

# Emotion AI in Job Interviews: Injustice, Emotional Labor, Identity, and Privacy

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## Abstract

The use of emotion artificial intelligence to evaluate job-seekers during the interview process raises concerns about injustice, particularly among minoritized individuals. However, we know little about how job-seekers experience emotion AI interviews compared to non-emotion AI or human resources (HR) interviews. We address this gap through a 3(Evaluation Source: Emotion AI, AI, HR) x 2(Outcome Favorability: Recommended, Not Recommended) experiment. Participants ( $n = 456$ ) underwent a mock interview assuming real-time evaluation. We find those who partook an interview evaluated by emotion AI perceived significantly lower levels of justice than that evaluated by HR, with this relationship partially dependent on outcome favorability. Additionally, identity attributes (e.g., gender, race, disability) and privacy concerns significantly influenced the information disclosed and emotional labor exerted during the interview. We discuss practical implications for emotion AI use in job interviews as well as broader methodological implications for capturing real-time engagement with AI systems.

## CCS Concepts

• Security and privacy → Privacy protections; • General and reference → Experimentation; • Social and professional topics → User characteristics.

## Keywords

emotion recognition, affective computing, emotional labor, organizational justice, information disclosure, hiring, employment, future of work

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## 1 Introduction

Emotion artificial intelligence (emotion AI) refers to a class of affective computing technologies [76] that uses computational techniques [90] promising to infer people's emotions [59] through analyzing data such as facial expression, tone of voice, language, and

body gestures [60]. Emotion AI has been deployed across industries including health [42, 54, 86], education [60], advertising [65], automotive [50], the workplace [88], and hiring [81, 87]. In fact, the emotion AI market is expected to exponentially increase from its current levels. One report estimates its market value will reach \$42.9 billion by 2027 [56]. Despite its growth, researchers have challenged its scientific validity [9, 96], accuracy [44, 54], and bias [54], along with ethical [4, 96] and privacy concerns [21, 62].

Emotion AI has received targeted scholarly and practical attention in the context of hiring, where it serves as an evaluator of job-seekers' virtual interview performance [81, 87]. Qualitative evidence suggests job-seekers perceive injustice and foresee the exertion of additional emotional labor if emotion AI is used in virtual job interviews [81]. This unjust reality contrasts with promises from emotion AI hiring vendors to improve accuracy and fit or reduce bias in hiring [87]. That being said, we lack a real-time assessment of individuals' experiences with and perceptions of an asynchronous job interview that is evaluated by emotion AI, including how its use may impact disclosure and exerted emotional labor. This is important not only because of the implications emotion AI use may have on job-seekers' livelihoods, but also due to the absence of reliable audits of existing systems [30] and the challenges those who may wish to audit these systems face [12]. Calls for greater fairness, justice, and protections against harms in algorithmic hiring [91] are even more pertinent with the inclusion of *emotion* data given its highly intimate nature [60] and private dimensions [4].

This study builds on qualitative research which has explored emotion AI use in hiring [81, 87] and experimental work which has uncovered the differences between virtual interviews conducted by AI and a human [64, 99]. It remains unclear how the presence of *emotion inference* engenders unique responses and perceptions about a virtual job interview. In light of this, we investigate individuals' interactions with an emotion AI hiring system, parsing distinct responses in terms of 1) disclosure, 2) justice, and 3) emotional labor as compared to alternative interview evaluators (i.e., AI without emotion inference capabilities, human resource (HR) professionals).<sup>1</sup> This comparison will demonstrate the causal effect of algorithmic emotion inference in hiring on job-seekers' behaviors and perceptions. Further, we examine how privacy concerns and identity factors like race, gender, and disability shape these relationships, as individuals from minoritized groups along these axis often bear the brunt of negative surveillance impacts [69, 84]. Building on previous research [1, 8] we also address how favorability of the interview outcome may moderate the relationship between the



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<sup>1</sup>Any reference to "asynchronous" or "virtual" job interviews/hiring systems throughout this paper maintains characteristics shared by all three interview systems.

evaluation source and perceptions of justice. An illustration of our conceptual framework is included in Figure 1.

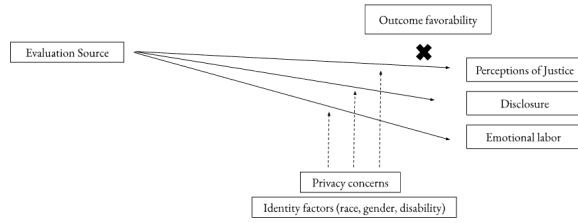


**Figure 1: Conceptual Framework.** The straight lines represent direct relationships whereas the dashed lines represent the moderating relationships explored in this study. The "X" represents an interaction effect between "Evaluation source" and "Outcome favorability" on "Perceptions of justice".

We conducted an online experiment with a representative United States (U.S.) sample and oversampled for individuals with disabilities, people of color (POC), and transgender and non-binary people ( $n = 456$ ). All participants underwent a mock virtual interview during which they were under the impression they were being evaluated by emotion AI, AI with no emotion inference capabilities, or an HR professional. After answering a series of interview questions via a video recording and being randomly presented with an outcome for their performance (favorable/unfavorable), participants answered questions about their experience.

Based on a real-time experience with an asynchronous mock interview, our findings demonstrate emotion AI is indeed perceived as an unjust evaluator for hiring compared to both non-emotion AI and HR. Regarding emotional labor, variation across gender, race, and disability status suggest emotion AI may struggle to capture a universally "authentic" representation of job-seekers, despite contrary claims by hiring system vendors [87]. Similar findings arise with respect to privacy concerns, highlighting the need for greater emphasis on safeguarding personal information to protect the integrity and authenticity of emotional expressions. We discuss implications for the use of emotion AI in hiring and contribute a higher level methodological advance regarding the ethical use of deception to observe real-time behavior in human subjects research.

## 2 Relevant Work

### 2.1 A Marketplace of Emotions: Excitement Overshadowed by Concern

Emotion AI proponents tout the benefits of emotion inference, citing the ability to better serve both citizens and organizations [58] as motivation to use emotion AI when warranted [60]. Claimed benefits include improving worker well-being by detecting signs of deflated mental health [21, 101], finding the best candidates for a job [87], or to effectively deliver consumer advertisements [60].

Despite growing interest [56], the use of emotion AI raises privacy [13, 21, 58, 88] and manipulation [4, 7] concerns due to the highly intimate nature of emotion data [4]. In fact, a recent empirical examination of the U.S. public's comfort with emotion AI

revealed discomfort across contexts of deployment [5]. For example, workers subjected to emotion AI wish to know *what* emotion inferences are going to be used for and *who* they will be shared with [24]. Further, emotion AI's scientific validity and accuracy has been contentious. Crawford & Paglen [22] argue a baseline problem with emotion AI is that it assumes that facial expressions are indicative of underlying emotion, fixed across all individuals. Indeed, most emotion AI systems draw from Basic Emotion Theory (BET), which identifies six universal emotions: happiness, sadness, fear, disgust, anger, surprise [27]. This theoretical paradigm to understand emotions has been heavily critiqued in emotion science [9, 47] and beyond [96], even referred to as "dangerous" [78]. Related to emotion AI's validity concerns are those around accuracy and bias [21, 33, 49, 66, 86]. Kaur et al. [44] show self-reported and observed emotion as inferred by emotion AI are not aligned [44]. Despite efforts to address these concerns [36, 104], there is evidence that emotion AI reinforces gender, racial, and disability biases [15, 43, 53, 66, 85, 102]. Thus, incorporating perspectives from minoritized individuals is crucial.

### 2.2 Emotions for Hire

Emotion AI has gained particular attention for its use in hiring [81, 87, 99], celebrated for its purported ability to reduce labor costs in initial screening interviews [108] as well as improve fit and reduce bias [87]. Emotion AI systems used in hiring typically include a virtual asynchronous platform where a job-seeker is required to upload a video answering interview questions or take employment tests without interacting with a human. A recent interview study with job-seekers highlighted concerns about this usage of emotion AI, including that surrounding the use of emotion data to inform hiring decisions [81]. Research has found people to be concerned about interview evaluators taking emotional displays out of context [44] in addition to broader worries about privacy, emotional burden, and manipulation [70]. For individuals with disabilities, who are already disadvantaged when seeking employment including in the presence of predictive technologies [16, 31, 31], emotion AI may be particularly discriminatory [66]. A recent report found individuals with disabilities perceive digitized hiring evaluations as not only unfair, but also emotionally burdensome [52].

Researchers have taken an experimental approach to compare job interviews evaluated by (non-emotion detecting) AI or a human [1, 8, 48, 71]. Results have been mixed; further, this work has not integrated the presence of *emotion* inference. Emotion inference is important given the uniquely intimate nature of emotion data [4]. Thus, this study's real-time assessment of interviews with asynchronous hiring systems—including one using emotion AI—fills a gap in the literature.

### 2.3 Chilling Opportunities at Employment

Assessing disclosure during interviews which are actively evaluated by emotion AI is one way to examine emotion AI's impact on job-seekers. The presence of emotion AI monitoring during an interview may have a chilling effect on information disclosure, thereby negatively influencing interview performances. Chilling effects refer to a conformity to opinions deemed more acceptable given the fear of surveillance-based consequences [74]. Indeed,

people alter their behavior with knowledge of being surveilled [55, 75]. For example, researchers demonstrated a chilling effect as a result of constant monitoring in educational settings [35, 83], where students expressed "discouragement" and "panic" in class [35]. Emotion AI heightens the level of surveillance beyond simply watching people given its collection of highly intimate data to make emotion inferences [4, 61].

With surveillance across video interviews being constant, research has distinguished behavioral differences on the basis of the *evaluator*. One study revealed that people prefer interviews evaluated by humans (i.e., "the devil they know") as opposed to AI [64]. However, a preference for human evaluation is not consistent across empirical research [77, 98]. It is possible that video interviews, as compared to text-based evaluation modalities, may contribute to a sense of discomfort regardless of the evaluation source [67]. That being said, video modality is appropriate to test the impact of emotion AI in an ecologically valid manner [99]. Given the discomfort data subjects have expressed about emotion AI's use in hiring, in addition to the higher sensitivity of information collected as compared to other asynchronous interviews, we hypothesize the following:

**H1: Compared to non-emotion AI or a HR interview, participants who engage in an emotion AI interview will have lower levels of disclosure.**

## 2.4 Putting in the Work to Get Work

When emotion AI is evaluating interviews, job-seekers may perceive a risk of heightened emotional labor [40, 81]. In traditional interview settings, emotional labor has a direct impact on job-seekers [51]. This may be particularly high when individuals lack feedback [51], as is the case in many existing emotion AI hiring services. However, this may also be the case in other types of asynchronous virtual interviews. Given the lack of evidence differentiating emotion AI interviews from alternative asynchronous interviews regarding emotional labor, we ask the following research question:

**RQ1: How does the exertion of emotional labor differ for individuals evaluated by emotion AI compared to HR or non-emotion AI during a virtual job interview?**

## 2.5 An Organizational Justice Lens

Concerns around injustice in AI and emotion AI use in hiring [8, 11, 81] necessitate this study's use of an organizational justice lens. Evaluations of organizational justice typically incorporate procedural, distributive, and interactional justice. *Procedural justice* refers to how decisions are being made [23], whereas *distributive justice* pertains to equitable allocations of rights and rewards [20]. *Interactional justice* concerns interpersonal treatment perceived during the process [18, 23]. Previous work has explored participants' reflections on AI use in interviews through an organizational justice lens [1, 64, 81]. Pyle et al. [81] found job-seekers perceived emotion AI to make inaccurate inferences (distributive injustice), contain identity related bias (procedural injustice), and lack meaningful transparency (interactional injustice). While Pyle et al. [81] present insightful findings, their methods do not capture job-seekers' actual experiences with emotion AI interviews. We hypothesize individuals who are subject to emotion AI during an interview will perceive

the experience as significantly less just than those who are evaluated by non-emotion detecting AI or HR.

**H2: Compared to non-emotion AI or HR, individuals subject to the evaluation of emotion AI during a job interview will perceive significantly lower a) procedural, b) distributive, and c) interactional justice.**

Perceptions of justice may also be shaped by favorability of the outcome received [1, 68]. For example, workers have reported to perceive positive outcomes decided by either AI or human evaluators as more respectful (i.e., interactional justice) than negative outcomes [8]. We predict an interaction effect between outcome favorability and perceptions of justice.

**H3: Outcome favorability will moderate the relationship between evaluation source and perceptions of organizational justice.**

## 2.6 Centering Individuals Most Likely to be Negatively Impacted

Similar to non-emotion detecting AI [8, 93], deploying emotion AI for hiring may disproportionately subject minoritized individuals to harm [41, 53]. Qualitative work on emotion AI use in the workplace, hiring, and healthcare has showcased this, providing evidence that people with disabilities, people of color, and those of minoritized genders anticipate risks associated with emotion AI [21, 81, 86]. These findings have been replicated quantitatively across contexts of emotion AI deployment, including job interviews [5]. Additionally, women [63] and POC [10] have historically been subjected to higher emotional labor expectations. However, previous emotion AI-related insights are based on hypothetical scenarios and are not generalizable. The surveillance afforded by emotion AI may heighten undesirable reactions during interviews for those who have previous experience of being over-surveilled. We pose the following research question:

**RQ2: How do a) race, b) gender, and c) disability impact the relationship between interview evaluation source and job-seekers' perceptions of organizational justice, emotional labor, and disclosure?**

Finally, it is possible that the variance in the aforementioned dependent variables may be partially explained by the privacy concerns participants have about the interview process [45]. Thus, our analysis as described hereafter will control for privacy concerns.

## 3 Methodology

### 3.1 Study Design

We employed a 3(Evaluation Source: Emotion AI, AI, HR) x 2(Outcome Favorability: Recommended, Not Recommended) between-subjects experimental design.

### 3.2 Participants

Participants were recruited from Prolific, which produces higher data quality than similar recruitment sources [73]. We recruited a representative adult U.S. sample and oversampled for individuals who may be disproportionately impacted by the use of emotion AI in hiring: people of color, transgender and non-binary individuals, and individuals reporting as having one or more disability ( $n = 456$ ).

In terms of gender, our sample included cisgender women ( $n = 207$ ), cisgender men ( $n = 193$ ), non-binary ( $n = 20$ ), and transgender ( $n = 36$ ) individuals. In terms of race, our sample included white ( $n = 256$ ), Black or African American ( $n = 105$ ), Hispanic or Latino ( $n = 38$ ), Asian ( $n = 23$ ), American Indian/Alaska Native ( $n = 8$ ), Middle Eastern ( $n = 3$ ), Native Hawaiian or Pacific Islander ( $n = 1$ ), or Mixed race ( $n = 22$ ) participants. Additionally, many reported having at least one disability ( $n = 159$ ) with some having multiple disabilities that impact their daily lives ( $n = 34$ ). A notable portion of participants were actively looking for a job ( $n = 183$ ).

### 3.3 Experimental Procedure

Participants were given the following directions about the study procedure:

*"We are creating a system that helps match job-seekers with open positions of interest. Based on a brief video interview, the system can determine whether a candidate should be recommended or not recommended for a position of interest, assuming there are relevant openings. We are currently testing our system and seeking to understand perceptions about the process and outcomes it produces.*

*Today, you will take part in a video interview that uses this system. We will then provide your outcome and kindly ask you to complete a brief survey to help improve our system for the future."*

Following previous work [49], we then asked participants to indicate a job they would be interested in applying for and instructed them to proceed under the assumption that they were interviewing for that specified role. Review of these responses confirmed variability in the roles of interest. Depending on the condition, we then informed the participants that their responses would be evaluated by emotion AI ( $n = 175$ ), AI ( $n = 139$ ) or a HR representative ( $n = 142$ ). To heighten the manipulation's salience, this was followed by a visual prompt that the system had begun monitoring. This monitoring indicator was present throughout the interview, with a banner above the video recorder indicating they were being monitored by emotion AI/AI/HR. Previous experimental design has similarly given participants the false impression they were interacting with AI through visual and textual cues [48, 51, 89, 99]. Once participants were familiar with the purpose and direction of the study, we prompted them to start the video recording and respond to six interview questions [49] one at a time.<sup>2</sup> After completing the questions, participants submitted their video file. These files were automatically submitted to file.io, which facilitated the temporary storage of encrypted data files through a private API key only accessible to one of the researchers. Although participants were under the impression that their videos were being recorded for analysis, only audio was collected. File.io automatically deleted audio files once they were downloaded to one of the researcher's secure computer for analysis.

When participants completed the interview, we told them the system was processing their responses to generate an outcome. Qualtrics automatically directed them to the next page after 30 seconds of "processing," where the system randomly decided if they had been recommended ( $n = 234$ ) or not recommended ( $n = 229$ ) for their job of interest. Participants then answered a series

<sup>2</sup>All interview questions can be found in Appendix A.1. Participants could take as much time as they wanted to respond to each question.

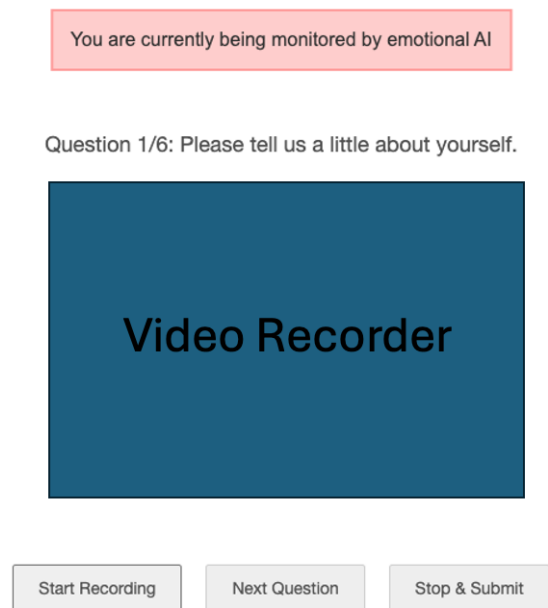


**Figure 2: Video Recording Interface for Mock Interview. Participants were instructed to click "Start Recording" when ready to begin. Participants were then able to click through each of the 6 interview questions by clicking "Next Question". When they were finished with the interview, they were instructed to hit "Stop & Submit".**

of questions directly reflecting on their interview experience. Finally, participants responded to demographic questions and were debriefed about the nature of the study.

### 3.4 Measures

All quantitative measures were evaluated on a 7-point Likert scale ranging from 1 ("Strongly disagree") to 7 ("Strongly agree") unless otherwise noted. All scale items are included in Table 1 in Appendix B.

**3.4.1 Disclosure.** We measured disclosure through analysis of interview word count [46]. Interview audio files were transcribed using Whisper Transcription. We supplemented this real-time measure of *actual* disclosure with a six-item scale measuring the *perceived* breadth of information shared [77] ( $M = 4.36$ ;  $SD = 1.08$ ;  $\alpha = .79$ ).

**3.4.2 Emotional labor.** We measured emotional labor using an adapted scale which segmented this construct into *deep acting* and *surface acting* [17]. While surface acting involves externally representing different emotions to those actually felt, deep acting requires a modification of inner feelings [32]. Following the prompt "During the interview I..." we asked participants to rate their level of agreement with statements which reflected surface acting ( $M = 2.54$ ;  $SD = 1.32$ ;  $\alpha = .86$ ) and deep acting ( $M = 4.49$ ;  $SD = 1.51$ ;  $\alpha = .92$ ).

**3.4.3 Perceptions of justice.** We measured justice perceptions across three dimensions comprising organizational justice. Procedural justice ( $M = 5.02$ ;  $SD = 1.10$ ;  $\alpha = .83$ ) was measured across six adapted items [18]. Distributive justice ( $M = 5.21$   $SD = 1.31$ ;  $\alpha = .95$ ) was measured across four adapted items [18]. To measure interactional justice, we used the treatment subset of Acikgoz et al.'s [1] scale ( $M = 5.21$ ;  $SD = 1.32$ ;  $\alpha = .92$ ).

**3.4.4 Privacy concerns.** We measured privacy concerns across three sub-dimensions developed by previous research [14]: perceived intrusion ( $M = 2.99$ ;  $SD = 1.57$ ;  $\alpha = .91$ ), perceived surveillance ( $M = 3.44$ ;  $SD = 1.53$ ;  $\alpha = .83$ ), and secondary usage ( $M = 3.45$ ;  $SD = 1.84$ ;  $\alpha = .97$ ).

## 3.5 Limitations

We took great care in designing this study to mimic a realistic interview experience. That being said, it is important to note this study's limitations. Despite our robust and ecologically valid methodology, a between-subjects design does not allow for the same individuals to reflect upon different source evaluations and outcomes. Moreover, like all controlled experimental studies [79], our findings lack high generalizability. However, we enhanced this through recruiting a representative sample and creating strong operationalizations for our manipulated variables [39]. In addition, it is possible our findings may be further explained by personality type [72] or digital literacy, which were outside of the scope of this study. We also elected to not collect or analyze participants' video data given the limited validity of nonverbal data when assessing mock interviews [38] in addition to our desire to maintain participant anonymity. Finally, we report on all significant findings, including those where  $\eta_p^2 < .01$ . Results with small effect sizes should be interpreted with caution.

## 4 Results

All relevant statistical assumptions were met prior to running analyses (e.g., linearity, normality of residuals, multicollinearity, equal distribution of variance across groups). Unless otherwise noted, each model contained the same control variables.<sup>3</sup>

### 4.1 Disclosure

**H1** predicted that compared to non-emotion AI and HR interviews, participants who participate in an emotion AI interview will have the lowest levels of disclosure. As previously mentioned, we analyzed disclosure in two ways: actual disclosure (word count) and perceived disclosure sensitivity (See Table 2 in Appendix A).

**4.1.1 Actual Disclosure:** When regressing on actual disclosure, 81 participants were excluded due to unusable transcripts.<sup>4</sup> The source of evaluation had no direct effect, so H1 was not supported. Gender showed a small but significant effect (partial  $\eta^2 < .01$ ): compared to cisgender men, cisgender women disclosed less ( $b = -70.53$ ,  $SE = 34.50$ ,  $p = .04$ ) and transgender individuals disclosed more

( $b = 137.63$ ,  $SE = 69.01$ ,  $p = .05$ ). In addition, current job-seekers had higher actual disclosure than participants who were not actively on the job market ( $b = 76.65$ ,  $SE = 32.84$ ,  $p = .02$ , partial  $\eta^2 < .01$ ).

**4.1.2 Perceived Disclosure:** Compared to emotion AI, neither evaluation by non-emotion AI ( $b = 0.01$ ,  $SE = 0.04$ ,  $p > .05$ ) nor HR ( $b = 0.03$ ,  $SE = 0.12$ ,  $p > .05$ ) had a significant impact on perceived disclosure, similarly opposing H1. That being said, across dimensions of privacy concerns, we found perceived intrusion to be positively predictive of perceived disclosure ( $b = 0.18$ ,  $SE = 0.04$ ,  $p < .001$ , partial  $\eta^2 = .03$ ), whereas concerns about secondary usage were negatively predictive of perceived disclosure ( $b = -0.09$ ,  $SE = 0.04$ ,  $p = .02$ , partial  $\eta^2 = .01$ ). Gender also significantly affected perceived disclosure (partial  $\eta^2 = .03$ ), with non-binary participants ( $b = -0.78$ ,  $SE = 0.10$ ,  $p = .002$ ) and cisgender women ( $b = -0.31$ ,  $SE = 0.10$ ,  $p = .003$ ) perceiving to have disclosed significantly less than cisgender men during the interview.

## 4.2 Emotional Labor

**RQ1** pertained to understanding if individuals evaluated by emotion AI would exert higher emotional labor than those evaluated by non-emotion AI or HR. We assessed emotional labor through both surface acting and deep acting (See Table 3 in Appendix A).

**4.2.1 Surface Acting:** Compared to emotion AI, evaluations by non-emotion AI ( $b = -0.07$ ,  $SE = 0.14$ ,  $p = .62$ ) and HR ( $b = 0.12$ ,  $SE = 0.14$ ,  $p = .40$ ) did not significantly influence surface acting. However, perceived intrusion ( $b = 0.21$ ,  $SE = 0.05$ ,  $p < .001$ , partial  $\eta^2 < .01$ ) and secondary usage ( $b = 0.12$ ,  $SE = 0.04$ ,  $p = .01$ , partial  $\eta^2 < .01$ ) were positively predictive of surface acting, indicating increased privacy concerns about data collection and usage led to more emotional labor. Additionally, younger individuals reported significantly higher levels of surface acting ( $b = -0.01$ ,  $SE = 0.00$ ,  $p = .02$ , partial  $\eta^2 < .01$ ).

**4.2.2 Deep Acting:** Compared to emotion AI, evaluations by non-emotion AI ( $b = 0.11$ ,  $SE = 0.17$ ,  $p = .51$ ) and HR ( $b = -0.01$ ,  $SE = 0.17$ ,  $p = .99$ ) did not significantly affect deep acting. In terms of race, Hispanic or Latino participants showed significantly higher levels compared to white participants ( $b = .59$ ,  $SE = 0.29$ ,  $p = .01$ , partial  $\eta^2 < .01$ ). On gender, we found cisgender women engaged in less deep acting than cisgender men ( $b = -0.37$ ,  $SE = 0.15$ ,  $p = .01$ , partial  $\eta^2 < .01$ ). Disability status also had a significant effect: individuals without disabilities reported less deep acting than those with disabilities ( $b = -0.43$ ,  $SE = 0.16$ ,  $p = .007$ , partial  $\eta^2 < .01$ ).

**4.2.3 Posthoc Analysis - Emotional Labor Under the Evaluation of Emotion AI.** : Given our core interest in emotion AI's impact, we ran a posthoc analysis with participants who underwent an interview with emotion AI ( $n = 175$ ) (See Table 5 in Appendix B). We also expanded the disability variable to analyze differences in perceptions across specific disabilities. Given the small samples of people with specific disabilities, these results should be interpreted with caution.<sup>5</sup> Perceived intrusion remained a significant positive predictor of surface acting ( $b = 0.28$ ,  $SE = 0.16$ ,  $p < .001$ , partial

<sup>3</sup>Control variables included in the models were: gender, race, disability status, age, job-seeking status, previous experience with virtual interviews, and privacy concerns (i.e., perceived intrusion, secondary usage, and perceived surveillance)

<sup>4</sup>Transcripts were discarded if audio was not effectively captured. This may have occurred in cases where participants had weak Internet connectivity or were doing the interview in the presence of substantial background noise.

<sup>5</sup>Demographics of the participants included in this analysis can be found in Appendix B.1

$\eta^2 = .18$ ). Additionally, perceived surveillance was predictive of deep acting ( $b = -0.34$ ,  $SE = 0.14$ ,  $p = .02$ , partial  $\eta^2 = .05$ ). This posthoc analysis also identified that compared to people with no disabilities, neurodiverse participants ( $b = -1.11$ ,  $SE = 0.55$ ,  $p = .05$ , partial  $\eta^2 = .11$ ) and those with a mental health condition ( $b = -0.73$ ,  $SE = 0.31$ ,  $p = .02$ , partial  $\eta^2 = .11$ ) reported significantly less surface acting. Additionally, people with multiple disabilities reported significantly lower levels of deep acting than participants with no disabilities ( $b = -1.34$ ,  $SE = 0.55$ ,  $p = .02$ , partial  $\eta^2 = .07$ ). Finally, age was a significant predictor of surface acting during an emotion AI interview ( $b = -0.02$ ,  $SE = 0.01$ ,  $p = .001$ , partial  $\eta^2 < .01$ ), with older participants reporting less surface acting compared to younger participants.

### 4.3 Organizational Justice

H2 predicted participants evaluated by emotion AI would perceive lower levels of a) procedural, b) distributive, and c) interactional justice compared to those evaluated by AI or HR. We also predicted an interaction effect between the evaluation source and the outcome received (H3). Patterns across models for procedural, distributive, and interactional justice largely support these predictions (See Table 4 in Appendix A).

**4.3.1 Procedural justice:** Participants who underwent an interview with HR reported lower levels of procedural justice than those in the emotion AI condition ( $b = -0.35$ ,  $SE = 0.16$ ,  $p = 0.03$ , partial  $\eta^2 < .01$ ). However, an interaction with outcome favorability showed higher procedural justice for HR when participants were recommended for the position, providing partial support for H3 ( $b = 0.55$ ,  $SE = 0.23$ ,  $p = 0.01$ , partial  $\eta^2 < .01$ ). Non-binary ( $b = -0.48$ ,  $SE = 0.24$ ,  $p = 0.04$ , partial  $\eta^2 < .01$ ) and transgender participants ( $b = -0.98$ ,  $SE = 0.19$ ,  $p < 0.001$ , partial  $\eta^2 < .01$ ) reported significantly lower perceptions of procedural justice than cisgender men across conditions. On race, Asian participants perceived lower procedural justice than white participants ( $b = -0.45$ ,  $SE = 0.21$ ,  $p = 0.03$ , partial  $\eta^2 < .01$ ) across conditions.

**4.3.2 Distributive justice:** Participants in the HR condition reported significantly higher levels of distributive justice than those in the emotion AI condition ( $b = 0.52$ ,  $SE = 0.23$ ,  $p = 0.03$ , partial  $\eta^2 < .01$ ). The non-emotion AI condition showed a marginally higher level of distributive justice than participants in the emotion AI condition ( $b = 0.42$ ,  $SE = 0.22$ ,  $p = 0.06$ , partial  $\eta^2 < .01$ ). On identity factors across conditions, transgender participants reported significantly lower distributive justice perceptions than cisgender men ( $b = -1.04$ ,  $SE = 0.27$ ,  $p < 0.001$ , partial  $\eta^2 = .04$ ).

**4.3.3 Interactional justice:** We found no significant effect of the evaluation source on interactional justice. That being said, non-binary ( $b = -0.65$ ,  $SE = 0.28$ ,  $p = 0.02$ , partial  $\eta^2 = .02$ ) and transgender participants ( $b = -0.62$ ,  $SE = 0.22$ ,  $p = 0.006$ , partial  $\eta^2 = .02$ ) perceived lower interactional justice than cisgender men across conditions. Race also had a significant effect on interactional justice across the sample (partial  $\eta^2 = .06$ ): American Indian/Alaska Native ( $b = 0.85$ ,  $SE = 0.41$ ,  $p = 0.04$ ) and Black or African American participants ( $b = 0.39$ ,  $SE = 0.14$ ,  $p = 0.004$ ) reported higher levels whereas Asian participants reported lower

levels ( $b = -0.73$ ,  $SE = 0.25$ ,  $p = 0.004$ ) of interactional justice than white participants.

Across conditions, participants recommended for the job perceived higher levels of distributive ( $b = 0.59$ ,  $SE = 0.15$ ,  $p < 0.001$ , partial  $\eta^2 = .19$ ), procedural ( $b = 1.63$ ,  $SE = 0.21$ ,  $p < 0.001$ , partial  $\eta^2 < .01$ ), and interactional justice ( $b = 0.83$ ,  $SE = 0.18$ ,  $p < 0.001$ , partial  $\eta^2 = .12$ ). Additionally, perceptions of secondary usage of data consistently demonstrated a negative association with procedural justice ( $b = -0.15$ ,  $SE = 0.04$ ,  $p < 0.001$ , partial  $\eta^2 < .01$ ), distributive justice ( $b = -0.14$ ,  $SE = 0.05$ ,  $p = 0.01$ , partial  $\eta^2 < .01$ ), and interactional justice ( $b = -0.18$ ,  $SE = 0.05$ ,  $p < 0.001$ , partial  $\eta^2 = .04$ ) across conditions.

**4.3.4 Posthoc Analysis - Organizational Justice Under the Evaluation of Emotion AI:** Similar to emotional labor, our interest in the impact of emotion AI provoked a posthoc analysis focusing only on participants who underwent an interview with emotion AI (See Table 6 in Appendix B). In this analysis, we found transgender ( $b = -0.97$ ,  $SE = 0.40$ ,  $p = 0.02$ , partial  $\eta^2 = .11$ ) and Asian ( $b = -1.01$ ,  $SE = 0.45$ ,  $p = 0.02$ , partial  $\eta^2 = .06$ ) participants perceived significantly lower procedural justice than cisgender men and white participants, respectively. Compared to cisgender men, transgender participants also reported lower levels of distributive justice when reflecting on their interview experience with emotion AI ( $b = -1.61$ ,  $SE = 0.57$ ,  $p = 0.005$ , partial  $\eta^2 = .07$ ). Further, participants with a motor limitation disability expressed higher levels of distributive justice than people without any disability ( $b = 3.40$ ,  $SE = 1.47$ ,  $p = 0.02$ , partial  $\eta^2 = .31$ ). Outcome remained a significant positive predictor of procedural ( $b = 0.58$ ,  $SE = 0.16$ ,  $p < 0.001$ , partial  $\eta^2 = .14$ ) distributive ( $b = 1.58$ ,  $SE = .23$ ,  $p < 0.001$ , partial  $\eta^2 = .06$ ) and interactional justice ( $b = .93$ ,  $SE = .20$ ,  $p < 0.001$ , partial  $\eta^2 = .13$ ) when looking at the emotion AI subsample.

## 5 Discussion

This paper makes novel contributions to the critical emotion AI literature using an innovative experimental methodology. Our results demonstrate those who underwent a mock interview evaluated by emotion AI perceived significantly lower levels of distributive and procedural justice than those who took part in an interview evaluated by HR, with the latter relationship being partially dependent on outcome favorability. Variation in perceptions and behavior along the lines of race, gender, and disability reveal the potential for injustice in interviews leveraging emotion AI. Moreover, privacy concerns significantly influenced perceptions of emotional labor exerted and information disclosed across all conditions, with notable effects in the context of emotion AI. We discuss the implications of these findings for emotion AI use and regulation along with broader methodological considerations.

### 5.1 Disclosure and Emotional Labor in Asynchronous Virtual Interviews

Our findings demonstrate that evaluation source did not significantly influence how much information participants disclosed during the mock interview. This goes against research suggesting differences in information disclosure during a job interview depend on *who* individuals interact with [64, 77, 98]. It also challenges chilling effects research, which has argued increased information

surveillance leads to lessened disclosure [35, 75, 83]. Hiring managers should take this finding as indicative that job-seekers feel surveilled during asynchronous interviews regardless of *who* is watching or *what* type of information may be inferred. To foster a more equitable and authentic candidate experience, it is essential to prioritize comfort—something pervasive surveillance inherently undermines.

We also found that the evaluation source did not influence perceptions of emotional labor exerted during the interview. This challenges qualitative evidence revealing that emotion AI use may impose additional emotional labor [81, 88]. This showcases the importance of 1) experimental methods that gauge perceptions based on real-time experiences, and 2) the power of representative sampling. Similar to our findings on disclosure, it is possible emotional labor was exerted consistently across conditions given the baseline emotional labor which occurs in response to surveillance [105]. Emotional labor is indeed an invisible yet taxing form of labor [51]. Researchers and practitioners should consider solutions which may lessen the emotional labor required to undergo any type of asynchronous virtual interview.

Taken together, these findings suggest proponents' claims that emotion AI systems' use in hiring would promote candidate comfort and disclosure, compared to engaging with a HR professional, [82, 87] may not be valid in practice.

## 5.2 The Influence of Privacy Concerns and Identity Factors on Disclosure and Emotional Labor

Although there was no significant difference in emotional labor across evaluators, the role of privacy concerns and identity factors underscore the complexity of developing hiring systems that are equitable and respectful of job-seekers.

**5.2.1 A Chilling Effect on Gender Minorities' Disclosures.** Results reveal non-binary individuals and cisgender women perceived themselves to disclose less sensitive information than that perceived by cisgender men. For cisgender women, though with a notably small effect size, this finding extended to actual disclosure. As such, our findings provide some evidence of a chilling effect on gender minorities across asynchronous virtual interviews, in alignment with previous literature [109]. These results extend research on gender discrimination in algorithmic hiring [6, 25] to systems which incorporate emotion AI. Considering disclosure as an opportunity to express one's qualities for a job, our findings mean gender minorities may do so less, possibly impacting their job outcomes. This falls in tension with emotion AI proponents' claims [87] that deploying emotion AI will help employers to know who the candidates "truly" are. When expression is chilled, as we show, proponents' claims regarding "authenticity" of candidates are questionable.

**5.2.2 Resigned No More: Individuals Reduce Disclosure in Light of Secondary Usage Concerns.** Our results contribute to Branconte's [14] proposal for a more nuanced measure of privacy concerns, as variation was dependent on what component of privacy participants believed may be compromised. Additionally, the relationship between perceived intrusion and disclosure reflects digital resignation across participants [26] in that disclosure was not reduced

by the perception that the system may collect more information than expected. However, when participants perceived a higher likelihood for secondary usage of data by unknown actors, they were less inclined to disclose personal information during the interview. Even though people may be resigned about their privacy [26], such resignation may be overridden by concerns about secondary data usage. Developers of asynchronous interview systems should clearly inform subjects if and how collected data and generated inferences 1) will remain securely within the system, or 2) are shared with third parties. This transparency is crucial for job-seekers to make informed decisions about disclosing information during the interview process. Recently passed and proposed state-level U.S. law has put forth requirements about transparency around what is sometimes referred to as "high risk" AI systems (e.g., Colorado AI Act; California AB 2013; Virginia HB2094). In fact, the EU AI Act has classified the use of emotion AI for hiring as high risk.

**5.2.3 The Influence of Individual-Level Variables on Perceived Emotional Labor Exerted in Emotion AI Interviews.** Both demographic variables and privacy concerns impacted emotional labor exerted during the interview. The effect sizes were particularly notable when looking specifically at the experiences of those who underwent the emotion AI interviews. We found people who underwent an emotion AI interview engaged in less deep acting when they perceived higher levels of surveillance. This demonstrates emotional labor is a *direct response* to a perceived lack of privacy during job interviews evaluated by emotion AI. Our results suggest the explicit monitoring of emotions may have prompted participants to cater such to what they believed the system expected from them.

Demographic variables also had a significant impact on perceived emotional labor exerted during the emotion AI interview. In this condition, we found that neurodiverse individuals and those with mental health conditions to report significantly lower levels of surface acting compared to individuals without disabilities. Additionally, participants with multiple disabilities reported significantly lower levels of deep acting than those without disabilities. These findings may be explained by the emotional dysregulation—including lower emotional inhibition—present for people with some disabilities [57]. The possible challenge for disabled participants and women to adapt to the desired emotions required for an interview, therefore exerting less deep acting, means while they may benefit from not changing their internal feelings, their interview outcomes may suffer. This finding provides further support for the unjust nature of emotion AI given its potential adverse impact on minoritized job-seekers.

## 5.3 Emotion AI is an Unjust Evaluator of Job Interviews

Results indicate significant differences across the evaluation source on job-seekers' perceptions of justice, providing evidence that emotion AI was perceived as an unjust interview evaluator as compared to both non-emotion AI and an HR professional. Participants in the HR condition reported significantly higher perceptions of distributive justice than those who underwent an interview evaluated by emotion AI, meaning the former participants felt the outcome was more just than the latter. The marginally significant contrast between those in the non-emotion AI and emotion AI conditions

glean people may think the outcome is more distributively just when emotion is *not* taken into consideration. However, the small effect sizes across these relationships highlight the need for future research to validate our findings.

Participants perceived the HR evaluation to be significantly *less* procedurally just than that by emotion AI. It is possible participants thought being evaluated by HR without reciprocated communication or the ability to parse specific traits about their evaluator [97] was more unjust than the emotion AI evaluator because the latter does not have human capabilities. However, when the outcome was favorable, perceptions of procedural justice were higher for those who underwent an interview with HR as opposed to emotion AI, in alignment with previous literature [8]. These results — in addition to the consistent positive relationship between outcome favorability and organizational justice perceptions — showcase that attitudes about emotion AI in hiring may be driven by the ultimate outcome.

**5.3.1 Identity Factors Impact Perceptions of Organizational Justice in Asynchronous Virtual Interviews.** Several minoritized racial and gender groups reported distinct perceptions of justice regarding the interview experience. Across conditions, we found Asian participants experienced significantly lower levels of interactional and procedural justice, while Black or African American participants reported significantly higher levels of interactional justice than their white counterparts. It is possible that cultural differences and norms around respectful treatment of others (i.e., interactional justice) as well as previous experiences in hiring may explain these results. For example, in a prevalent Black/white binary racial classification system such as that in the U.S. [3], Asian people may feel like an invisible minority [100, 107], which may exacerbate their perceptions of injustice in interviews. It is also possible that because Black or African American participants may have experienced racial prejudice and disrespect in job interviews [103, 106], they would not consider the conditions in our study to be any more unjust and disrespectful. Gender also shaped perceptions of justice. Transgender participants across the sample reported significantly lower levels of perceived procedural, distributive, and interactional justice than cisgender men. When focusing on the emotion AI subsample, this result held with strong effect sizes on procedural and distributive justice. Non-binary participants similarly expressed lower levels of interactional and procedural justice perceptions than cisgender men. It may be the case that transgender and non-binary people's experiences with employment discrimination in general [94] shapes their perceptions of injustice regarding virtual asynchronous job interviews including those using emotion AI.

These results mean employers choosing to deploy emotion AI in their hiring processes, similar to those adopting alternative asynchronous interview systems— may be systematically disadvantaging gender and racial minorities. Minorities' perceptions matter for employers who wish to promote workplace diversity initiatives intended to increase and retain employees of diverse genders and races [37]. Perceptions of injustice also matter because experiences with racial and gender discrimination impact well-being [34, 80]. Our findings show that people minoritized along axis of race and gender perceived injustice particularly when evaluated by emotion AI during an asynchronous virtual interview. This is significant, as

it shows how emotion AI [87] proponents' claims that their hiring systems mitigate the bias and discrimination that traditional HR hiring processes suffer from, is not perceived by job-seekers as such in practice.

## 5.4 Implications for the Use and Regulation of Emotion AI in Hiring

Our results support *not* deploying emotion AI in hiring given its chilling effect and the perceived injustice, particularly for individuals of minoritized identity groups. One of the pitfalls of algorithmic decision-making is the lack of transparency around how decisions are made [41]. Congruent with this reality, we provided no transparency to participants around how outcomes were decided. Our results reflecting lower perceptions of justice regarding emotion AI and non-emotion AI interviews compared to those evaluated by HR suggest there may be greater uncertainty around how algorithmic hiring systems work. These results should encourage regulation which facilitates the evaluation of and transparency provided about asynchronous hiring systems, echoing the sentiment that this is a corporate responsibility [2].

Results from this study present policy implications for regulators grappling with emotion AI governance. AI use in hiring has been classified as "high risk" by the EU's AI Act [19]. Our findings support this risk classification and urge U.S. policymakers to consider restricting the collection, generation, and use of emotion data in hiring. Additionally, building on their existing efforts to protect consumers from the harmful effects of AI [29], the Federal Trade Commission (FTC) may consider mandating audits [30] of algorithmic hiring systems' consideration of organizational justice values, including a distinct process for those that infer emotion.

While the FTC can have a sweeping impact akin to common law [95], they do not handle employment discrimination. The responsible federal body in the U.S., the Equal Employment Opportunity Commission (EEOC), has noted the potential for liability when employers use algorithmic decision-making tools [28] including a call-out to "video interviewing software that evaluates candidates based on their facial expressions and speech patterns." Our results demonstrate that emotion AI such as that referenced by the EEOC should be taken seriously.

Finally, federal and state governing bodies may use findings from this study to bolster their recommendations to developers and deployers of asynchronous hiring services, ensuring that privacy concerns, emotional labor, and chilling effects are adequately considered. Discrepancies across participants on the axis of gender, race, and disability support going beyond a focus on accuracy of algorithmic hiring systems and instead attending to these systems' justice implications. This can be done, for example, by examining the unique experiences of minoritized people to make these systems just for all [102] and decrease existing power asymmetries between stakeholders [106].

## 6 Conclusion

This experimental study investigates emotion AI's impact in real-time through comparing mock asynchronous job interviews evaluated by emotion AI, non-emotion AI and an HR professional. Results show asynchronous video interviews, regardless of *who* or *what*

the evaluator is, can chill disclosure, impact emotional labor, and lessen perceptions of organizational justice for disabled people and those of minoritized genders and races. Our findings on emotional labor—specifically within participants who underwent an emotion AI-evaluated interview—challenge claims made by emotion AI advocates regarding the technology’s ability to capture authentic representations of candidates. Moreover, we quantify the perceived injustice of emotion AI in hiring, particularly for individuals from gender minority groups and who have disabilities. Together, our results urge caution for hiring managers and other decision-makers who are considering the use of emotion AI in recruitment.

## 7 Ethical Considerations Statement

We took care to create the impression that the mock interview system was collecting more data about participants than it actually was. This deception was necessary to measure real-time responses. Participants could see themselves on camera being recorded during the mock interview, but we did not capture video files or collect any personally identifiable information. Instead, audio data were securely transmitted via an encrypted, private API and were immediately deleted after transcription into text for analysis. Although more insights could have been drawn by actually monitoring video interviews, we assessed this as unnecessary for the goals and scope of this study.

With this in mind, a strength of this study is its methodological contribution. This study is, to the best of our knowledge, the first to invite participants to undergo a mock interview with the belief they were actually being monitored by an emotion AI system. A study which resembles and informed ours was conducted by Suen & Hung [99], comparing impression management across AI and human raters of an asynchronous video interview. However, their procedure required participant videos to be recorded and stored with unclear data privacy protections. Additionally, Suen & Hung [99] did not leverage any of the data collected from their mock interview, relying on self-report measures for their analysis [99]. Our integration of a video recorder into Qualtrics, followed by the isolated transmission of audio files for transcription and analysis, offers an innovative method for ethically simulating ecologically valid interviews while prioritizing participant privacy and data minimization [82, 92]. Other researchers can replicate this methodological approach through accessing our GitHub page.<sup>6</sup>

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## References

- [1] Yalcin Acikgoz, Kristl H Davison, Maira Compagnone, and Matt Laske. 2020. Justice perceptions of artificial intelligence in selection. *International Journal of Selection and Assessment* 28, 4 (2020), 399–416.
- [2] Ifeoma Ajunwa. 2020. An auditing imperative for automated hiring systems. *Harv. J.L. & Tech.* 34 (2020), 621.
- [3] Linda Martin Alcoff. 2003. Latino/as, Asian Americans, and the black-white binary. *The Journal of Ethics* 7, 1 (2003), 5–27.
- [4] Nazanin Andalibi and Justin Buss. 2020. The human in emotion recognition on social media: Attitudes, outcomes, risks. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–16.
- [5] Nazanin Andalibi and Alexis Shore Ingber. 2025. Public Perceptions About Emotion AI Use Across Contexts in the United States. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery. <https://doi.org/10.1145/3706598.3713501>
- [6] Lori Andrews and Hannah Bucher. 2022. Automating Discrimination: AI Hiring Practices and Gender Inequality. *Cardozo L. Rev.* 44 (2022), 145.
- [7] Vian Bakir, Alexander Laffer, Andrew McStay, Diana Miranda, and Lachlan Urquhart. 2024. On Manipulation by Emotional AI: UK Adults’ Views and Governance Implications. *Frontiers in Sociology* 9 (2024), 1339834.
- [8] Sarah Bankins, Paul Formosa, Yannick Griep, and Deborah Richards. 2022. AI decision making with dignity? Contrasting workers’ justice perceptions of human and AI decision making in a human resource management context. *Information Systems Frontiers* 24, 3 (2022), 857–875.
- [9] Lisa Feldman Barrett, Ralph Adolphs, Stacy Marsella, Aleix M Martinez, and Seth D Pollak. 2019. Emotional expressions reconsidered: Challenges to inferring emotion from human facial movements. *Psychological science in the public interest* 20, 1 (2019), 1–68.
- [10] Catherine White Berheide, Megan A Carpenter, and David A Cotter. 2022. Teaching college in the time of COVID-19: Gender and race differences in faculty emotional labor. *Sex Roles* 86, 7 (2022), 441–455.
- [11] Reuben Binns, Max Van Kleek, Michael Veale, Ulrik Lyngs, Jun Zhao, and Nigel Shadbolt. 2018. ‘It’s Reducing a Human Being to a Percentage’ Perceptions of Justice in Algorithmic Decisions. In *Proceedings of the 2018 Chi conference on human factors in computing systems*. 1–14.
- [12] Abeba Birhane, Ryan Steed, Victor Ojewale, Briana Vecchione, and Inioluwa Deborah Raji. 2024. SoK: AI Auditing: The Broken Bus on the Road to AI Accountability. In *2nd IEEE Conference on Secure and Trustworthy Machine Learning*.
- [13] Karen L Boyd and Nazanin Andalibi. 2023. Automated emotion recognition in the workplace: How proposed technologies reveal potential futures of work. *Proceedings of the ACM on human-computer interaction* 7, CSCW1 (2023), 1–37.
- [14] Vanessa Bracamonte, Sebastian Pape, and Sascha Loebner. 2022. “All apps do this”: Comparing Privacy Concerns Towards Privacy Tools and Non-Privacy Tools for Social Media Content. *Proceedings on Privacy Enhancing Technologies* (2022).
- [15] Maarten Buyl, Christina Cociancig, Cristina Frattone, and Nele Roekens. 2022. Tackling Algorithmic Disability Discrimination in the Hiring Process: An Ethical, Legal and Technical Analysis. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* (Seoul, Republic of Korea) (FAccT ’22). Association for Computing Machinery, New York, NY, USA, 1071–1082. <https://doi.org/10.1145/3531146.3533169>
- [16] Maarten Buyl, Christina Cociancig, Cristina Frattone, and Nele Roekens. 2022. Tackling algorithmic disability discrimination in the hiring process: An ethical, legal and technical analysis. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*. 1071–1082.
- [17] Pengfei Cheng, Sanbin Xie, and Jingxuan Jiang. 2022. The Impact of Perceived Customer Participation on Employees’ Emotional Labor: The Cross-Level Moderating Effect of Customer Orientation. In *Proceedings of the 6th International Conference on Information System and Data Mining*. 138–144.
- [18] Jason A Colquitt. 2001. On the dimensionality of organizational justice: a construct validation of a measure. *Journal of applied psychology* 86, 3 (2001), 386.
- [19] European Commission. 2023. Regulatory framework proposal on Artificial Intelligence. <https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai> Retrieved August 12, 2024.
- [20] Karen S Cook and Karen A Hegtvædt. 1983. Distributive justice, equity, and equality. *Annual review of sociology* 9, 1 (1983), 217–241.
- [21] Shanley Corvite, Kat Roemmich, Tillie Ilana Rosenberg, and Nazanin Andalibi. 2023. Data Subjects’ Perspectives on Emotion Artificial Intelligence Use in the Workplace: A Relational Ethics Lens. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW1 (2023), 1–38.
- [22] Kate Crawford and Trevor Paglen. 2021. Excavating AI: The politics of images in machine learning training sets. *AI & Society* 36, 4 (2021), 1105–1116.
- [23] Russell Cropanzano, Cynthia A Prehar, and Peter Y Chen. 2002. Using social exchange theory to distinguish procedural from interactional justice. *Group & organization management* 27, 3 (2002), 324–351.
- [24] Vedant Das Swain, Lan Gao, Abhirup Mondal, Gregory D Abowd, and Munmun De Choudhury. 2024. Sensible and Sensitive AI for Worker Wellbeing: Factors that Inform Adoption and Resistance for Information Workers. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–30.
- [25] Adio-Adet Dinika and Mona Sloane. 2023. AI and Inequality in Hiring and Recruiting: A Field Scan. In *Weizenbaum Conference “AI, Big Data, Social Media, and People on the Move”*. DEU, 1–13.
- [26] Nora A Draper and Joseph Turov. 2019. The corporate cultivation of digital resignation. *New media & society* 21, 8 (2019), 1824–1839.
- [27] Paul Ekman. 1992. Are there basic emotions? *Psychological Review* 99, 3 (1992), 550–553.

<sup>6</sup><https://github.com/shoreingber/ethicaldeception/blob/main/QualtricsVideoRecorder>

- [28] Equal Employment Opportunity Commission. 2024. Select Issues in Assessing the Adverse Impact of Software, Algorithms, and Artificial Intelligence. <https://www.eeoc.gov/laws/guidance/select-issues-assessing-adverse-impact-software-algorithms-and-artificial> Accessed: 2024-09-09.
- [29] Federal Trade Commission. 2024. FTC Submits Comment to FCC on Work to Protect Consumers from Potential Harmful Effects of AI. <https://www.ftc.gov/news-events/news/press-releases/2024/07/ftc-submits-comment-fcc-work-protect-consumers-potential-harmful-effects-ai> Accessed: 2024-09-09.
- [30] Carmen Fernández-Martínez and Alberto Fernández. 2020. AI and recruiting software: Ethical and legal implications. *Paladyn, Journal of Behavioral Robotics* 11, 1 (2020), 199–216.
- [31] Kate Glazko, Yusuf Mohammed, Ben Kosa, Venkatesh Potluri, and Jennifer Mankoff. 2024. Identifying and Improving Disability Bias in GPT-Based Resume Screening. In *The 2024 ACM Conference on Fairness, Accountability, and Transparency*. 687–700.
- [32] Alicia A Grandey. 2003. When “the show must go on”: Surface acting and deep acting as determinants of emotional exhaustion and peer-rated service delivery. *Academy of management Journal* 46, 1 (2003), 86–96.
- [33] Gabriel Grill and Nazanin Andalibi. 2022. Attitudes and folk theories of data subjects on transparency and accuracy in emotion recognition. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW1 (2022), 1–35.
- [34] Ruth A Hackett, Myra S Hunter, and Sarah E Jackson. 2024. The relationship between gender discrimination and wellbeing in middle-aged and older women. *Plos one* 19, 3 (2024), e0299381.
- [35] Bingyi Han, George Buchanan, and Dana McKay. 2022. Learning in the Panopticon: Examining the Potential Impacts of AI Monitoring on Students. In *Proceedings of the 34th Australian Conference on Human-Computer Interaction*. 9–21.
- [36] Fabio Hellmann, Silvan Mertes, Mohamed Benouis, Alexander Hustinx, Tzung-Chien Hsieh, Cristina Conati, Peter Krawitz, and Elisabeth André. 2024. Ganonymization: A gan-based face anonymization framework for preserving emotional expressions. *ACM Transactions on Multimedia Computing, Communications and Applications* (2024).
- [37] Cedric Herring. 2009. Does diversity pay?: Race, gender, and the business case for diversity. *American sociological review* 74, 2 (2009), 208–224.
- [38] Louis Hickman, Louis Tay, and Sang Eun Woo. 2024. Are automated video interviews smart enough? Behavioral modes, reliability, validity, and bias of machine learning cognitive ability assessments. *Journal of Applied Psychology* (2024).
- [39] Scott Highhouse. 2009. Designing experiments that generalize. *Organizational Research Methods* 12, 3 (2009), 554–566.
- [40] Arlie Russell Hochschild. 2019. *The managed heart: Commercialization of human feeling*. University of California press.
- [41] Guusje Juijn, Niya Stoimenova, João Reis, and Dong Nguyen. 2023. Perceived algorithmic fairness using organizational justice theory: An empirical case study on algorithmic hiring. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society*. 775–785.
- [42] Nadia Karizat, Alexandra H Vinson, Shobita Parthasarathy, and Nazanin Andalibi. 2024. Patent Applications as Glimpses into the Sociotechnical Imaginary: Ethical Speculation on the Imagined Futures of Emotion AI for Mental Health Monitoring and Detection. *Proceedings of the ACM on Human-Computer Interaction* 8, CSCW1 (2024), 1–43.
- [43] Amelia Katirai. 2024. Autism and emotion recognition technologies in the workplace. *Autism* (2024), 13623613241279704.
- [44] Harmanpreet Kaur, Daniel McDuff, Alex C Williams, Jaime Teevan, and Shamsi T Iqbal. 2022. “I didn’t know I looked angry”: Characterizing observed emotion and reported affect at work. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–18.
- [45] Sanne Kruijkemeier, Sophie C Boerman, and Nadine Bol. 2020. Breaching the contract? Using social contract theory to explain individuals’ online behavior to safeguard privacy. *Media Psychology* 23, 2 (2020), 269–292.
- [46] Yi-Chieh Lee, Naomi Yamashita, Yun Huang, and Wai Fu. 2020. “I hear you, I feel you”: encouraging deep self-disclosure through a chatbot. In *Proceedings of the 2020 CHI conference on human factors in computing systems*. 1–12.
- [47] Ruth Leys. 2019. *The ascent of affect: Genealogy and critique*. University of Chicago Press.
- [48] Bingjie Liu. 2021. In AI we trust? Effects of agency locus and transparency on uncertainty reduction in human–AI interaction. *Journal of computer-mediated communication* 26, 6 (2021), 384–402.
- [49] Bingjie Liu, Lewen Wei, Mu Wu, and Tianyi Luo. 2023. Speech production under uncertainty: how do job applicants experience and communicate with an AI interviewer? *Journal of Computer-Mediated Communication* 28, 4 (2023), zmad028.
- [50] Shu Liu, Kevin Koch, Zimu Zhou, Simon Föll, Xiaoxi He, Tina Menke, Elgar Fleisch, and Felix Wortmann. 2021. The Empathetic Car: Exploring Emotion Inference via Driver Behaviour and Traffic Context. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 5, 3, Article 117 (sep 2021), 34 pages. <https://doi.org/10.1145/3478078>
- [51] Zhuoran Lu, Patrick Li, Weilong Wang, and Ming Yin. 2022. The effects of AI-based credibility indicators on the detection and spread of misinformation under social influence. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW2 (2022), 1–27.
- [52] M. Luria, M. U. Scherer, D. Thakur, A. Aboulafia, H. Claypool, and W. Negrón. 2024. Screened Out: The Impact of Digitized Hiring Assessments on Disabled Workers. <https://cdt.org/insights/screened-out-the-impact-of-digitized-hiring-assessments-ondisabled-workers/>
- [53] Peter Mantello, Manh-Tung Ho, Minh-Hoang Nguyen, and Quan-Hoang Vuong. 2023. Bosses without a heart: socio-demographic and cross-cultural determinants of attitude toward Emotional AI in the workplace. *AI & society* 38, 1 (2023), 97–119.
- [54] Samuel Marcos, Francisco José García Peñalvo, and Andrea Vázquez Ingelmo. 2021. Emotional AI in Healthcare: a pilot architecture proposal to merge emotion recognition tools. In *Ninth International Conference on Technological Ecosystems for Enhancing Multiculturality (TEEM’21)* (Barcelona, Spain) (TEEM’21). Association for Computing Machinery, New York, NY, USA, 342–349. <https://doi.org/10.1145/3486011.3486472>
- [55] Ben Marder, Adam Joinson, Avi Shankar, and David Houghton. 2016. The extended ‘chilling’ effect of Facebook: The cold reality of ubiquitous social networking. *Computers in Human Behavior* 60 (2016), 582–592.
- [56] MarketsandMarkets. 2024. Emotion Detection and Recognition Market by Component, Technology, Application, and Region - Global Forecast to 2024. <https://www.marketsandmarkets.com/Market-Reports/emotion-detection-recognition-market-23376176.html> Accessed: 2024-09-05.
- [57] Carla A Mazefsky and Susan W White. 2014. Emotion regulation: Concepts & practice in autism spectrum disorder. *Child and Adolescent Psychiatric Clinics* 23, 1 (2014), 15–24.
- [58] Andrew McStay. 2016. Empathic media and advertising: Industry, policy, legal and citizen perspectives (the case for intimacy). *Big data & society* 3, 2 (2016), 205395171666868.
- [59] Andrew McStay. 2018. *Emotional AI: The rise of empathic media*. SAGE Publications Ltd.
- [60] Andrew McStay. 2020. Emotional AI and EdTech: serving the public good? *Learning, Media and Technology* 45, 3 (2020), 270–283.
- [61] Andrew McStay. 2020. Emotional AI, soft biometrics and the surveillance of emotional life: An unusual consensus on privacy. *Big Data & Society* 7, 1 (2020), 2053951720904386.
- [62] Andrew McStay. 2024. *Automating empathy: Decoding technologies that gauge intimate life*. Oxford University Press.
- [63] Amanda Menking and Ingrid Erickson. 2015. The heart work of Wikipedia: Gendered, emotional labor in the world’s largest online encyclopedia. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*. 207–210.
- [64] Agata Mirowska and Laura Mesnet. 2022. Preferring the devil you know: Potential applicant reactions to artificial intelligence evaluation of interviews. *Human Resource Management Journal* 32, 2 (2022), 364–383.
- [65] Emmanuel Mogaji, Sunday Olaleye, and Dandison Ukpabi. 2020. Using AI to personalise emotionally appealing advertisement. *Digital and social media marketing: Emerging applications and theoretical development* (2020), 137–150.
- [66] Scott Monteith, Tasha Glenn, John Geddes, Peter C Whybrow, and Michael Bauer. 2022. Commercial use of emotion artificial intelligence (AI): implications for psychiatry. *Current Psychiatry Reports* 24, 3 (2022), 203–211.
- [67] Emily Namey, Greg Guest, Amy O’Regan, Christine L Godwin, Jamilah Taylor, and Andres Martinez. 2022. How does qualitative data collection modality affect disclosure of sensitive information and participant experience? Findings from a quasi-experimental study. *Quality & Quantity* 56, 4 (2022), 2341–2360.
- [68] Sean M. Noble, Lori L. Foster, and S. Bartholomew Craig. 2021. The procedural and interpersonal justice of automated application and resume screening. *International Journal of Selection and Assessment* 29, 2 (2021), 139–153. <https://doi.org/10.1111/ijsa.12320>
- [69] Selin E Nugent and Susan Scott-Parker. 2022. Recruitment AI has a Disability Problem: anticipating and mitigating unfair automated hiring decisions. In *Towards trustworthy artificial intelligent systems*. Springer, 85–96.
- [70] Hyanghee Park, Daehwan Ahn, Kartik Hosanagar, and Joonhwan Lee. 2021. Human-AI interaction in human resource management: Understanding why employees resist algorithmic evaluation at workplaces and how to mitigate burdens. In *Proceedings of the 2021 CHI conference on human factors in computing systems*. 1–15.
- [71] Hyanghee Park, Daehwan Ahn, Kartik Hosanagar, and Joonhwan Lee. 2021. Human-AI Interaction in Human Resource Management: Understanding Why Employees Resist Algorithmic Evaluation at Workplaces and How to Mitigate Burdens. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) (CHI ’21). Association for Computing Machinery, New York, NY, USA, Article 154, 15 pages. <https://doi.org/10.1145/3411764.3445304>
- [72] Delroy L Paulhus, Bryce G Westlake, Stryker S Calvez, and Peter D Harms. 2013. Self-presentation style in job interviews: The role of personality and culture.

- Journal of Applied Social Psychology* 43, 10 (2013), 2042–2059.
- [73] Eyal Peer, Laura Brandimarte, Sonam Samat, and Alessandro Acquisti. 2017. Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology* 70 (2017), 153–163. <https://doi.org/10.1016/j.jesp.2017.01.006>
  - [74] Jon Penney. 2017. Internet surveillance, regulation, and chilling effects online: A comparative case study. *Regulation, and Chilling Effects Online: A Comparative Case Study* (May 27, 2017) 6, 2 (2017).
  - [75] Jonathon W Penney. 2016. Chilling effects: Online surveillance and Wikipedia use. *Berkeley Tech. Lj* 31 (2016), 117.
  - [76] Rosalind W Picard. 2000. *Affective computing*. MIT press.
  - [77] Matthew D Pickard, Catherine A Roster, and Yixing Chen. 2016. Revealing sensitive information in personal interviews: Is self-disclosure easier with humans or avatars and under what conditions? *Computers in Human Behavior* 65 (2016), 23–30.
  - [78] Lena Podoletz. 2023. We have to talk about emotional AI and crime. *AI & SOCIETY* 38, 3 (2023), 1067–1082.
  - [79] Philip M Podsakoff and Nathan P Podsakoff. 2019. Experimental designs in management and leadership research: Strengths, limitations, and recommendations for improving publishability. *The Leadership Quarterly* 30, 1 (2019), 11–33.
  - [80] Naomi Priest, Yin Paradies, Brigid Trenerry, Mandy Truong, Saffron Karlsen, and Yvonne Kelly. 2013. A systematic review of studies examining the relationship between reported racism and health and wellbeing for children and young people. *Social science & medicine* 95 (2013), 115–127.
  - [81] Cassidy Pyle, Kat Roemmich, and Nazanin Andalibi. 2024. US Job-Seekers' Organizational Justice Perceptions of Emotion AI-Enabled Asynchronous Interviews. *Proceedings of the ACM on Human-Computer Interaction* (2024).
  - [82] Manish Raghavan, Solon Barocas, Jon Kleinberg, and Karen Levy. 2020. Mitigating bias in algorithmic hiring: Evaluating claims and practices. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 469–481.
  - [83] Joel R Reidenberg and Florian Schaub. 2018. Achieving big data privacy in education. *Theory and Research in Education* 16, 3 (2018), 263–279.
  - [84] Lauren Rhue. 2018. Racial influence on automated perceptions of emotions. Available at SSRN 3281765 (2018).
  - [85] Lauren Rhue. 2019. Understanding the hidden bias in emotion-reading AIs.
  - [86] Kat Roemmich, Shanley Corvite, Cassidy Pyle, Nadia Karizat, and Nazanin Andalibi. 2024. Emotion AI Use in US Mental Healthcare: Potentially Unjust and Techno-Solutionist. *Proceedings of the ACM on Human-Computer Interaction* 8, CSCW1 (2024), 1–46.
  - [87] Kat Roemmich, Tillie Rosenberg, Serena Fan, and Nazanin Andalibi. 2023. Values in emotion artificial intelligence hiring services: Technosolutions to organizational problems. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW1 (2023), 1–28.
  - [88] Kat Roemmich, Florian Schaub, and Nazanin Andalibi. 2023. Emotion AI at work: Implications for workplace surveillance, emotional labor, and emotional privacy. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–20.
  - [89] Supraja Sankaran, Chao Zhang, Henk Aarts, and Panos Markopoulos. 2021. Exploring peoples' perception of autonomy and reactance in everyday ai interactions. *Frontiers in psychology* 12 (2021), 713074.
  - [90] Anvita Saxena, Ashish Khanna, and Deepak Gupta. 2020. Emotion recognition and detection methods: A comprehensive survey. *Journal of Artificial Intelligence and Systems* 2, 1 (2020), 53–79.
  - [91] Candice Schumann, Jeffrey Foster, Nicholas Mattei, and John Dickerson. 2020. We need fairness and explainability in algorithmic hiring. In *International Conference on Autonomous Agents and Multi-Agent Systems (AAMAS)*.
  - [92] Divya Shanmugam, Fernando Diaz, Samira Shabani, Michèle Finck, and Asia Biega. 2022. Learning to limit data collection via scaling laws: A computational interpretation for the legal principle of data minimization. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*. 839–849.
  - [93] Renee Shelby, Shalaleh Rismani, Kathryn Henne, AJung Moon, Negar Rostamzadeh, Paul Nicholas, N'Mah Yilla-Akbari, Jess Gallegos, Andrew Smart, Emilio Garcia, et al. 2023. Sociotechnical harms of algorithmic systems: Scoping a taxonomy for harm reduction. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society*. 723–741.
  - [94] Deirdre A Shires and Kim Jaffee. 2015. Factors associated with health care discrimination experiences among a national sample of female-to-male transgender individuals. *Health & social work* 40, 2 (2015), 134–141.
  - [95] Daniel J Solove and Woodrow Hartzog. 2014. The FTC and the new common law of privacy. *Colum. L. Rev.* 114 (2014), 583.
  - [96] Luke Stark and Jesse Hoey. 2021. The ethics of emotion in artificial intelligence systems. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*. 782–793.
  - [97] Anna Lena Schulte Steinberg and Christoph Hohenberger. 2023. Can AI close the gender gap in the job market? Individuals' preferences for AI evaluations. *Computers in Human Behavior Reports* 10 (2023), 100287.
  - [98] Hung-Yue Suen and Kuo-En Hung. 2023. Building trust in automatic video interviews using various AI interfaces: Tangibility, immediacy, and transparency. *Computers in Human Behavior* 143 (2023), 107713.
  - [99] Hung-Yue Suen and Kuo-En Hung. 2024. Revealing the influence of AI and its interfaces on job candidates' honest and deceptive impression management in asynchronous video interviews. *Technological Forecasting and Social Change* 198 (2024), 123011.
  - [100] Wei Sun and William J Starosta. 2006. Perceptions of minority invisibility among Asian American professionals. *The Howard Journal of Communications* 17, 2 (2006), 119–142.
  - [101] Gavin Tay, Annette Zimmerman, and Bern Elliot. 2021. Maverick\* Research: Emotional Wellness Will Rescue Your Organization and Distributed Workforce.
  - [102] Nicholas Tilmes. 2022. Disability, fairness, and algorithmic bias in AI recruitment. *Ethics and Information Technology* 24, 2 (2022), 21.
  - [103] Margery Austin Turner, Michael Fix, and Raymond J Struyk. 1991. *Opportunities denied, opportunities diminished: Racial discrimination in hiring*. The Urban Institute.
  - [104] Md Taufeeq Uddin, Lijun Yin, and Shaun Canavan. 2023. Spatio-Temporal Graph Analytics on Secondary Affect Data for Improving Trustworthy Emotional AI. *IEEE Transactions on Affective Computing* (2023).
  - [105] Madison Van Oort. 2019. The emotional labor of surveillance: Digital control in fast fashion retail. *Critical Sociology* 45, 7–8 (2019), 1167–1179.
  - [106] Lynette Yarger, Fay Cobb Payton, and Bikalpa Neupane. 2020. Algorithmic equity in the hiring of underrepresented IT job candidates. *Online information review* 44, 2 (2020), 383–395.
  - [107] Tiffany Yip, Charissa SL Cheah, Lisa Kiang, and Gordon C Nagayama Hall. 2021. Rendered invisible: Are Asian Americans a model or a marginalized minority? *American Psychologist* 76, 4 (2021), 575.
  - [108] Yifan Yu, Lin Jia, and Yong Tan. 2022. Emotion AI Meets Strategic Users. Available at SSRN 4218083 (2022).
  - [109] Lixuan Zhang and Christopher Yench. 2022. Examining perceptions towards hiring algorithms. *Technology in Society* 68 (2022), 101848.

## A Appendix

### A.1 Interview questions

- (1) Please tell us a little about yourself.
- (2) What are your long-term career plans? For example, where do you see yourself in five years?
- (3) What is your biggest strength as a professional?
- (4) What is your greatest weakness, and how do you plan to overcome, or work with it?
- (5) Tell me about a time when you disagreed with a coworker or teammate. How did you handle the situation?
- (6) Describe a situation where you were part of a failed project. What did you do about it?

### A.2 Covariate demographic operationalizations

**Disability:** Participants were asked if they had any of the following disabilities or chronic conditions: None ( $n = 297$ ), Deaf/deaf or have serious difficulty hearing ( $n = 3$ ), Blind or have serious difficulty seeing, even when wearing glasses ( $n = 1$ ), Mobility limitation including serious difficulty walking or climbing stairs ( $n = 15$ ), Motor limitation including manual dexterity ( $n = 1$ ), Learning disability ( $n = 1$ ), Neurodiverse ( $n = 24$ ), Speech or language impairment ( $n = 0$ ), Chronic illness that is neurological or physical ( $n = 16$ ), Mental health condition ( $n = 54$ ), Prefer to self-describe ( $n = 10$ ).

**Employment status (Job-seeker Identification):** We included this item due to the confounding role it may play when assessing participants' comfort with emotion AI in the workplace or during interviews. We asked "What is your current employment status?" Responses informed a binary variable which identified people as currently employed ( $n = 393$ ) or actively looking for work ( $n = 55$ ).

**Table 1: Scale Items**

| Value                                 | Items                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               |
|---------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Perceived Sensitive Disclosure</b> | <ul style="list-style-type: none"> <li>- To provide a truthful answer, I provided a detailed response to the interview questions.</li> <li>- I disclosed a lot in order to answer the interview questions truthfully.</li> <li>- I provided a comprehensive answer to the interview questions.</li> <li>- I revealed sensitive information in response to the interview questions.</li> <li>- I revealed private information answering the interview questions.</li> <li>- I revealed secrets in response to the interview questions.</li> </ul>                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    |
| <b>Emotional Labor</b>                | <p><b>Surface Acting:</b></p> <ul style="list-style-type: none"> <li>...resisted expressing my true feelings</li> <li>...pretended to have emotions that I didn't really have</li> <li>...hid my true feelings about a question</li> </ul> <p><b>Deep Acting:</b></p> <ul style="list-style-type: none"> <li>...made an effort to actually feel the emotions that I need to display to others</li> <li>...tried to actually experience the emotions I must show</li> <li>...really tried to feel the emotions I had to show as part of this interview</li> </ul>                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    |
| <b>Privacy Concerns</b>               | <p><b>Perceived Intrusion:</b></p> <ul style="list-style-type: none"> <li>...others would know about me more than I am comfortable with.</li> <li>...information about me that I consider private would be more readily available to others than I would want.</li> <li>...information about me would be out there that, if used, would invade my privacy.</li> </ul> <p><b>Perceived Surveillance:</b></p> <ul style="list-style-type: none"> <li>- I believe that my personal information was monitored at least part of the time during the interview process.</li> <li>- I am concerned that the interview process collected too much information about me.</li> <li>- I am concerned that the interview process could monitor my personal information.</li> </ul> <p><b>Secondary Usage:</b></p> <ul style="list-style-type: none"> <li>- I am concerned that the interview process could use my personal information for other purposes without notifying me or getting my authorization.</li> <li>- I am concerned that personal information I gave during the interview process could be used for other purposes.</li> <li>- I am concerned that the interview process could share my personal information with other entities without getting my authorization.</li> </ul> |
| <b>Perceptions of Justice</b>         | <p><b>Distributive Justice:</b></p> <ul style="list-style-type: none"> <li>- The outcome of my interview reflects the effort that I put into it.</li> <li>- The outcome of my interview was appropriate.</li> <li>- The outcome of my interview reflects what I contributed.</li> <li>- The outcome of my interview is justified, given my performance.</li> </ul> <p><b>Procedural Justice:</b></p> <ul style="list-style-type: none"> <li>- I was able to express my views and feelings during the interview.</li> <li>- I had influence over the outcome arrived at by this interview.</li> <li>- I feel like this interview procedure was applied consistently across candidates.</li> <li>- I feel like this interview procedure was free of bias.</li> <li>- The outcome of this interview was based on accurate information.</li> <li>- This interview upheld ethical and moral standards.</li> </ul> <p><b>Interactional Justice:</b></p> <ul style="list-style-type: none"> <li>- I was treated politely.</li> <li>- I was treated considerately.</li> <li>- I felt treated with respect.</li> <li>- I felt at ease.</li> <li>- I was satisfied with my treatment.</li> </ul>                                                                                              |

**Table 2: Regression models for Perceived and Actual Disclosure**

| Variable                                                   | Perceived Disclosure Sensitivity | Actual Disclosure (Word Count) |
|------------------------------------------------------------|----------------------------------|--------------------------------|
| <i>Source of Evaluator (Emotion AI as reference group)</i> |                                  |                                |
| AI                                                         | 0.01 (0.12)                      | -50.74 (39.65)                 |
| HR                                                         | 0.03 (0.12)                      | 8.14 (38.50)                   |
| Perceived Intrusion                                        | 0.18 (0.04) ***                  | -3.71 (14.56)                  |
| Perceived Surveillance                                     | 0.09 (0.06) ·                    | -6.60 (17.71)                  |
| Secondary Usage                                            | -0.09 (0.04) *                   | -5.13 (13.10)                  |
| <i>Race (white as reference group)</i>                     |                                  |                                |
| American Indian or Alaska Native                           | 0.33 (0.37)                      | 143.39 (111.74)                |
| Asian                                                      | -0.29 (0.22)                     | 36.45 (82.79)                  |
| Black or African American                                  | 0.19 (0.12)                      | -13.89 (41.24)                 |
| Hispanic or Latino                                         | -0.02 (0.18)                     | 81.23 (58.55)                  |
| Middle Eastern                                             | 0.55 (0.60)                      | 359.27 (181.44) *              |
| Mixed race                                                 | 0.36 (0.23)                      | -5.23 (74.79)                  |
| Native Hawaiian or Pacific Islander                        | 0.97 (1.03)                      | -                              |
| <i>Gender (Cisgender man as reference group)</i>           |                                  |                                |
| Cisgender Woman                                            | -0.31 (0.10) **                  | -70.53 (34.50) *               |
| Non-binary                                                 | -0.78 (0.25) **                  | 74.24 (83.25)                  |
| Transgender                                                | -0.37 (0.20) ·                   | 137.63 (69.01) *               |
| Disability (Yes)                                           | -0.05 (0.11)                     | -9.14 (36.33)                  |
| Job-seeker                                                 | -0.04 (0.10)                     | 76.66 (32.84) *                |
| Virtual Interview Experience                               | 0.01 (0.03)                      | 17.47 (9.75) ·                 |
| Age                                                        | -0.00 (0.00)                     | -0.15 (1.14)                   |
| <b>Adjusted R-squared</b>                                  | 0.11                             | 0.06                           |

**Note:** Estimates are reported with standard errors in parentheses. Significance codes: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ , ·  $p < 0.1$ .

**Table 3: Regression Results for Surface Acting and Deep Acting**

| Variable                                                   | Surface Acting  | Deep Acting     |
|------------------------------------------------------------|-----------------|-----------------|
| <i>Source of Evaluator (Emotion AI as reference group)</i> |                 |                 |
| AI                                                         | -0.07 (0.14)    | 0.11 (0.17)     |
| HR                                                         | 0.10 (0.14)     | -0.02 (0.17)    |
| Perceived Intrusion                                        | 0.21 (0.05) *** | 0.11 (0.06) .   |
| Perceived Surveillance                                     | 0.01 (0.07)     | -0.16 (0.08) .  |
| Secondary Usage                                            | 0.12 (0.05) *   | -0.00 (0.06)    |
| <i>Race (white as reference group)</i>                     |                 |                 |
| American Indian or Alaska Native                           | -0.06 (0.44)    | 0.40 (0.54)     |
| Asian                                                      | 0.49 (0.27) .   | -0.11 (0.33)    |
| Black or African American                                  | 0.03 (0.15)     | 0.20 (0.18)     |
| Hispanic or Latino                                         | -0.10 (0.22)    | 0.60 (0.26) *   |
| Middle Eastern                                             | 0.24 (0.72)     | 0.43 (0.88)     |
| Mixed race                                                 | -0.04 (0.28)    | 0.22 (0.34)     |
| Native Hawaiian or Pacific Islander                        | 0.08 (1.23)     | 1.95 (1.51)     |
| <i>Gender (Cisgender man as reference group)</i>           |                 |                 |
| Cisgender Woman                                            | -0.12 (0.12)    | -0.37 (0.15) *  |
| Non-binary                                                 | 0.30 (0.30)     | 0.13 (0.37)     |
| Transgender                                                | 0.10 (0.24)     | -0.36 (0.30)    |
| Disability (Yes)                                           | -0.02 (0.13)    | -0.43 (0.16) ** |
| Job-seeker                                                 | 0.02 (0.12)     | -0.11 (0.14)    |
| Virtual Interview Experience                               | -0.03 (0.04)    | 0.04 (0.04)     |
| Age                                                        | -0.01 (0.00) *  | 0.00 (0.01)     |
| <b>Adjusted R-squared</b>                                  | 0.16            | 0.04            |

**Note:** Estimates are reported with standard errors in parentheses. Significance codes: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ , .  $p < 0.1$ .

**Table 4: Regression Results for Perceptions of Justice**

| Variable                                                   | Procedural Justice | Distributive Justice | Interactional Justice |
|------------------------------------------------------------|--------------------|----------------------|-----------------------|
| <i>Source of Evaluator (Emotion AI as reference group)</i> |                    |                      |                       |
| AI                                                         | 0.10 (0.15)        | 0.42 (0.22) .        | 0.07 (0.18)           |
| HR                                                         | -0.35 (0.16) *     | 0.52 (0.24) *        | -0.22 (0.19)          |
| Outcome (Recommended)                                      | 0.59 (0.15) ***    | 1.63 (0.21) ***      | 0.83 (0.18) ***       |
| Perceived Intrusion                                        | -0.01 (0.04)       | 0.01 (0.06)          | 0.03 (0.05)           |
| Perceived Surveillance                                     | -0.02 (0.05)       | 0.13 (0.07) .        | -0.08 (0.06)          |
| Secondary Usage                                            | -0.15 (0.04) ***   | -0.14 (0.05) *       | -0.18 (0.05) ***      |
| <i>Race (white as reference group)</i>                     |                    |                      |                       |
| Asian                                                      | -0.45 (0.21) *     | -0.34 (0.30)         | -0.73 (0.25) **       |
| Black or African American                                  | 0.20 (0.11) .      | 0.17 (0.16)          | 0.39 (0.14) **        |
| Hispanic or Latino                                         | 0.07 (0.17)        | -0.02 (0.25)         | 0.07 (0.20)           |
| Middle Eastern                                             | -0.15 (0.56)       | -0.61 (0.81)         | -0.78 (0.67)          |
| Mixed race                                                 | -0.09 (0.21)       | -0.09 (0.31)         | -0.07 (0.26)          |
| Native Hawaiian or Pacific Islander                        | 0.68 (0.95)        | 1.21 (1.39)          | 1.16 (1.15)           |
| <i>Gender (Cisgender man as reference group)</i>           |                    |                      |                       |
| Cisgender Woman                                            | -0.11 (0.10)       | 0.06 (0.14)          | -0.08 (0.12)          |
| Non-binary                                                 | -0.48 (0.24) *     | -0.21 (0.34)         | -0.65 (0.28) *        |
| Transgender                                                | -0.98 (0.19) ***   | -1.04 (0.27) ***     | -0.62 (0.23) **       |
| Disability (Yes)                                           | 0.01 (0.10)        | 0.17 (0.15)          | 0.07 (0.12)           |
| Job Seeker                                                 | -0.11 (0.09)       | -0.07 (0.13)         | -0.03 (0.11)          |
| Virtual Interview Experience                               | -0.03 (0.03)       | 0.01 (0.04)          | 0.03 (0.03)           |
| Age                                                        | 0.00 (0.00)        | -0.00 (0.00)         | -0.00 (0.00)          |
| Source (AI) * Outcome (Recommended)                        | 0.00 (0.22)        | -0.53 (0.32)         | -0.07 (0.26)          |
| Source (HR) * Outcome (Recommended)                        | 0.54 (0.22) *      | -0.51 (0.32)         | 0.04 (0.26)           |
| <b>Adjusted R-squared</b>                                  | 0.28               | 0.22                 | 0.25                  |

**Note:** Estimates are reported with standard errors in parentheses. Significance codes: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ , .  $p < 0.1$ .

## B Posthoc Analysis for Emotion AI Condition

### B.1 Demographics of participants included in posthoc analysis

In terms of gender, this subsample included cisgender women ( $n = 95$ ), cisgender men ( $n = 64$ ), non-binary ( $n = 4$ ), and transgender ( $n = 12$ ) individuals. In terms of race, this subsample included white ( $n = 90$ ), Black or African American ( $n = 45$ ), Hispanic or Latino ( $n = 20$ ), Asian ( $n = 6$ ), American Indian/Alaska Native ( $n = 2$ ), Middle Eastern ( $n = 2$ ), Native Hawaiian or Pacific Islander ( $n = 1$ ), or Mixed race ( $n = 9$ ) participants. Within this sample, a portion described themselves as actively looking for a job ( $n = 71$ ). In terms of disability, some participants in this subsample had no disabilities ( $n = 117$ ). Participants also reported being neurodiverse ( $n = 8$ ), having a mobility limitation ( $n = 7$ ), chronic illness ( $n = 6$ ), motor limitation ( $n = 1$ ), mental health condition ( $n = 20$ ), multiple disabilities ( $n = 11$ ), learning disability ( $n = 1$ ) or preferred to self describe ( $n = 4$ ).

**Table 5: Regression Results for Surface Acting and Deep Acting (Emotion AI Condition Sub-Sample Only)**

| Variable                                         | Surface Acting  | Deep Acting    |
|--------------------------------------------------|-----------------|----------------|
| Perceived Intrusion                              | 0.28 (0.08) *** | 0.18 (0.11) .  |
| Perceived Surveillance                           | -0.02 (0.11)    | -0.34 (0.14) * |
| Secondary Usage                                  | 0.06 (0.08)     | 0.11 (0.10)    |
| <i>Race (White as reference group)</i>           |                 |                |
| American Indian or Alaska Native                 | 0.76 (0.92)     | -1.17 (1.17)   |
| Asian                                            | 0.70 (0.51)     | 0.34 (0.65)    |
| Black or African American                        | 0.16 (0.23)     | -0.17 (0.29)   |
| Hispanic or Latino                               | -0.28 (0.32)    | 0.42 (0.41)    |
| Middle Eastern                                   | -1.73 (0.92) .  | -1.71 (1.17)   |
| Native Hawaiian or Pacific Islander              | -0.47 (1.24)    | 1.13 (1.58)    |
| Mixed race                                       | -0.33 (0.46)    | 0.21 (0.59)    |
| <i>Gender (Cisgender Man as reference group)</i> |                 |                |
| Cisgender Woman                                  | -0.10 (0.21)    | -0.25 (0.26)   |
| Non-binary                                       | 0.55 (0.46)     | 0.30 (0.92)    |
| Transgender                                      | 0.11 (0.24)     | -0.65 (0.62)   |
| <i>Disability (None as reference group)</i>      |                 |                |
| Mobility limitation                              | -0.36 (0.50)    | -0.02 (0.63)   |
| Motor limitation                                 | -1.56 (1.25)    | 0.73 (1.59)    |
| Learning disability                              | 0.11 (1.22)     | 0.46 (1.56)    |
| Neurodiverse                                     | -1.11 (0.55) *  | -0.22 (0.70)   |
| Chronic illness                                  | 1.63 (0.55) **  | 1.29 (0.71) .  |
| Mental health                                    | -0.73 (0.31) *  | -0.76 (0.40) . |
| Multiple disabilities                            | 0.03 (0.43)     | -1.34 (0.55) * |
| Prefer to self-describe                          | -0.88 (0.66)    | 0.10 (0.84)    |
| Age                                              | -0.02 (0.01) ** | -0.01 (0.01)   |
| Job-seeker                                       | 0.11 (0.20)     | -0.29 (0.25)   |
| Virtual Interview Experience                     | -0.06 (0.06)    | 0.04 (0.08)    |
| <b>Adjusted R-squared</b>                        | 0.25            | 0.06           |

**Note:** Estimates are reported with standard errors in parentheses. Significance codes: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ , .  $p < 0.1$ .

**Table 6: Regression Results for Perceptions of Justice (Emotion AI Condition Sub-Sample Only)**

| Variable                                         | Procedural Justice | Distributive Justice | Interactional Justice |
|--------------------------------------------------|--------------------|----------------------|-----------------------|
| Outcome (Recommended)                            | 0.59 (0.16) ***    | 1.58 (0.23) ***      | 0.93 (0.20) ***       |
| Perceived Intrusion                              | -0.03 (0.07)       | -0.15 (0.10)         | -0.03 (0.09)          |
| Perceived Surveillance                           | -0.06 (0.09)       | 0.24 (0.13) .        | -0.05 (0.12)          |
| Secondary Usage                                  | -0.10 (0.06)       | -0.12 (0.09)         | -0.14 (0.08) .        |
| <i>Race (white as reference group)</i>           |                    |                      |                       |
| American Indian or Alaska Native                 | 0.77 (0.75)        | 1.40 (1.09)          | 0.00 (0.35)           |
| Asian                                            | -1.01 (0.42) *     | -0.86 (0.60)         | -0.30 (0.37)          |
| Black or African American                        | -0.16 (0.19)       | -0.10 (0.27)         | -0.21 (0.21)          |
| Hispanic or Latino                               | -0.25 (0.26)       | -0.31 (0.38)         | -0.31 (0.38)          |
| Middle Eastern                                   | -0.76 (0.75)       | -1.70 (1.08)         | -0.35 (0.54)          |
| Native Hawaiian or Pacific Islander              | 0.47 (1.01)        | 1.69 (1.45)          | 0.30 (1.33)           |
| Mixed race                                       | -0.25 (0.38)       | 0.02 (0.54)          | -0.11 (0.46)          |
| <i>Gender (Cisgender man as reference group)</i> |                    |                      |                       |
| Cisgender Woman                                  | 0.05 (0.17)        | -0.17 (0.24)         | -0.17 (0.21)          |
| Non-binary                                       | -0.68 (0.58)       | -0.82 (0.84)         | -1.26 (0.72) .        |
| Transgender                                      | -0.97 (0.40) *     | -1.61 (0.57) **      | -0.56 (0.50)          |
| <i>Disability (None as reference group)</i>      |                    |                      |                       |
| Mobility limitation                              | 0.02 (0.40)        | -0.64 (0.58)         | 0.22 (0.51)           |
| Motor limitation                                 | 0.85 (1.02)        | 3.40 (1.47) *        | 1.65 (1.32)           |
| Learning disability                              | -1.27 (0.99)       | -0.20 (1.43)         | -1.31 (1.29)          |
| Neurodiverse                                     | -0.87 (0.45) .     | -0.37 (0.65)         | 0.06 (0.57)           |
| Chronic illness                                  | 0.38 (0.45)        | 0.41 (0.65)          | 0.30 (0.56)           |
| Mental health                                    | -0.16 (0.25)       | 0.06 (0.37)          | -0.22 (0.32)          |
| Multiple disabilities                            | 0.05 (0.35)        | 0.62 (0.51)          | -0.11 (0.46)          |
| Prefer to self-describe                          | 0.47 (0.54)        | -0.21 (0.78)         | 1.00 (0.66)           |
| Age                                              | -0.01 (0.01)       | -0.01 (0.01)         | -0.01 (0.01)          |
| Job-Seeker                                       | -0.19 (0.16)       | -0.16 (0.23)         | -0.05 (0.21)          |
| Virtual Interview Experience                     | 0.01 (0.05)        | 0.03 (0.07)          | 0.02 (0.06)           |
| <b>Adjusted R-squared</b>                        | 0.25               | 0.30                 | 0.15                  |

**Note:** Estimates are reported with standard errors in parentheses. Significance codes: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ , .  $p < 0.1$ .