour, per Prolific's suggestion given the survey length (an average of 20 minutes). We used Prolific's inclusion feature to ensure participants were over the age of 18 and lived in the U.S., and manually reviewed all responses. We excluded 50 responses due to failing attention checks [2] or providing incomplete survey responses. This study was approved by our university's institutional review board.

We labeled participants as having one or more disabilities if they reported having any of the listed disabilities in the survey (See Supplementary Materials A.1.5) (n = 313). We classified participants as POC if they identified with any race outside of solely white (n = 297). Informed by prior work [39], we grouped transgender and nonbinary participants together as representing a minoritized gender identity who may perceive technology differently than cisgender participants. To gauge participants' baseline understanding about emotion AI, we asked the extent to which they had previously heard about the technology. A large portion of our sample had "never heard of" emotion AI (n = 211). Table 1 shows a breakdown of participants' demographic information and perceived emotion AI knowledge.

3.2 Procedure

Since participants did not necessarily know what emotion AI was or their understandings of it may have been different from this study's framing, we provided a definition of emotion AI adopted from past work [20] at the beginning of the survey and as appropriate throughout as a reminder. This definition was as follows:

"Please keep in mind the following definition of emotion AI: systems that promise to automatically detect your emotions and moods (e.g., stress, boredom, calmness, fear, fatigue, attentiveness, happiness, sadness, disgust, surprise, anger) based on various kinds of data (e.g., facial expressions, voice, text/language, biometric information).

Participants then answered a series of quantitative measurements, as described below. Following best practices [37], we randomized all items to reduce order effects. The complete survey instrument is included in Appendix A.1.

[2] We included two attention checks randomly within the survey: "To ensure you are paying attention, please select 'Very Uncomfortable' for this statement," and "To ensure you are paying attention, please select 'Strongly agree' for this statement."

3.3 Measurements

General attitudes toward emotion AI. We used four Likert-style items ranging from "Strongly disagree" (1) to "Strongly agree" (7) adapted from a validated scale for general attitudes towards AI more broadly [35]. All items and reliability metrics are reported in Table 2.

Comfort with emotion AI. We measured comfort across public spaces, children's toys, education, healthcare, workplace, job interviews, consumer research, border control, social media, cars, and personal pursuits. Informed by previous literature and existing deployed systems [11, 13, 43, 54, 56, 57, 93], items were measured through having participants complete the following sentence, "I would feel comfortable with emotion AI being used…" (e.g., "...by schools to assess student engagement and attention to improve student learning). Participants ranked items on a Likert scale ranging from 1 ("Very uncomfortable") to 7 ("Very comfortable"). All items and reliability metrics are reported in Table 2.

Comfort with inferences of particular emotions. The survey prompted participants with the following statement: "Emotion AI tools may infer a range of emotions about people. Please indicate your comfort level for emotion AI tools that infer the following:" followed by happiness, surprise, sadness, anger, disgust and fear which were ranked on a scale from 1 ("Very uncomfortable") to 7 ("Very comfortable").

Perceptions of emotion AI accuracy. Participants reported their level of agreement with the following statement: "Emotion AI would make accurate inferences about me" on a scale ranging from 1 ("Strongly disagree") to 7 ("Strongly agree") (M = 3.33, SD = 1.71).

Demographic variables. We measured a set of demographic variables that may have influence on individual attitudes or comfort levels with particular contexts of emotion AI. (See Appendix A.1.5).

3.4 Limitations

This study assessed a broad suite of contexts within-subjects, which allowed us to compare perceptions across contexts on the same sample. Future research may be structured as a between-subjects experiment that allows each participant to respond to more items about an individual context, which can then be compared to other individuals and contexts. Additionally, there may be other use cases for the deployment of emotion AI use within each of these contexts; however, we focused on those most relevant in practice to avoid survey fatigue.

Some reported significant effects have very small effect sizes. In the subsections that follow, we report on all significant findings, including those where $\eta_p^2 < .01$. Significant results with small effect sizes should be interpreted with caution. Further, this study does not assess differences across specific types of disabilities and races. Finally, there are limitations to our models in that there may be alternative factors at play that could influence attitudes toward emotion AI [23]. For example, whether someone is in a managerial position could shape their attitudes towards emotion AI in the workplace. Examining these factors was outside of the scope of this study. Additionally, we did not explore differences between transgender men and transgender women because the sample sizes for these subgroups were too small to allow for statistically meaningful contrasts.

Table 1: Sample breakdown on demographics and emotion AI knowledge

Variable	Identification	N
Gender	Cisgender Woman	288
	Cisgender Man	212
	Transgender/Nonbinary	99
Race	White	302
	Black or African American	141
	Hispanic or Latino	37
	Southeast Asian	13
	East Asian	15
	South Asian	11
	American Indian/Alaska Native	3
	Middle Eastern	1
	Mixed Race	76
Disability	No disability	286
	At least one disability	313
Education	Less than high school	11
	High school or equivalent	97
	Some college	200
	Bachelor's degree	181
	Some graduate school	18
	Master's or professional degree	79
	Doctoral degree	13
Income Level	Less than $20,000	89
	$20,000 to $34,999	85
	$35,000 to $49,999	94
	$50,000 to $74,999	101
	$75,000 to $99,999	80
	$100,000 to $149,999	92
	$150,000 to $199,999	47
	$200,000 to $249,999	3
	$250,000 or more	8
Age	18-24	98
	25-34	164
	35-44	127
	45-54	86
	55-82	124
Emotion AI Knowledge	Never heard of it	211
	Heard of it but don't know what it is	99
	Know a little about it	154
	Somewhat knowledgeable	67
	Fairly knowledgeable	46
	Very knowledgeable	20
	Expert	2

4 Results

Type II ANCOVAs were appropriate for most of our analyses as they allow for the examination of each identity factor's effect on the dependent variable after accounting for the effects of other predictors. This model is particularly useful for handling unbalanced data, as it calculates main effects after adjusting for covariates. All statistical assumptions, including homoskedasticity, multicollinearity, and equal variance, were met. The models analyzed contrasts in gender, race, and disability, adjusting for perceived accuracy of emotion AI, income, education, age, and comfort with distinct emotions (excluding surprise and disgust due to multicollinearity). We included these *baseline controls* in all models unless otherwise noted. Following previous work [83] we ran post-hoc Tukey HSD tests using the *emmeans* package in R to assess significant contrasts between groups if such were detected within the ANCOVA. We adjusted estimated marginal means for continuous controls and averaged across factor-level variables (See Table 16 in the Appendix).

4.1 General Attitudes Toward Emotion AI

RQ1 asked about individuals' **general attitudes** towards emotion AI. Descriptive statistics reveal that generally, participants had relatively negative attitudes toward emotion AI (M = 3.30; SD = 1.71). Type II ANCOVA results (See Table 3) revealed that gender, race, perceptions of emotion AI accuracy, and comfort with happiness inference each had a significant effect on general attitudes toward emotion AI. A Tukey HSD test revealed that cisgender women had significantly less positive attitudes toward emotion AI than cisgender men ($t(591)$ = -2.45, p = .04, $d = -0.23$). Further, POC had significantly more positive attitudes toward emotion AI than white participants.

Variable	Sum of Squares	df	F	Effect Size (η_p^2)
Gender	6.69	2	3.55*	0.01
Disability	0.02	1	0.02	< .01
Race	11.83	1	12.62**	0.02
Perceived EAI Accuracy	305.31	1	329.67**	0.36
Education	3.25	1	3.51	< .01
Income	1.62	1	1.75	< .01
Age	3.18	1	3.43	< .01
Happiness	42.02	1	45.83**	0.07
Fear	0.14	1	0.15	< .01
Anger	0.55	1	0.60	< .01
Sadness	1.75	1	1.89	< .01

Table 2: ANCOVA Results for General Attitudes toward Emotion AI

* p-values are less than 0.001; df = degree of freedom.

4.2 Comfort with Emotion AI and Emotion Inferences

RQ2a considered if there would be differences between people's comfort levels with emotion AI making inferences about specific emotions (See Figure 1). Paired samples t-tests (Table 4) revealed that participants were significantly more comfortable with emotion AI inferring happiness (***M*** = 4.19, ***SD*** = 2.01) than any other emotion type: surprise (***M*** = 3.97, ***SD*** = 1.95)„ sadness (***M*** = 3.49, ***SD*** = 1.90), anger (***M*** = 3.39, ***SD*** = 1.92), disgust (***M*** = 3.38, ***SD*** = 1.83), and fear (***M*** = 3.38, ***SD*** = 1.92). With the exception of happiness, participants were also significantly more comfortable with surprise inferences than other emotions.

Figure 1: Box plot of participants' comfort with different emotion types as identified by BET. The horizontal line represents the average whereas the width represents the range of scores.

Table 3: Paired samples t-tests contrasting happiness and surprise with all other emotions per BET

Emotion Contrast	df	t
Happiness-Surprise	598	5.48*
Happiness-Sadness	598	12.04*
Surprise-Sadness	598	8.80*
Happiness-Disgust	598	13.76*
Surprise-Sadness	598	8.80*
Happiness-Anger	598	12.52*
Surprise-Sadness	598	8.80*
Happiness-Fear	598	12.73*
Surprise-Sadness	598	8.80*

* p-values are less than 0.001; df = degree of freedom; t = t-score statistic.

4.3 Comfort with Emotion AI Use Across Contexts and Identity Groups

RQ2b sought to examine how comfort levels with emotion AI differed across contexts (See Figure 2). Descriptive statistics reveal participants to be least comfortable with emotion AI use in the workplace (***M*** = 2.34, ***SD*** = 1.65) whereas they were most comfortable with its use by healthcare professionals (***M*** = 3.07, ***SD*** = 1.76).

Table 4: Measurement items regarding perceptions of emotion AI

Context	Measurement Items	α	M (SD)
General attitudes	I believe that emotion AI will improve my life. I believe that emotion AI will improve my work. I think I will use emotion AI technology in the future. I think emotion AI technology is positive for humanity.	0.95	3.30 (1.71)
Healthcare	...by my healthcare providers to improve diagnostics in my mental healthcare. ...in my home so my doctors can keep track of my emotional states as associated with my health. ...by my healthcare providers to improve treatment and intervention in my mental healthcare. ...in senior living facilities to report residents' emotional state to their healthcare providers.	0.91	3.61 (1.76)
Personal pursuits	...to infer my emotions using a wearable device so I can reflect on and gain more insights into my emotional life. ...to infer my emotions using a smart home device (e.g., Alexa, Google Home) so I can reflect on and gain more insights into my own emotional life.	0.87	3.54 (1.95)
Cars	...in cars to infer my stress while driving to improve safety. ...in cars to infer my distraction while driving to improve safety. ...in cars to infer my fatigue while driving to improve safety. ...in cars to infer my stress, fatigue, or distraction while driving to inform my insurance rates.	0.91	3.45 (1.75)
Education	...by schools to assess student engagement and attention to improve student learning.	N/A	3.31 (2.00)
Public spaces	...by public transportation authorities to infer passengers' emotions to increase safety. ...by public entertainment venues like stadiums and parks to infer people's emotions to improve safety and security. ...by airport security to infer people's truthfulness to improve security and safety. ...by governments in public spaces to identify potential malicious actors.	0.91	3.12 (1.78)
Children's toys	...by Internet-connected toys to infer and report a child's emotional state to parents, such as whether they are happy, stressed, angry, or sad. ...in Internet-connected toys to infer a child's emotional state to report to appropriate authorities if inferred that a child might be being abused, self-harming, or otherwise highly distressed.	0.86	3.13 (1.89)
Border control	...by the government to infer the truthfulness of individuals trying to enter the US as immigrants to improve security and safety. ...by the government to infer the truthfulness of individuals trying to enter the US as asylum seekers to improve security and safety.	0.95	3.01 (2.03)
Job interviews	...by employers during video interviews to assess my fit for the job. ...by employers during video interviews to assess my true interest in the job.	0.97	2.42 (1.74)

Continued on next page

Context	Measurement Items	α	M (SD)
	...by employers during video interviews to assess my qualifications for the job. ...by employers during video interviews to infer my truthfulness.		
Social media	...by social media companies to infer if I am in emotional distress and may need social support. ...by social media companies to infer if I am in emotional distress and may need to be admitted to a psychiatric hospital. ...by social media companies to infer if I am in emotional distress and may hurt myself. ...by social media companies to infer if I am in emotional distress and may hurt others.	0.95	2.38 (1.67)
Consumer Research	...by online advertisers to tailor ads I see to my emotional state. ...by advertisers to tailor outdoor ads I see in public to my emotional state. ...by retail stores to infer customers' emotions to increase sales.	0.94	3.01 (2.03)
Workplace	...by my employer to assess my work performance. ...by my employer to assess if I need emotional or mental health support.	0.85	2.34 (1.65)

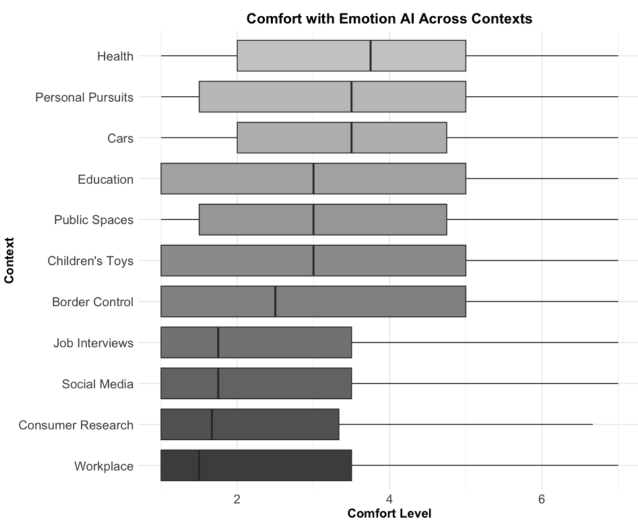

Figure 2: Box plot of participants' comfort with emotion AI use across contexts. The horizontal line represents the average whereas the width represents the range of scores.

RQ2c pertained to how identity factors shaped comfort levels across contexts. We present results below from most to least comfortable contexts. We report on all ANCOVA models in tables corresponding to the relevant in-text results.

Health: Race had a significant effect on comfort with the use of emotion AI in healthcare, with white respondents being significantly less comfortable than POC ($t(591) = -2.89$, $p = .004$). Perceptions of emotion AI accuracy as well as comfort with happiness and fear inference were also significant positive predictors of comfort with emotion AI use in healthcare.

Variable	Sum of Squares	df	F	Effect Size (η_p^2)
Gender	5.54	2	2.19	<.01
Disability	0.23	1	0.18	<.01
Race	10.28	1	8.14 **	.01
Perceived EAI Accuracy	91.41	1	72.38 **	.11
Education	0.15	1	0.12	<.01
Income	0.82	1	0.65	<.01
Age	1.40	1	1.11	<.01
Happiness	102.38	1	81.06 **	.12
Fear	9.76	1	7.73 **	.01
Anger	0.38	1	0.30	<.01
Sadness	0.66	1	0.53	<.01

Table 5: ANCOVA Results for Comfort with Emotion AI in Healthcare

* p < .05; ** p < .01

Personal pursuits. While none of the identity factors were significant in this model, perceptions of emotion AI accuracy and comfort with happiness and fear inference were positive, significant predictors of comfort with emotion AI use in personal pursuits.

Variable	Sum of Squares	df	F	Effect Size (η_p^2)
Gender	2.67	2	0.73	<.01
Disability	4.94	1	2.71	<.01
Race	2.64	1	1.45	<.01
Perceived EAI Accuracy	110.67	1	60.68 **	.09
Education	3.13	1	1.72	<.01
Income	0.54	1	0.29	<.01
Age	0.34	1	0.19	<.01
Happiness	97.16	1	53.28 **	.08
Fear	22.37	1	12.27 **	.02
Anger	0.04	1	0.019	<.01
Sadness	0.55	1	0.20	<.01

Table 6: ANCOVA Results for Comfort with Emotion AI in Personal Pursuits

* p < .05; ** p < .01

Cars. In addition to baseline controls, this model controlled for participants' primary means of transport.[3] Results demonstrate that disability and race significantly impacted comfort with the use of emotion AI in cars. Additionally, comfort with happiness inference, fear inference, and perceived emotion AI accuracy were positive predictors. Post-hoc tests revealed disabled participants were less comfortable with emotion AI use in cars than people who were not disabled ($t(591) = -1.98$, $p = .047$, $d = -0.34$) and that POC were more comfortable than white participants ($t(591) = 2.78$, $p = .04$, $d = -0.18$).

Variable	Sum of Squares	df	F	Effect Size (η_p^2)
Gender	3.32	2	0.97	<.01
Disability	6.71	1	3.93 *	.01
Race	7.40	1	4.33 *	.01
Perceived EAI Accuracy	42.40	1	24.85 **	.23
Education	0.34	1	0.20	<.01
Income	2.70	1	1.59	<.01
Age	1.85	1	0.30	<.01
Happiness	74.78	1	43.83 **	.07
Fear	10.83	1	6.35 *	.01
Anger	4.08	1	2.39	<.01
Sadness	0.43	1	0.25	<.01
Car Transport	1.82	1	1.07	<.01

Table 7: ANCOVA Results for Comfort with Emotion AI in Cars

* p < .05; ** p < .01

Education. In addition to baseline controls, this model controlled for participants' parental status given the influence this may have on comfort with emotion AI use in education[4]. While none of the identity factors were significant, participants were more comfortable with emotion AI use for education purposes if they perceived emotion AI to be accurate. Participants also expressed higher comfort with emotion AI in education if they were more comfortable with it inferring happiness.

Variable	Sum of Squares	df	F	Effect Size (η_p^2)
Gender	0.10	2	0.02	<.01
Disability	1.36	1	0.59	<.01
Race	1.10	1	0.48	<.01
Perceived EAI Accuracy	81.99	1	35.64 **	.06
Education	0.04	1	0.02	<.01
Income	0.01	1	0.00	<.01
Age	4.63	1	2.01	<.01
Happiness	107.43	1	46.71 **	.07
Fear	4.14	1	1.80 *	<.01
Anger	5.85	1	2.54	<.01
Sadness	0.05	1	0.02	<.01
Parents	1.40	1	0.61	<.01

Table 8: ANCOVA Results for Comfort with Emotion AI in Education

* p < .05; ** p < .01

Public spaces. In addition to baseline controls, this model also accounted for variance explained by participants' reliance on public transportation. Gender differences were significant, with cisgender men ($t(591) = 3.03$, $p = .007$, $d = .41$) and cisgender women ($t(591) = 2.69$, $p = .01$, $d = .34$) being more comfortable than transgender and nonbinary individuals with the use of emotion AI in public spaces. Disability also showed significant effects, with disabled participants being less comfortable than those without disabilities ($t(591) = 2.28$, $p = .02$, $d = .20$). Further, age, perceived emotion AI accuracy, and comfort with happiness inference were positive predictors of comfort with emotion AI use in public spaces.

Variable	Sum of Squares	df	F	Effect Size (η_p^2)
Gender	15.09	2	4.80 **	.02
Disability	8.18	1	5.20 *	<.01
Race	2.49	1	1.58	<.01
Perceived EAI Accuracy	60.12	1	38.23 **	.06
Education	2.66	1	1.69	<.01
Income	3.48	1	2.21	<.01
Age	10.66	1	6.78 **	.01
Happiness	96.30	1	61.24	.09
Fear	5.58	1	3.55	<.01
Anger	2.33	1	1.48	<.01
Sadness	0.49	1	0.31	<.01
Public transport	1.14	1	0.73	<.01

Table 9: ANCOVA Results for Comfort with Emotion AI in Public Spaces

* p < .05; ** p < .01

Children's toys. In addition to baseline control variables, this model also accounted for participants' parental status. We observed significant contrasts regarding race in that white participants were significantly less comfortable than POC ($t(591) = -3.40$, $p = .007$, $d = -0.30$) with the use of emotion AI in children's toys. Additionally, perceptions of emotion AI accuracy, as well as comfort with happiness and fear inference were significant, positive predictors of comfort with emotion AI use in children's toys.

[3]Participants reported using a car (n = 490) or public transit (n = 32) as their primary mode of transportation.

[4]Participants reported having children (n = 269) or no children (n = 330).

Variable	Sum of Squares	df	F	Effect Size (η_p^2)
Gender	2.97	2	0.69	<.01
Disability	0.70	1	0.35 *	<.01
Race	25.76	1	11.98 **	.02
Perceived EAI Accuracy	70.81	1	32.92 **	.05
Education	2.08	1	0.97	<.01
Income	1.88	1	0.87	<.01
Age	1.66	1	0.74	<.01
Happiness	70.21	1	32.64 **	.05
Fear	37.69	1	17.53 **	<.01
Anger	0.76	1	0.35	<.01
Sadness	1.33	1	0.62	<.01
Parents	3.77	1	1.76	<.01

Table 10: ANCOVA Results for Comfort with Emotion AI in Children's Toys

* p > .05; ** p > .01

Border control. In addition to baseline controls, this model included variance explained by political orientation given the politicized nature of the use of AI to enhance border security [5]. Disability showed significant effects within this context, with disabled individuals being less comfortable with the use of emotion AI for border control than non-disabled participants ($t(591) = -3.04$, $p = .003$, $d = 0.27$). Additionally, more liberal participants were less comfortable with emotion AI use for border control. Further, age, perceived emotion AI accuracy, and comfort with happiness and anger inference were positive predictors of comfort with emotion AI for border control.

Variable	Sum of Squares	df	F	Effect Size (η_p^2)
Gender	3.31	2	0.66	<.01
Disability	22.90	1	9.19	<.01
Race	3.16	1	1.12	<.01
Perceived EAI Accuracy	72.10	1	28.95 **	.05
Education	1.39	1	0.56	<.01
Income	0.14	1	0.06	<.01
Age	37.63	1	15.11 **	.03
Happiness	21.89	1	8.79 **	.01
Fear	6.92	1	2.78	<.01
Anger	19.17	1	7.70	.01
Sadness	5.59	1	2.24	<.01
Political orientation	103.27	1	41.46 **	.03

Table 11: ANCOVA Results for Comfort with Emotion AI in Border Control

* p < .05; ** p < .01

Job interviews. In addition to baseline control variables, this model accounted for whether participants were actively looking for work [6]. Gender significantly impacted comfort with emotion AI use to evaluate job interviews. Cisgender men felt significantly more comfortable than cisgender women ($t(591) = 3.48$, $p = .001$, $d = 0.32$) with this use case. Disability also affected comfort with the use of emotion AI during job interviews, with disabled participants being less comfortable than those without disabilities ($t(591) = -3.15$, $p = .002$, $d = 0.26$). Additionally, older participants were more comfortable with emotion AI use in this context. Further, perceived emotion AI accuracy and comfort with happiness inference were significant predictors of comfort with emotion AI use in job interviews.

Variable	Sum of Squares	df	F	Effect Size (η_p^2)
Gender	22.64	2	6.07 **	.02
Disability	15.91	1	8.53 **	.02
Race	4.58	1	2.45	<.01
Perceived EAI Accuracy	117.53	1	62.99 **	.10
Education	0.37	1	0.20	<.01
Income	0.24	1	0.13	<.01
Age	22.27	1	11.94 **	.02
Happiness	45.51	1	24.40 **	.04
Fear	3.39	1	1.82	<.01
Anger	0.97	1	0.52	<.01
Sadness	3.47	1	1.86	<.01
Looking for Work	0.10	1	0.05	<.01

Table 12: ANCOVA Results for Comfort with Emotion AI in Job Interviews

* p < .05; ** p < .01

Social media. Disability significantly affected comfort with emotion AI use on social media, with disabled individuals reporting less comfort than non-disabled ones ($t(591) = -3.58$, $p = .004$, $d = 0.32$). Race also showed significant differences, with white participants less comfortable than POC ($t(591) = 2.06$, $p = .004$, $d = 0.18$). Further, perceived emotion AI accuracy, and comfort with happiness and fear inference were positive predictors of comfort with emotion AI use on social media.

Variable	Sum of Squares	df	F	Effect Size (η_p^2)
Gender	7.09	2	1.95	<.01
Disability	23.31	1	12.82 **	<.01
Race	7.71	1	4.24 *	<.01
Perceived EAI Accuracy	70.31	1	38.67 **	.06
Education	3.77	1	2.07	<.01
Income	0.20	1	0.74	<.01
Age	0.08	1	0.04	<.01
Happiness	16.78	1	9.23 **	.02
Fear	20.22	1	11.12 **	.02
Anger	0.63	1	0.35	<.01
Sadness	1.89	1	1.04	<.01

Table 13: ANCOVA Results for Comfort with Emotion AI in Social Media

* p < .05; ** p < .01

Consumer research. Disability significantly affected comfort with emotion AI usage for consumer research. Disabled individuals were significantly less comfortable than non-disabled individuals ($t(591) = -2.36$, $p = .02$, $d = -0.21$). Race also impacted comfort, with POC more comfortable than white participants ($t(591) = -2.57$, $p = .01$, $d = -0.22$). Further, perceived emotion AI accuracy and comfort with happiness inference positively predicted comfort with emotion AI use in consumer research.

[5] We measured political orientation on a 7-point Likert scale ranging from "Very conservative" to "Very liberal" (***M*** = 3.60, ***SD*** = 1.23).

[6] We asked about work status as a binary variable, where 55 people reported actively looking for work (See Appendix 1.5)

Variable	Sum of Squares	df	F	Effect Size (η_p^2)
Gender	4.94	2	1.41	<.01
Disability	9.71	1	5.57 *	<.01
Race	11.56	1	6.62 *	.01
Perceived EAI Accuracy	103.03	1	59.03 **	.09
Education	5.25	1	3.00	<.01
Income	0.22	1	0.72	<.01
Age	2.37	1	1.36	<.01
Happiness	48.05	1	27.53 **	.04
Fear	0.43	1	0.25	<.01
Anger	3.47	1	1.99	<.01
Sadness	4.37	1	2.50	<.01

* p < .05; ** p < .01

Table 14: ANCOVA Results for Comfort with Emotion AI in Consumer Research

Workplace. This model, in addition to baseline controls, controlled for variance that may be explained by participants' employment status. [7] Results demonstrate gender had a significant effect on comfort with emotion AI use in the workplace, with cisgender men being more comfortable than cisgender women ($t(591) = 3.63$, $p = .003$, $d = 0.34$) and transgender and nonbinary individuals ($t(591) = 2.43$, $p = .01$, $d = 0.33$). Race also mattered, with white participants less comfortable than POC ($t(591) = -3.06$, $p < .002$, $d = -0.27$). Additionally, disability affected comfort with emotion AI use in the workplace, with disabled participants less comfortable ($t(591) = -2.01$, $p = .045$, $d = 0.18$). Further, perceived emotion AI accuracy as well as comfort with happiness and fear inference were positive predictors. Lastly, higher income was associated with less comfort with emotion AI use in the workplace.

Variable	Sum of Squares	df	F	Effect Size (η_p^2)
Gender	21.62	1	6.96**	.02
Disability	6.25	1	4.02 *	< .01
Race	14.46	1	9.39 **	.02
Perceived EAI Accuracy	132.95	1	85.41 **	.13
Education	1.84	1	1.17	<.01
Income	7.19	1	4.69 *	< .01
Age	0.08	1	0.05	< .01
Happiness	33.72	1	21.44 **	<.01
Fear	12.57	1	8.03 **	.01
Anger	0.02	1	0.011	< .01
Sadness	2.97	1	1.90	< .01
Currently employed	0.28	1	0.18	< .01

Table 15: ANCOVA Results for Comfort with Emotion AI in the Workplace

* p < .05; ** p < .01

5 Discussion

This study contributes a comprehensive understanding of people's 1) general attitudes towards emotion AI, and 2) comfort with emotion AI use across 11 high-impact contexts, attending to identity and the role of AI-inferred emotion. Our findings contribute a quantitative characterization of public perceptions of emotion AI across contexts, showcasing differences across gender, race, and disability status. We discuss these findings' implications for emotion AI development, use, and regulation in the U.S.

5.1 Identity's Role in Comfort with Emotion AI and Emotion Inferences

Our findings offer quantitative evidence that race, gender, and disability influence comfort with emotion AI across high-impact contexts. This contrasts with previous research conducted in the U.K., which found no significant differences in comfort levels across contexts (such as entertainment and advertising), gender, socioeconomic status, or region [55]. We speculate that the difference between the U.S. and the U.K. studies may be the result of study scopes (e.g., our survey captures more contexts, identities, and factors), local differences in both privacy laws, and manifestation of identity-based discrimination.

Additionally, our findings extend qualitative investigations in the U.S. that focus on emotion AI in mental healthcare and the workplace, highlighting concerns raised by POC, gender minorities, and individuals with disabilities [20, 76]. This qualitative research suggests that subjects of emotion AI perceive its use as having the potential for identity-based discrimination and bias. Our findings quantitatively illustrate that identity factors do indeed significantly affect individuals' comfort (and thus, perceptions of risk) with emotion AI use. Taken together, our findings expand on existing literature in three key ways by: 1) examining a broader range of contexts; 2) quantitatively assessing general attitudes towards emotion AI; and 3) identifying differences in context-specific comfort levels related to gender, race, disability, and inferred emotions.

Gender. We found that cisgender men were significantly more comfortable with emotion AI than cisgender women in job interviews and the workplace, while also having more positive attitudes towards emotion AI in general. This is consistent with previous work which has found men to be more positive about (non-emotion-detecting) AI than women [35]. Cisgender men were also significantly more comfortable with emotion AI use in the workplace than transgender and nonbinary people. Acknowledging that emotion AI systems can suffer from gender bias [33, 100], these results quantify and generalize existing qualitative evidence [20, 78] which suggests that women may have unique concerns about emotion AI use in the workplace (e.g., additional emotional labor). Further, transgender and non-binary people often face negative job outcomes due to workplace inequities [7, 22], with one report finding that 47% of transgender respondents experience negative job outcome (e.g., fired, not hired, not promoted) due to their gender identity [34].

Our results indicate workplace and job interviews as two of the most highly uncomfortable contexts of emotion AI use for everyone. That cisgender men were the most comfortable group and transgender and nonbinary people were the least comfortable group in these contexts aligns with existing experiences of gender minorities in these contexts [84], suggesting that gender minorities' experiences and concerns should be prioritized in emotion AI deployments. The U.S. Equal Employment Opportunity Commission has referenced gender discrimination in the use of AI for hiring and workflow, indicating this to also be a priority for policymakers [28].

[7] We asked about employment status as a binary variable, where 393 people were currently employed (See Appendix 1.5)

Additionally, cisgender men and women were significantly more comfortable with emotion AI than transgender and nonbinary people in public spaces. This may be because transgender people experience more victimization in public spaces than cisgender people [29, 34], and as a result are more attuned to possible harms they may face from emotion AI surveillance in public spaces. This suggests the disparate impact emotion AI would have across gender groups if deployed to make inferences about people in public spaces.

It is unclear why we did not observe the above trend in other contexts such as healthcare where cisgender women [87], and transgender and nonbinary people [84] experience gender-based discrimination. It is possible that, while still overall uncomfortable, gender minorities anticipate comparatively more benefits of emotion AI use in healthcare than the workplace because they find the inference of affective states more *contextually* relevant in healthcare compared to work settings. These results, however, differ from findings on non-emotion-detecting AI use across domains (e.g., therapy, personal assistance, air traffic control). While this recent research found people similarly uncomfortable with AI across contexts, they identified AI in therapeutic and surgical roles as the *least* comfortable applications [62]. Interestingly, these cases would fall under the 'healthcare' category in our study, which participants rated as the most comfortable use case of emotion AI. This contrast reveals emotion AI as distinct from non-emotion-inferring AI, reinforcing the need for separate investigation.

Disability. Individuals with disabilities were significantly less comfortable with emotion AI than individuals without a disability when considering its use in cars, public spaces, job interviews, social media, consumer research, and the workplace. This finding corroborates and expands upon qualitative work regarding emotion AI deployment in the workplace and hiring [20, 69]. The discomfort expressed by individuals with disabilities may be shaped by awareness or sensitivity to existing disability bias in emotion AI [44, 60, 97] which may lead to negative consequences for people with mental illnesses [43, 59] or disabilities [60]. Our findings indicate that disabled people are not only significantly more uncomfortable with emotion AI use in the workplace and job interview contexts but also a range of other key contexts compared to individuals who are not disabled.

That being said, disability did not have a significant effect on comfort with emotion AI use in health, personal pursuits, education, children's toys, or border control. It is possible that disabled people feel less targeted in these contexts, given that some emotion AI proponents in healthcare, personal pursuits, education, and toys see disabled people as beneficiaries [60]. Future work should more deeply explore disabled people's perspectives on emotion AI use in these contexts to provide further explanation for our findings.

Race. POC have historically been subject to surveillance and discrimination [12]. It is notable that POC were significantly more comfortable than white people with emotion AI use across all contexts *except for* public spaces [88], border control [81], and job interviews [92]—three contexts in which POC experience some of the most racial prejudice.

To POC, more surveillance may not be new, but rather *expected*. This is not necessarily the case for many white people. That white people express more discomfort than POC, holding other pertinent identity factors constant, may be indicative of how an absence of regular surveillance may make people more sensitive and attuned to its nuisance. That we did not observe POC having significantly more discomfort compared to white respondents may signal digital resignation [25]—a sense of helplessness in controlling one's information and associated outcomes—which under conditions of being used to intense surveillance is a possible explanation for our findings. As such, we strongly caution against reading our findings as justification for deploying emotion AI in POC communities.

Taken together, these findings emphasize the importance of including identity factors (e.g., gender, race, disability) in an intersectional manner when examining perceptions about emotion AI or other emerging technologies. Our analytical approach allowed for an intersectionality-informed analysis [17, 17, 19] by examining people's comfort with emotion AI that is *simultaneously* sensitive to *multiple* identity factors.

5.2 Developing Emotion AI in the Absence of Regulation

Our findings provoke implications for the future of emotion AI system development. We advocate against the advancement and deployment of emotion AI, as our findings point to significant public discomfort across a number of high-stakes contexts, and often significantly more discomfort expressed by minoritized groups. That said, the following recommendations are based on the acknowledgment that effective regulation of emotion AI will take time, and its development, deployment, and use are likely to continue in the interim.

We wanted to understand how the emotion inferred by emotion AI impacted comfort levels with this technology. Notably, not only were people more comfortable with the inference of happiness than any other emotion, but this was predictive of comfort with emotion AI use across all contexts. This may be because emotions typically conceived as "negative" have more stigma attached to them [72], and by extension perhaps the inference of negative emotions may be deemed as stigmatizing [3]. In some contexts, however, comfort with other emotion types emerged as predictive of comfort with emotion AI use. For example, comfort with inference of fear was predictive of comfort with emotion AI use in healthcare, cars, social media, and the workplace. This may be because inferring when people are afraid, presuming this technology works accurately, may be perceived red as more beneficial than harmful in these contexts (e.g., to promote safety). Our results also demonstrate comfort with anger inference was predictive of comfort using emotion AI in border control. We speculate participants may believe the ability to accurately infer anger could be helpful in identifying dangerous individuals who may act on their anger; however, this is under the assumption that this technology works accurately for all, which it does not [71].

Realistically, many emotion AI systems do not simply infer positive emotions like happiness. They tend to be interested in inferring a range of emotional states and valences [11]. For instance, an existing mobile application aims to detect symptoms of depression through live analysis of facial expressions [46]. Our finding that people were the most comfortable with happiness inferences than other emotions challenge emotion AI developments such as those in mental healthcare, suggesting it would be unlikely for people to be comfortable with emotion AI that infers negatively-valenced emotions.

Further, our findings that people have varying levels of comfort across contexts, inferred emotions, and identities are important to emotion AI developers, who like many other AI developers [98], may not be know how to address the ethical implications of their technological developments. Knowing, for example, that disabled people are uncomfortable with emotion AI challenges the prevalent assumption that emotion AI helps improve the lives of disabled people [15] and can help shape developers' approaches to their work.

Additionally, emotion AI's potential inaccuracy is frequently noted as an ethical concern [6, 45]. While higher accuracy of emotion inference may spark more privacy concerns [36], our findings suggest the more accurate people perceive emotion AI to be, the more comfortable they are with its use. This is a hard tension to reconcile; while our findings may be interpreted as supporting the development of more accurate emotion AI systems to improve people's comfort, the comfort level is still low even in the most comfortable case of emotion AI deployment. These systems are likely to be developed and deployed across various contexts without regulation [52]. As such, it is essential for developers and vendors to transparently communicate about the accuracy of their products with prospective investors and deployers for different gender, race, and disability groups. Decision-makers, in turn, should convey this information to the individuals who may be affected by these systems. Furthermore, they must resist the temptation to treat the system's inferences as 'truth,' especially if they decide to deploy systems they know exhibit bias or inaccuracies for certain groups. However, simply providing this information is not sufficient to protect impacted groups from potential harms associated with emotion AI [1]. Therefore, regulation is essential to protect people against emotion AI harms.

5.3 Regulating Emotion AI and Emotion Data in the U.S.

Emotion AI—and by extension emotion data— is not regulated in the U.S. Evidence from this study suggests that it should be. We are certainly not alone in this assertion [2, 4, 21, 86]. Recognizing the complexity in regulating emotion data, law scholars have contemplated emotion data as thoughts and beliefs, protected health information, and "sensitive" personal identifiable data, among others [4]. Others have advocated for banning emotion AI entirely, citing the invalidity of facial emotion recognition's technological and theoretical foundations [5, 21, 85, 95] in particular. Emotion AI was recently banned in the EU as part of the AI bill in the workplace and education with the exception of safety and medical reasons [94]. This ban went into effect on August 1st, 2024. While this it is not perfect, the U.S. lags behind the EU in any regulation of emotion data and emotion AI.

This study provides much-needed empirical evidence for policymakers and advocates to approach emotion data regulation in the U.S. Our findings reflect a consistent discomfort with emotion AI use cases that are banned in the EU as well as medical and safety purposes that fall within the EU AI Act exception. While comfort varied across different contexts (Figure 2) with uses in healthcare as most comfortable followed by personal pursuits and cars, the overall comfort level was *still* low. That we find some contexts are less uncomfortable than others should not be read as those contexts being publicly acceptable use cases for emotion AI. In fact, our findings highlight medical and safety uses of emotion AI as uncomfortable to the U.S. public. Across our operationalizations of each context (see Table 2), medical-related use is reflected in healthcare, personal pursuits, and social media use cases. Safety is relevant in cars, public spaces, children's toys, border control, and social media. Taken together, we see that within a representative U.S. sample, medical and safety use cases of emotion AI are *also* uncomfortable. EU policymakers should consider investigating these other contexts more closely to guide future EU regulation. Further, U.S. policymakers should consider regulating emotion AI and emotion data *across* contexts rather than *select* contexts as the EU has done.

6 Conclusion

This study offers the first quantitative, cross-context evaluation of attitudes towards and comfort with emotion AI, considering both identity factors and specific inferred emotions. Our results demonstrate variance in comfort across contexts, with healthcare uses as most comfortable and workplace uses as least comfortable. However, individual's comfort with emotion AI use is notably low across *all* contexts. Further, minority gender groups and individuals with disabilities consistently report lower comfort levels with emotion AI across contexts. This underscores the necessity for those making development and deployment decisions for emotion AI to account for comfort levels and associated identity-based disparities, particularly in the absence of regulation. The widespread discomfort across different contexts highlights the urgent need for restrictive regulations in the U.S. As emotion AI becomes more mainstream, and given the relevance of emotions to all humans, protecting emotion data is critical.

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A Appendix

A.1 Survey Instrument

A.1.1 General Attitudes.

- I believe that emotion AI will improve my life.
- I believe that emotion AI will improve my work.
- I think I will use emotion AI technology in the future.
- I think emotion AI technology is positive for humanity.

A.1.2 Comfort with Emotion AI. All items followed the prompt: "I would feel comfortable with emotion AI being used…".

Healthcare.

- ...by my healthcare providers to improve diagnostics in my mental healthcare.
- ...in my home so my doctors can keep track of my emotional states as associated with my health.
- ...by my healthcare providers to improve treatment and intervention in my mental healthcare.
- ...in senior living facilities to report residents' emotional state to their healthcare providers.

Personal Pursuits.

- ...to infer my emotions using a wearable device so I can reflect on and gain more insights into my emotional life.
- ...to infer my emotions using a smart home device (e.g., Alexa, Google Home) so I can reflect on and gain more insights into my own emotional life.

Cars.

- ...in cars to infer my stress while driving to improve safety.
- ...in cars to infer my distraction while driving to improve safety.
- ...in cars to infer my fatigue while driving to improve safety.
- ...in cars to infer my stress, fatigue, or distraction while driving to inform my insurance rates.

Education.

- ...by schools to assess student engagement and attention to improve student learning.

Public Spaces.

- ...by public transportation authorities to infer passengers' emotions to increase safety.
- ...by public entertainment venues like stadiums and parks to infer people's emotions to improve safety and security.
- ...by airport security to infer people's truthfulness to improve security and safety.
- ...by governments in public spaces to identify potential malicious actors.

Children's Toys.

- ...by Internet-connected toys to infer and report a child's emotional state to parents, such as whether they are happy, stressed, angry, or sad.
- ...in Internet-connected toys to infer a child's emotional state to report to appropriate authorities if inferred that a child might be being abused, self-harming, or otherwise highly distressed.

Border Control.

- ...by the government to infer the truthfulness of individuals trying to enter the US as immigrants to improve security and safety.
- ...by the government to infer the truthfulness of individuals trying to enter the US as asylum seekers to improve security and safety.

Job Interviews.

- ...by employers during video interviews to assess my fit for the job.
- ...by employers during video interviews to assess my true interest in the job.
- ...by employers during video interviews to assess my qualifications for the job.
- ...by employers during video interviews to infer my truthfulness.

Social Media.

- ...by social media companies to infer if I am in emotional distress and may need social support.
- ...by social media companies to infer if I am in emotional distress and may need to be admitted to a psychiatric hospital.
- ...by social media companies to infer if I am in emotional distress and may hurt myself.
- ...by social media companies to infer if I am in emotional distress and may hurt others.

Consumer Research.

- ...by online advertisers to tailor ads I see to my emotional state.
- ...by advertisers to tailor outdoor ads I see in public to my emotional state.
- ...by retail stores to infer customers' emotions to increase sales.

Workplace.

- ...by my employer to assess my work performance.
- ...by my employer to assess if I need emotional or mental health support.

A.1.3 Perceptions of Emotion AI Accuracy.

- Emotion AI would make accurate inferences about me.

A.1.4 Comfort with Emotion Inference.

- Emotion AI tools may infer a range of emotions about people. Please indicate your comfort level for emotion AI tools that infer the following: happiness, surprise, sadness, anger, disgust, fear.

A.1.5 Demographics.

- **Gender**: Woman, Man, Nonbinary, Not sure, Prefer to self-describe.
- **Transgender Status**: Yes, No, Not sure, Prefer to self-describe.
- **Race/Ethnicity**: American Indian or Alaska Native, East Asian, Black or African American, Hispanic or Latino, Middle Eastern, Native Hawaiian or Pacific Islander, South Asian, Southeast Asian, White, Prefer to self-describe. (Participants could select more than one option.)
- **Disability Status**: None, Deaf or have serious difficulty hearing, Blind or have serious difficulty seeing, Mobility limitation, Motor limitation, Learning disability, Neurodiverse, Speech or language impairment, Chronic illness, Mental health condition, Prefer to self-describe.
- **Education Level**: Less than high school, High school diploma or equivalent, Some college, Bachelor's degree, Some graduate school, Master's or professional degree, Doctoral degree.

- **Income Level**: Less than $20,000; $20,000–$34,999; $35,000–$49,999; $50,000–$74,999; $75,000–$99,999; $100,000–$149,999; $150,000–$199,999; $200,000–$249,999; $250,000 or more.
- **Employment Status**: Employed full-time, Employed part-time, Unemployed and looking for work, Unemployed and not looking for work, Stay-at-home parent, Student, Military, Retired, Unable to work, Prefer to self-describe.
- **Political Orientation**: Very conservative, Conservative, Moderate, Liberal, Very liberal, Prefer to self-describe.
- **Primary Means of Transportation**: Personal vehicle, Ride-sharing apps/cabs, Train/Metro/Subway, Air travel, Other.
- **Parental Status**: I have children in K-12 school, I have children in college/university, I have working adult children, I have no children.

Table 16: Estimated Marginal Means (EMM) for Significant Contrasts

Variable	Contrast	EMM	SE	95% CI
General attitudes	Cis Man	3.46	0.07	3.32 – 3.59
	Cis Woman	3.24	0.07	3.10 – 3.38
	Trans/Nonbinary	3.19	0.11	2.98 – 3.39
	POC	3.44	0.06	3.32 – 3.56
	Non-POCs	3.44	0.06	3.32 – 3.56
Healthcare	POC	3.76	0.09	3.62 – 3.91
	Non-POCs	3.48	0.07	3.34 – 3.62
Cars	Disabled	3.39	0.10	3.19 – 3.59
	No Disability	3.62	0.09	3.44 – 3.81
	POC	3.62	0.09	3.44 – 3.81
	Not POC	3.38	0.09	3.20 – 3.57
Public spaces	Cis Man	3.27	0.10	3.08 – 3.46
	Cis Woman	3.17	0.09	3.00 – 3.35
	Trans/Nonbinary	2.75	0.14	2.47 – 3.03
	Disabled	2.94	0.08	2.77 – 3.10
	No Disability	3.19	0.10	3.00 – 3.38
Children's toys	POC	3.33	0.10	2.71 – 3.08
	Not POC	2.89	0.09	3.14 – 3.52
Border control	Disabled	2.84	0.10	2.65 – 3.03
	No Disability	3.27	0.11	3.06 – 3.48
Job interviews	Cis Man	2.68	0.13	2.43 – 2.94
	Cis Woman	2.24	0.12	2.01 – 2.47
	Trans/Nonbinary	2.34	0.16	2.02 – 2.66
	Disabled	2.24	0.11	2.02 – 2.47
	No Disability	2.60	0.12	2.02 – 2.47
Social media	Disabled	2.17	0.08	2.01 – 2.33
	No Disability	2.59	0.09	2.42 – 2.77
	POC	2.50	0.09	2.33 – 2.67
	Not POC	2.26	0.09	2.10 – 2.42
Consumer research	Disabled	2.24	0.08	2.09 – 2.40
	No Disability	2.52	0.09	2.34 – 2.69
	POC	2.53	0.08	2.36 – 2.70
	Not POC	2.23	0.09	2.07 – 2.39
Workplace	Cis Man	2.61	0.09	2.43 – 2.80
	Cis Woman	2.19	0.08	2.04 – 2.34
	Trans/Nonbinary	2.20	0.14	1.93 – 2.47
	Disabled	2.22	0.08	2.08 – 2.37
	No Disability	2.45	0.08	2.28 – 2.62
	POC	2.50	0.08	2.34 – 2.67
	Non-POCs	2.17	0.08	2.01 – 2.32

EMM = Estimated Marginal Means; SE = Standard Error; CI = Confidence Interval. EMMs are means of each identity factor, averaging over other identity factors (i.e., EMMs for gender are averaged over disability and race) and controlling for the continuous variables included in each model. The SE is a measure of how much the EMM varies from the true population mean. The 95% CI tells us the range of values within which we are 95% confident the true population mean lies.