

U.S. Job-Seekers' Organizational Justice Perceptions of Emotion AI-Enabled Interviews

CASSIDY PYLE, University of Michigan School of Information, USA

KAT ROEMMICH, University of Michigan School of Information, USA

NAZANIN ANDALIBI, University of Michigan School of Information, USA

Emotion AI is increasingly used to automatically evaluate asynchronous hiring interviews. Although touted for increasing hiring fit and reducing bias, it is unclear how job-seekers perceive emotion AI-enabled asynchronous interviews. This gap is striking, given job-seekers' marginalized position in hiring and how job-seekers with marginalized identities may be particularly vulnerable to this technology's potential harms. Addressing this gap, we conducted exploratory interviews with 14 U.S.-based participants with direct, recent experience with emotion AI-enabled asynchronous interviews. While participants acknowledged the asynchronous, virtual modality's potential benefits to employers and job-seekers, they perceived harms to job-seekers associated with automatic emotion inferences that our analysis maps to distributive, procedural, and interactional injustices. We find that social identity can inform job-seekers' perceptions of emotion AI, extending prior work's understandings of the factors contributing to job-seekers' perceptions of AI (broadly) in hiring. Moreover, our results suggest that emotion AI use may reconfigure demands for emotional labor in hiring and that deploying this technology in its current state may unjustly risk harmful outcomes for job-seekers – or, at the very least, perceptions thereof, which shape behaviors and attitudes. Accordingly, we recommend against the present adoption of emotion AI in hiring, identifying opportunities for the design of future asynchronous hiring interview platforms to be meaningfully transparent, contestable, and privacy-preserving. We emphasize that only a subset of perceived harms we surface may be alleviated by these efforts; some injustices may only be resolved by removing emotion AI-enabled features.

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

Additional Key Words and Phrases: Emotion recognition, affective computing, workplace, employment, hiring, future of work, algorithms, algorithmic decision-making, transparency, explainability, contestability, privacy, justice, organizational justice, relational ethics, privacy harms

ACM Reference Format:

Cassidy Pyle, Kat Roemmich, and Nazanin Andalibi. 2024. U.S. Job-Seekers' Organizational Justice Perceptions of Emotion AI-Enabled Interviews. *Proc. ACM Hum.-Comput. Interact.* 8, CSCW2, Article 454 (November 2024), 36 pages. <https://doi.org/10.1145/3686993>

1 Introduction

Emotion AI intends to recognize, evaluate, and interact with individuals' emotional and affective states based on inferences derived from physiological signals, facial expressions, vocal patterns, text-based communications, etc. [96]. Global forecasts value the emotion AI industry at \$50 billion

Authors' Contact Information: [Cassidy Pyle](mailto:cpyle@umich.edu), cpyle@umich.edu, University of Michigan School of Information, Ann Arbor, MI, USA; [Kat Roemmich](mailto:roemmich@umich.edu), roemmich@umich.edu, University of Michigan School of Information, Ann Arbor, MI, USA; [Nazanin Andalibi](mailto:andalibi@umich.edu), andalibi@umich.edu, University of Michigan School of Information, Ann Arbor, MI, USA.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

© 2024 Copyright held by the owner/author(s). Publication rights licensed to ACM.

ACM 2573-0142/2024/11-ART454

<https://doi.org/10.1145/3686993>

USD by 2026 [103], with widespread adoption spanning consumer [85], education [82, 100, 116], healthcare [99, 100], workplace [20, 38, 80, 100, 119, 138] and hiring [4, 100, 125] domains.

Companies already use emotion AI for talent acquisition [22, 163] to attempt to remedy constraints in traditional recruitment processes. Facing a growing number of applicants, expanded workloads, and pressure to reduce labor expenditures [3–5], AI-enabled technologies promise hiring organizations appealing options to automate recruitment tasks (e.g., talent acquisition and training [139]) across myriad products including conversation agents [81, 155], gamified pre-employment assessments [11, 56, 153, 154], and video interviewing systems [77, 88, 145]. Research investigating emotion AI-enabled hiring technologies finds that vendors appeal to organizational ideals like data-driven decision-making and claim the technology facilitates “objective” and “unbiased” hiring processes that better meet organizational needs and, by proxy, also benefit job-seekers [125].

Yet, in contexts beyond hiring, emotion AI is critiqued for exacerbating bias and facilitating additional harms. Prior work reveals that some emotion AI algorithms exhibit biases along identity dimensions, including race [117, 118], gender [49], and disability [161, 164], and are often trained on demographically skewed data sets [29, 99, 149]. Fundamentally, what emotions are and whether they can accurately be computed is a controversial topic [16, 143], as most emotion recognition models classify emotion based on debated theories of emotions as discrete and universally expressed [50–52]. Consequently, the inferences generated by emotion AI have limited scientific validity, reliability, and generalizability [16]. Despite the apparent risks associated with organizations adopting fallible emotion AI, a dearth of research exists on job-seekers’ perspectives of emotion AI use in hiring.

Job-seekers rely on employers to access social and economic resources and have little agency in hiring processes, interactions, and outcomes. Their *marginalized* position constrains their ability to access employment, exercise individual agency, and participate as equal members of society [42], dynamics further shaped by identity attributes like gender, race, etc. [102]. Given job-seekers’ marginalized position in power-laden hiring contexts, our limited knowledge about their perceptions of emerging technologies that risk amplifying their marginalization is striking. The importance of addressing this absence is underscored by recent calls by the U.S. Office of Science and Technology Policy for input on using “biometric technologies for... inferences of attributes including individual mental and emotional states” [151]. What shapes job-seekers’ perceptions of emotion AI is a cogent question, as surfacing these factors can guide research and policy efforts to ensure design, implementation, and regulation of the technology aligns with job-seekers’ preferences and mitigates their exposure to harm.

While all job-seekers are in a marginalized *position* in the hiring context, job-seekers with one or more marginalized *identities* may disparately experience marginalization via unique identity-based challenges in the hiring context [98, 107, 108, 111–113, 144], and may disproportionately experience AI-inflicted harms [84, 99, 117, 118, 161]. Although the link between marginalization and identity is well-established [102], we know little about the role of identity in shaping job-seekers’ perceptions of and marginalizing experiences within algorithmic hiring systems [65, 94]. Eliciting the perspectives of job-seekers with marginalized identities has the potential to uncover the relevance of these identities to job-seekers’ perceptions and suggest opportunities for policy and design to address possible disparate experiences.

Aligning with a relational ethics approach [18], our study centers job-seekers’ perspectives of emotion AI-enabled asynchronous hiring interviews – impacted and marginalized groups with intimate knowledge of the potential harms of emerging technologies via their social positionality – with a focus on the role that marginalized racial/ethnic, gender, and disability-related identities can play in shaping them. Accordingly, our work joins the emerging body of AI ethics and Computer-Supported Cooperative Work (CSCW) scholarship attending to marginalized impacted groups’ perspectives of emerging technologies (e.g., [6, 19, 23, 124, 161]).

We conducted semi-structured, in-depth interviews with 14 U.S. adult job-seekers. Via an interpretivist approach [33], our analysis elicits rich, contextualized, and generative insights into participants' perceptions about emotion AI-enabled asynchronous interviews and the role of identity in shaping them by asking:

- **RQ1: How do U.S.-based job-seekers perceive potential benefits and harms of emotion AI-enabled asynchronous interviews?**
- **RQ2: What role, if any, does social identity play in shaping U.S. job-seekers' perceptions of emotion AI-enabled asynchronous interviews?**

Although participants associated potential benefits with asynchronous interview formats for employing organizations and — to a lesser extent — job-seekers, they overwhelmingly perceived harm to applicants associated with emotion analysis¹ in ways that mapped onto dimensions of organizational injustice [34, 61, 121] (i.e., distributive, procedural, and interactional injustice). These perceived harms included inaccurate, discriminatory, or identity-laden inferences, demands for increased emotional labor, and lack of transparency and contestability. Importantly, while we note perceived benefits, all perceived benefits to job-seekers correspond to the asynchronous virtual format of the interviews and *not* emotion AI-enabled features. By sampling participants with a neurological or mental disability and/or minoritized racial/ethnic and gender identities, we show how participants' social identities may shape their justice-related perceptions of emotion AI use in hiring.

We examine the merits of our ethically-positioned methodological approach and organizational justice analytical frame and consider how emotion AI-enabled asynchronous interviews may (re)configure demands for emotional labor [70] in hiring. Given the potential harms we surface, we recommend against adopting emotion AI in hiring. Further, we identify opportunities to enhance participants' perceived benefits associated with *asynchronous* hiring interviews and mitigate harms associated with emotion AI analysis with more meaningfully transparent, contestable, and privacy-preserving designs and policy considerations. Importantly, we emphasize that these (and other technical) fixes may attend to distributive justice concerns but fail to address procedural and interactional justice concerns, which may only be remedied by refusing to use emotion AI-enabled features.

2 Related Work

This study draws interdisciplinary perspectives from philosophy, psychology, anthropology, human-computer interaction/affective computing, and human resources/management studies to describe relevant emotion theories, the state of emotion AI, and job-seekers' reactions to AI-mediated hiring processes.

2.1 Theories of Emotion, Emotion AI, and Perceived Benefits/Harms

Basic Emotion Theory (BET) [50, 51], the dominant choice for algorithmic representations of inferred emotion [143], suggests emotion families can be categorized into universal, easily discerned categories (i.e., anger, disgust). However, contemporary scholarship considers emotion a complex mix of social, cultural, physiological, phenomenological, and psychological elements [15, 16, 27, 57, 131, 143]. Indeed, the BET approach is challenged by theories viewing emotions as cognitive states [101, 136], experiential phenomena [137, 143], or social constructs [15, 16, 57, 115], thus

¹Throughout the paper, we distinguish between the asynchronous and virtual *format* of interviews on these platforms and the *automated analysis* of emotion and affective phenomena from these interviews as two components of broader “emotion AI-enabled asynchronous hiring platforms.”

questioning the validity, accuracy, and reliability of emotion recognition/AI across people and cultures.

The increasing uptake of emotion AI is furthermore critiqued for facilitating harms, including privacy intrusions and biased decision-making. Research demonstrates myriad concerns among “data subjects” impacted by this technology [10, 39, 73, 124], including social media users viewing it as invasive [10, 55, 124], with individual and societal-level risks [10]. Emotion AI harms may be exacerbated for marginalized individuals, potentially conferring identity-based harms like stigmatization and discrimination, even if emotion inferences are “accurate” [38, 106].

Shifting our attention to the workplace context, while vendors claim emotion AI supports employee compliance, productivity, and well-being [20], employees perceive it as harmful, with the potential to worsen employee well-being and amplify workplace bias and stigma, particularly against those with marginalized identities [38]. Past work demonstrates the need for more research centering emotion AI’s data subjects in other high-stakes domains. Our relational ethics approach [18, 38, 124, 157] contributes to efforts examining perspectives of groups impacted by emerging algorithmic technologies [6, 10, 19, 23, 124, 161] by studying job-seekers’ perspectives — including those embodying marginalized identities — on emotion AI-enabled asynchronous hiring interviews.

One lens through which to examine (emotion) AI’s privacy harms is Citron and Solove’s privacy harms taxonomy [32], which argues that these harms span more tangible, immediately recognizable harms (e.g., physical, economic) and harms that are less readily recognizable and more abstract (e.g., reputational harms, psychological harms). Recent workplace surveillance scholarship [126] has advanced this taxonomy by identifying emotion AI-enabled harms beyond that recognized in Citron and Solove’s more general privacy harms framework, including amplified emotional labor, which may be disproportionately experienced by those who embody marginalized identities and facilitates “chilling effects to workers’ own, felt emotions.” We draw on this expanded privacy harms taxonomy in our analysis and interpretation of job-seekers’ perceptions of emotion AI-enabled asynchronous interviews.

2.2 Hiring, Job Interviews, and Emotion (AI)

Traditional hiring processes involving resume reviews and face-to-face/phone interviews have faced criticism for bias against specific applicant groups [98, 107, 108, 112, 113, 162] and organizational inefficiencies [60, 72, 90, 146]. Traditional hiring is indeed subjective, influenced by dynamic and co-constitutive emotions between interviewers and job-seekers [120]. Emotion AI vendors claim to mitigate traditional hiring deficiencies by replacing the interviewers’ emotions in hiring assessments with “objective” and “accurate” emotion inferences [125].

Increasingly [20, 22, 125, 163], asynchronous video interviews use emotion AI to evaluate job-seekers’ suitability, analyzing facial movements, mannerisms, and voice patterns [105] to infer their emotions and other affective phenomena during the interview [125]. However, the use of emotion AI in recruitment, and especially asynchronous interviews, is controversial, threatening negative implications for the future of work and equity by potentially exacerbating bias, especially against disabled applicants [99, 161], and (re)shaping the role of emotions in hiring. For instance, the accuracy of emotion AI may be compromised via training data and models that do not reflect the experiences of disabled individuals in the hiring and work context or that reflect societal stigma against disabled people [99]. Yet, job-seekers’ perspectives on *emotion AI-enabled asynchronous interviewing* remain unknown. This is important to uncover because incorporating algorithmic emotion analysis into hiring may uniquely affect emotions, be ill-equipped to infer across socio-demographic groups, and enable biased decision-making at scale. Emotions in hiring and the workplace are complex and sensitive, and using automatic emotional inferences to inform hiring decisions may potentially reshape who can access employment opportunities that determine one’s

livelihood. Thus, with attention to job-seekers' social identities and marginalities, this study focuses on the emotional dimension of AI technologies in a high-stakes context in which emotion AI, specifically, is scarcely examined.

2.3 Applicant Perceptions of Automated Interviewing

Extensive research on “applicant reactions” [1, 95, 134] to hiring processes – including AI-enabled ones – shows they are shaped by applicant attitudes, motivation, and organizational justice perceptions [61, 66]. Organizational justice as perceived fairness in a workplace [43, 121] encompasses distributive, procedural, and interactional dimensions. Distributive justice pertains to fair allocation of rights, rewards, and resources [37]; procedural justice to formal decision-making processes [44]; and interactional justice to informal interpersonal interactions [34, 35, 44]. Research using organizational justice frameworks to study applicant reactions in AI-based interviewing indicates applicants perceive the technology as less just than traditional interviews [1], partly due to the depersonalizing nature of AI-enabled asynchronous interviewing.

Our examination of job-seekers' perspectives of *emotion* AI in hiring and social identity's role in shaping these perceptions builds upon and extends extant “applicant reactions” research [65] in the following ways. First, prior (often quantitative) work on job applicants' reactions toward hiring processes (inclusive of “traditional” and technology-mediated processes) notes that “age, gender, and race” are unrelated to applicants' justice-related and broader perceptions of hiring processes [65]. Recent work using quantitative and qualitative approaches found socio-demographic differences in perceptions of emotion AI in workplace monitoring [38, 94]. This work builds on these findings to explore the relevance of social identity in applicants' perceptions using qualitative methods, a relational ethics lens, and sampling marginalized job-seekers.

Second, emotion AI is largely based on debated, controversial scientific theories of emotion [16, 143] (i.e., Basic Emotion Theory [50]) and is susceptible to bias from demographically skewed data sets [4]. Thus, applicants may have unique perceptions stemming from concerns about how accurate and valid automatic inferences of emotion are compared to, say, automatic inferences of one's leadership skills or other job-related, non-affective phenomena, necessitating work on perceptions of *emotion* AI in hiring, specifically. Further, emotions are often deemed private [10, 106, 131], therefore inferring them has unique implications in high-stakes contexts. For example, whereas leadership skills may be immediately relevant to one's capacity as an employee, emotions do not carry this same relevance, and they are sensitive attributes. Thus, the *private dimensions of emotions*, combined with emotion AI's reliance on *challenged emotion theories and biased training data*, can facilitate unique harms for those who do not express emotion in narrow ways prescribed by emotion AI. These distinctions between emotion AI and more general forms of AI used in hiring warrant investigations of the justice perceptions of *emotion* AI, specifically, in hiring.

Third, both ethically and for theoretical advancement, it is important to ascertain job-seekers' perspectives on emotion AI in hiring because hiring is high-stakes, with immediate and longer-term implications for job-seekers' livelihood and well-being [12, 25, 122, 147]. Much of the past work on applicants' reactions, including reactions to automated interviewing, has omitted the perspectives of actual job-seekers, opting instead for experimental lab studies with college students and MTurk samples [1, 65]. By contrast, our study ascertains justice perceptions of emotion AI in hiring by eliciting in-depth interview data with current or recent job-seekers with direct experience with (though not always awareness of) emotion AI-enabled asynchronous hiring interview platforms.

Taken together, existing work on applicants' reactions to increasingly automated hiring processes motivates the need for research that involves job-seekers, considers social identity, and disambiguates *emotion* AI's distinct role in increasingly technology-mediated hiring processes, gaps which the present study aims to fill.

P#	Industry	Gender	Race/Ethnicity	(Dis)ability Status	Emotion AI Awareness
1	IT/Admin.	Man	Hispanic or Latino/a/x	Mental Illness	AA
2	Restaurant	Non-Binary	White	NI, LD, Mobility Impairment, MI	AEA
3	Recruiting	Man	White	SI, MI	AEA
4	Technology	Man	East Asian	Prefer Not to Disclose	AA
5	Film/TV	Woman	Hispanic or Latino/a/x	Prefer Not to Disclose	AA
6	Healthcare	Non-Binary	Indigenous/First Nations, White	MI	AA
7	Comms./Environmental	Woman	White	MI	AA
8	Medical/Aerospace	Man	Hispanic or Latino/a/x	Prefer Not to Disclose	AA
9	Finance	Woman	African, White	None	AEA
10	Retail	Man	Hispanic or Latino/a/x	None	AEA
11	Finance	Man	White	None	AEA
12	Finance	Woman	Asian-American, East Asian, White	LMI, Mobility Impairment	AEA
13	Medical	Woman	White	NI, TI	AEA
14	Finance/Data Science	Woman	Asian-American, Southeast Asian	None	AEA

Table 1. Participants' Self-Described Socio-Demographic Data. NI = Neurological Impairment; LD = Learning Disability; SI = Sensory Impairment; LMI = Long-Term Medical Illness; TI = Temporary Impairment; MI = Mental Illness; AA = Awareness of Automated Analysis of Asynchronous Interviews; AEA = Awareness of Automated *Emotional* Analysis of Asynchronous Interviews

3 Methods

We conducted exploratory semi-structured interviews with job-seekers ($n = 14$) who recently experienced emotion AI-enabled asynchronous video interviews. Our institution's IRB exempted this study from ongoing oversight.

3.1 Participants and Recruitment

Inclusion criteria for participation required that all participants recently (within the past six months) 1) participated in asynchronous interviews and 2) were aware the interview was automatically analyzed. We used Prolific, a paid recruitment firm, and institutional email listservs to target job-seekers. 268 interested participants first completed a pre-screener (Appendix A); following a purposive sampling approach to include a range of marginalized identities and levels of awareness of the emotion AI component of these interview platforms, we invited 26 to interview, with 14 participants completing interviews. We stopped inviting interviewees when the second author's analytical memos taken after each interview and discussions between the second and last author indicated no new themes [104]. Participants were compensated \$40 USD for their time. Approximately 43% of participants were men, 43% were women, and 14% were non-binary. 50% of participants were white, 29% were Hispanic or Latino/a/x, 21% were Asian, and 50% of participants had a disability. All but one participant (93%) reported at least one demographic characteristic that is marginalized in the job search process (i.e., gender, race/ethnicity, (dis)ability). Table 1 contains our sample's demographic information. The pre-screening survey (Appendix A) used conditional logic to assess respondents' awareness that emotion AI was used to analyze their interview. Respondents were first asked if they used asynchronous hiring platforms, what hiring platforms they used (from a list of hiring platforms known by the researchers to be emotion AI-enabled), and what information they thought was collected and/or inferred by the platform(s), including identity characteristics and interior/affective phenomena including attention, emotions, motivations, etc. The pre-screener then confirmed participants' awareness with an open-ended question asking all eligible participants to briefly explain how they knew their interview was automatically analyzed to infer the information they indicated. We purposively sought to balance the participant pool to include participants with ($n=8$) and without ($n=6$) *explicit awareness* that automatic analysis of their asynchronous job interviews included inference of their emotions to avoid biasing findings with a self-selected sample of participants particularly concerned about emotion AI in hiring. Importantly, *all* participants used

an emotion AI-enabled asynchronous interview platform. Not all of them *knew* that the platforms they used would involve emotion analysis components. Thus, throughout the paper, we use “AA” to denote those who knew their asynchronous interviews were automatically analyzed but who did *not* know that this automatic analysis included emotional inferences. We use “AEA” to denote those who *knew* their emotions were automatically analyzed in their asynchronous interviews.

In addition, we purposefully sought representation of interview participants who self-reported having a neurological or mental disability and/or a minoritized racial/ethnic or gender identity. We chose these dimensions because individuals with these identity characteristics may be disproportionately impacted by emotion AI [84, 99, 117, 118, 161], experience identity-related hiring challenges [98, 107, 108, 111–113, 144], can more readily recognize potential harms of emerging technology [18], and are underrepresented in studies on impacted parties' perceptions of these technologies [10, 62, 124].

3.2 Data Collection: Interviews

The second and third authors designed the interview protocol. The second author conducted semi-structured interviews via Zoom between November 2021 and April 2022. The first interview phase asked participants about their experience with asynchronous interviews. Before beginning the second phase, we established common ground for all participants regardless of their level of awareness of automated emotion analysis, specifically by stating that we wanted to discuss what they thought about one-way video interviews that use an intelligent computer program to analyze information from the video (e.g., what they looked like, what they said, or how they said it) to make inferences about how they felt during the interview – without using technical terminology. Then, we asked about participants' perceptions of the automatic analysis of those interviews, grounded in context from the first phase.

Scenario-based interviews are commonly used to elicit participants' values, especially when values may not otherwise emerge in interviews [74, 78]. In social computing, researchers apply scenario-based methods to elicit participants' values toward emerging technologies they may not have conscious experience with [8, 10, 24, 67]. For those without explicit awareness of emotion AI before the interview, the interview protocol for the second phase varied in that we used scenario-based questions that asked participants what they *would* think about emotion analysis rather than what they *did* think. Interview protocols are included in Appendix B. Additional interview topics included participants' job search and experiences with, conceptions about, and attitudes toward video interview platforms.

3.3 Data Analysis

The second author used Rev to transcribe interviews. The first author conducted thematic analysis with Atlas.ti, using deductive and inductive approaches [21] in the open coding process, drawing directly from the data to elicit new codes *and* allowing our understanding of emotion AI, organizational justice, and hiring to inform coding. The open coding process [135] resulted in a preliminary codebook, which all authors discussed, collapsing and expanding codes. Through our discussions and given our familiarity with organizational justice and algorithmic/AI harms literature, we agreed that our codes mapped well to organizational justice frameworks and organized our final coding scheme by organizational justice dimensions. Next, the first author engaged in second-cycle coding [135], applying the final codebook to the entire corpus of data. As no new codes were created in this process, we determined our analysis reached theoretical saturation [53, 130]. We also ensured that the data set's commonalities and edge cases were represented in the coding process, following theoretical saturation guidelines [92].

While we organize our findings around justice types, we did not explicitly set out to do so, nor did we use the term “justice” with participants to avoid priming terminology [26, 59]. Rather, our inductive analytic approach [148] mapped data to justice types as it surfaced during our analysis that participants’ perceptions aligned with justice dimensions, aligning with prior social computing work mapping data to relevant frameworks [9, 47, 48, 110, 156].

3.4 Limitations, Reflections, and Opportunities for Future Work

This study has several limitations. First, it is U.S.-based. Findings may not apply to non-U.S. contexts, as justice perceptions [36, 54, 91] and emotion’s role in hiring vary across cultural contexts [64, 79]. Future work may examine how these findings extend to or differ in diverse cultural contexts.

Second, while the goal of interview studies like ours is not representativeness and generalizability but rather rich, contextualized insights into participants’ perceptions [28, 33, 45], it is important to acknowledge associated limitations. We recognize that a sample size of 14 individuals is a limitation even when data is rich, making our study an exploratory one. As such, findings are presented as exploratory conclusions that should be built upon in future work. Nevertheless, targeting a small but purposeful sample for interviews was appropriate to generate data grounded in diverse job-seekers’ experiences, aligned with a relational ethics approach [18]. Our work contributes timely insights that can be built upon in future work using surveys, for instance, and aligns with similar CSCW scholarship examining impacted groups’ perceptions of emerging technologies by drawing from samples of similar size and composition [63, 124, 126].

Third, we designed scenarios grounded in participants’ lived experiences to ensure validity. As we uncovered similar themes between those without awareness of emotion AI, for whom we used scenario-based questions, and those already aware, we are confident in our findings’ validity. Additionally, the decision to sample those with *and* without awareness of emotion AI may have yielded findings based on participants’ conceptions of technology that may not reflect the technical functionality of the platform(s) they had experience with. Importantly, our focus in the present study is not to make claims about emotion AI’s technical functionality but to highlight the importance of impacted groups’ conceptions and attitudes toward the technology. These conceptions are valuable regardless of accuracy because they shape impacted groups’ behaviors toward technologies [152]. Additionally, job-seekers’ perceptions are important considering the information asymmetries between job-seekers and employers involved in emotion AI-enabled hiring technologies [125]. Future work may study the perspective of recruiters and/or emotion AI developers to understand how job-seekers’ perceptions relate to other involved parties. Additionally, future work may build on our findings through algorithmic audits to measure the impacts of these technologies and whether/how measured impacts relate to job-seekers’ perceptions of them.

Fourth, our sample consisted of job-seekers, limited to the past six months at the time of data collection. However, we did not ask participants to specify when they encountered one-way interviews in greater granularity. As commercial emotion AI systems used in the hiring context take time to develop and deploy, it is possible but unlikely that design changes since participants’ exposure would result in meaningful differences between the technologies and participants’ perceptions. Relatedly, we acknowledge that outcome favorability [17, 30] may shape perceptions toward these technologies and encourage future work to assess if/how outcome favorability may serve as a confounding variable, which our qualitative research design is unable to determine.

Fifth, we do not quantify theme frequency when reporting findings, as these quantities would neither be valuable given our small sample size nor appropriate given our interpretivist approach [45]. Future work with larger and representative samples could quantify and rank how impacted groups perceive potential benefits and harms.

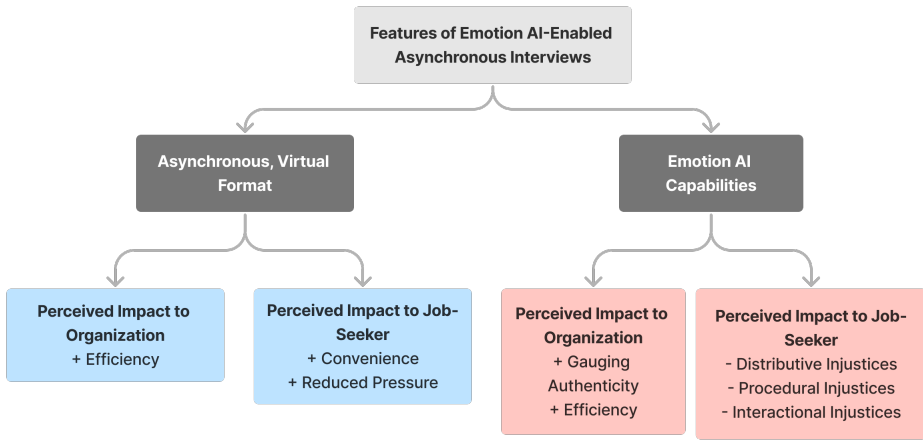


Fig. 1. Diagram demonstrating perceived benefits (denoted with +) and harms (denoted with -) to organizations and job-seekers of two distinctive components of asynchronous interview platforms – the asynchronous virtual format and emotion AI-enabled features of these interviews

Finally, we note that while 93% of our participants reported at least one marginalized identity, our sample still could have been more diverse. Specifically, our sample would have benefited from incorporating more perspectives of job-seekers of color, particularly Black job-seekers. Though we sent interview invitations to all eighteen Black job-seekers who completed the screening survey, only one completed an interview. Future work may partner with community organizations that primarily serve Black job-seekers to elicit their perspectives, as they have historically been subject to race-based discrimination in hiring [112, 113, 150]. However, we expect that injustice-related concerns would prevail across various races and ethnicities. Additionally, while our study uncovers that identity can inform job-seekers’ perceptions of emotion AI in hiring, future work using quantitative approaches like surveys can disentangle how and to what extent various identities – or intersections thereof – shape perceptions.

4 Findings

RQ1 asked how job-seekers perceive the potential benefits and harms of emotion AI-enabled asynchronous interviews; RQ2 asked what relevance social identity may have to these perceptions. Overall, while participants perceived asynchronous interview formats benefiting hiring organizations and, to a lesser extent, job-seekers, they raised concerns about harms stemming from being subjected to emotion AI inferences in particular. We first present participants’ perceived benefits to employing organizations, followed by participants’ perceptions of benefits for job-seekers. We then describe participants’ perceived harms, which we organize using an organizational justice lens (distributive, procedural, interactional) [61, 66], and the privacy harms taxonomy [32]. Table 2 includes definitions and example themes corresponding to organizational justice dimensions. Where applicable, we demonstrate how social identities informed job-seekers’ perceptions, supported

Justice Types	Definitions	Relevant Themes
Perceived Distributive Justice	<i>Fair allocation of "valued rewards, resources, rights, obligations, etc." [37]</i>	1) Inaccurate inferences 2) Identity-laden or discriminatory inferences * 3) Data security/privacy implications
Perceived Procedural Justice	<i>Fairness of "structural features of the decision-making process" [44]</i>	1) Rigid algorithm(s) 2) Identity-related bias *
Perceived Interactional Justice	<i>Fairness of the "quality of the interpersonal interaction between individuals" [44]</i>	1) Emotional harms 2) Emotional labor harms 3) Lack of meaningful transparency and contestability

Table 2. Justice types and corresponding perceived harms to job-seekers. * indicates relevance to social identity surfaced in our analysis (RQ2).

and contextualized with participants' demographic information. Figure 1 summarizes perceived benefits and harms to organizations and job-seekers from two components of emotion AI-enabled asynchronous interview platforms.

4.1 Job-Seekers' Perceived Benefits of Emotion AI-Enabled Asynchronous Interviews to Employers and Job-Seekers

While participants felt that emotion AI in hiring was harmful and unjust to job-seekers (as described in Section 4.2), they reported understanding its uptake from an organizational standpoint due to the benefits they associated with its use for employers.

4.1.1 Perceived Benefits to Employers. Participants perceived emotion AI could benefit organizations by 1) gauging applicants' "authenticity" and 2) managing hiring processes efficiently – the latter of which stems from the asynchronous virtual nature of interviews and *not* emotion AI (in contrast to the perceived benefit of gauging authenticity).

Gauging Authenticity. Participants noted that emotion AI could benefit organizations if it [could] gauge applicants' honesty and 'authentic' interest in the job. For example, P7 (white, woman, disabled, communications/environmental industries, AA) remarked:

I guess it would be good to know that someone actually wanted to do the job... if you could use emotions to know if someone's telling an honest story... I can see it being most useful... to gauge if someone is showing genuine excitement for the job because you could definitely contribute differently if you really want to work there, then you might be a better fit on the team than someone who doesn't.

P7 highlights the perceived potential for emotion AI to benefit organizations by detecting whether job-seekers are portraying themselves "*honestly*" and identifying "*genuine excitement*" as a proxy for who would be a good "*fit*" for a job. Regardless of the extent to which emotion AI accurately does so, this participant perceives that if it does, it would be helpful to organizations – shaping their attitudes towards emotion AI use in hiring.

Efficiency in Hiring. Participants also reported that asynchronous virtual interviews could make organizations' hiring processes more efficient. For instance, P2 (white, non-binary, disabled, restaurant industry, AEA) noted:

You don't have to have a recruiter talking to somebody or a hiring manager, so [there's] less staff needed to hire you... somebody [just] goes back and checks the recording. They don't have to waste their time in the interview. If they don't like a question, they can just stop listening to the recording. If you're in an interview, usually you still go through all the questions.

By comparing asynchronous virtual interviews to face-to-face interviews, P2 describes perceptions of asynchronous virtual interviews as demanding less time and personnel from the employing organization.

4.1.2 Perceived Benefits to Job-Seekers. Participants described two perceived benefits of asynchronous interviews for job-seekers: 1) convenience and 2) reduced pressure in the interviewing environment. Both perceived benefits correspond to the asynchronous format rather than the use of *emotion AI*, specifically. **Convenience.** Participants perceived that asynchronous virtual interviews could be more convenient for job-seekers, who can record their interviews anywhere or at any time. As P11 (white, man, finance industry, AEA) notes:

The only thing I like is you can take the interview on your own time. You can do it at 3:00 AM if you want. So I do like that. They work around your schedule that way, and you can do it whenever you want.

Interestingly, P11 refers to convenience as the “*only thing*” they like, exemplifying our findings that the perceived benefits job-seekers associated with these platforms were limited strictly to the asynchronous virtual format rather than the emotion AI component of these services.

Participants noted that “convenience” could particularly benefit certain groups, such as P5 (Hispanic/Latina/o/x, woman, film/tv industry, AA), who suggested added convenience in hiring could benefit “*people that are busy maybe, maybe they’re college students, or maybe they work at home.*” Similarly, P9 (African/white, woman, finance industry, AEA) reflected:

Yeah, I think it was much easier on me... considering that I was still working full-time [when] I had these interviews. It was really good that I could record them and get that feedback during my own time, and not have to schedule an interview and take time out of work to be there for an interview. So I just think it was the most efficient [use] of my time.

These findings indicate that job-seekers constrained by logistical challenges associated with in-person interviews, such as those who work from home, may especially benefit from the convenience provided by asynchronous, virtual interviews – not their possible emotion AI components.

Reduced Pressure. Participants reported feeling less pressure in asynchronous virtual interviews than in face-to-face interviews. As P2 (non-binary, white, disabled, restaurant industry, AEA) suggested, “*it also gives you a little less pressure to get it right the first time because you’re able to redo it.*” P2, an autistic participant who reported having trouble communicating without “*stutters*” and “*filler words*,” particularly felt that they benefited from the asynchronous virtual format. Similarly, P1 (Hispanic/Latino/a/x, man, disabled, IT/administrative industries, AA) elaborates:

It takes a bit of the pressure off because you don’t need to immediately respond to things. You don’t need to think of things on the spot... you can have a script, or you can have a set of bullet points.

Participants also noted how reduced pressure could be particularly valuable to certain groups, including job-seekers who are anxious or introverted. For instance, P4 (man, East Asian, technology industry, AA) says, “*I can see it would give a lot of advantages to those people who have difficulty talking to other people, introverts, [people with] anxiety... They can redo their response.*” Similarly, P5 (Hispanic/Latino/a/x, woman, film/TV industry, AA) elaborates:

I think it can benefit people with... shyer personalities just because I know that a lot of people deal with anxiety when it comes to having a face-to-face interview. Whereas they would probably not get the job from a face-to-face interview, they might actually succeed in getting to the next step [in an] asynchronous interview just because they don’t have the added pressure of being in front of someone. They might be able to

manage their emotions and not let things like wide eyes or nervousness show through in an asynchronous interview.

As these examples demonstrate, asynchronicity afforded job-seekers opportunities to think through their answers and redo the interview if necessary, reducing perceived pressure for job-seekers, particularly those who may be disadvantaged in traditional formats. Importantly, the benefit of reduced pressure resulted from the asynchronous, virtual nature of these interviews and not emotion AI's evaluation of them.

4.2 Job-Seekers' Perceived Harms of Emotion AI-Enabled Asynchronous Interviews to Job-Seekers

Though participants acknowledged emotion AI's potential benefits to employers, they perceived myriad harms to job-seekers, which our analysis maps to distributive, procedural, and interactional organizational justice dimensions (see Table 2).

4.2.1 Perceived Distributive Injustices. First, participants referenced how emotion AI-enabled asynchronous interviews could elicit unjust outcomes, namely one's ability to obtain a job, through 1) inaccurate inferences; 2) inferences made, irrespective of accuracy, that are informed by an applicant's social identity; and 3) privacy and security violations.

Inaccurate Inferences. Participants reported concerns that emotion AI could make inaccurate inferences about candidates that could prevent them from obtaining employment, signaling distributive injustice. For example, participants like P2 (white, non-binary, disabled, customer service industry, AEA) referenced their knowledge of the currently contested technological capabilities of emotion AI, saying, "*So technology's gotten really advanced, but computers aren't to the point where I think they can tell tonality and expression quite well yet.*" Similarly, P1 (Hispanic or Latino/a/x, man, disabled, IT/administrative industries, AA) notes concern that emotion AI may be unable to reconcile technical glitches or difficulties, leading to inaccuracies:

Maybe there's a skip in the video, or there's some other kind of technical difficulty because they got interrupted by a phone call or something. The AI isn't sophisticated enough yet to be able to make those judgments, to be able to look at the context of things. It's going to regard such things as black marks against the interviewee... All sorts of technical glitches can go wrong because of this if you're relying solely on AI.

In addition, socio-economic status could preclude access to an environment conducive to recording an asynchronous interview, as described by P13 (white, woman, disabled, medical industry, AEA):

If you're an employee that doesn't have the capability of having a nicer setup laptop or a background, or you don't have a good home environment, it can definitely be the make it [or] break it for a lot of people... And without access to things, it's going to be rough for a lot of people. And that's what I worry about is communities that don't have access or don't have the money to afford [the] technology to do it.

Thus, participants like P13 and P1 referenced how social identity, namely socio-economic status, can inform technological limitations that facilitate inaccurate emotional inferences, which may, in turn, prevent an applicant from obtaining employment, signaling *distributive* injustice. P13's remarks highlight how socio-economic status informs how disparities in access to new, advanced technology *and* the lack of money or time to create a quiet, aesthetically pleasing environment for recording interviews. P13 perceives that these disparities could influence the inaccurate inferences AI may make about interviewees. This is particularly striking given recent work showing that cues from one's background in asynchronous video interviews *do* inform interview performance ratings

by human raters [109, 128]. Participants' perceptions are important regardless of whether their concerns map to the technical functionality of these technologies, as they shape their behaviors and attitudes [152]. Notably, even if emotion AI accounts for "*technical glitches*" in the data it processes, the continuous stress about *if* these glitches could impact their interview outcomes could constitute significant emotional harms [32], which we elaborate on in Section 4.2.3. Taken together, these quotes demonstrate how participants – both aware and unaware of emotion AI before the interview – perceived that emotion AI could make inaccurate inferences indirectly informed by social identity (i.e., from technical limitations informed by socio-economic status), that could ultimately result in distributive injustices including loss of job opportunities.

Identity-laden or Discriminatory Inferences. Participants noted that emotion AI could generate inferences that, irrespective of accuracy, were perceived to hinge upon candidates' social identities and, at worst, discriminate based on identity and preclude employment opportunities. Specifically, participants perceived that emotion AI could 1) facilitate hiring discrimination, 2) make inferences based on problematic notions of how certain demographic groups express emotion, and 3) screen out those inferred to have mental health conditions. Participants like P4 (East Asian, man, technology industry, AA) referenced opportunities for emotion AI to facilitate an employment organization's discriminatory hiring practices:

If [an organization is] racist, or if they don't have this diversity pressure, they can really just hide who they want. If they don't like certain races, they just [say], "Okay, I don't see [the position] as a cultural fit." They see [an applicant's] race. They basically can see their features, facial expressions, skin, color, whatever, they can make judgments on that. They won't say [it] out loud, obviously, but they would just say, "Oh, I don't think it's a cultural fit." So, basically, my concern is that they can filter out candidates based on appearance, race, or whatever.

P4 notes that organizations that may hold rigid and/or discriminatory notions of "cultural fit" can deploy emotion AI-enabled asynchronous interviews in ways that justify rejecting applicants who possess a certain racial or ethnic identity under the veneer of an "objective" assessment of "cultural fit" [4, 125]. This signals distributive injustice as it directly pertains to withholding a desired outcome (employment) based on a combination of organizational notions of "cultural fit" and using identity-laden emotion AI inferences to determine who is (not) a "cultural fit." Interestingly, P4 self-described as an Asian man and "*an overrepresented minority*" in the technology industry and reported experiencing racism within the technology industry that informed his perceptions. Relatedly, P7 (white, woman, disabled, communications/environmental industries, AA) noted concerns that societal stigmas could be programmed into emotion AI, especially concerning discriminatory inferences for those, including herself, that do not conform to gendered displays of emotion:

If stigmas and things would be built into the system, like how girls are expected to smile more... I think all those stigmas exist and will be of least concern if you are a white man, then increasing concern if you're just anyone else... my biggest concern for myself would be gender if they have it in a way that women should be expressing differently.

In addition to racial/ethnic and gender-based discrimination, participants referenced the possibility that emotion AI-enabled asynchronous interviews could unjustly screen out candidates with mental health conditions or those experiencing symptoms during an interview. P6 (Indigenous American or First Nations & white, non-binary, disabled, healthcare industry, AA) shares:

I'm kind of scared that it's going to pick up on [me] being anxious, having anxiety, and having mental health issues... being scared, being frustrated again that it's doing that, and feeling like I don't have a fair chance.

P6 expresses concern that their mental health-related conditions could be (accurately) inferred by emotion AI, which could preclude their ability to obtain employment since employers have historically [68, 132, 144] and may continue to discriminate against those living with mental health conditions, for instance by deeming them unfit for work or refusing to make accommodations. P6 identifies ways that emotion AI-enabled asynchronous interviews could be distributively unjust, discriminatory, and emotionally harmful despite the inferences themselves being “accurate.” Importantly, P6 notes that they have anxiety and “*always struggled with making the correct facial expressions. My face is usually very plain, it’s very blank.*” Again, regardless of how these systems *actually* work and how accurate they are in practice, perceptions of both accurate and inaccurate emotion AI and their respective harms were reported by a range of participants across levels of awareness, including those with marginalized social identities.

In a similar vein, P5 (Hispanic/Latino/a/x, woman, film/TV industries, AA) expressed concerns with identity-laden, potentially discriminatory emotion inferences. Importantly, P5 noted that “*some people tend to speak louder than others, at least in my culture... there’s some aspects of my culture that would influence the way that I speak and the way that I act.*” Concerning emotion AI, she remarked:

There’s always the fear of not getting the job because of something like that. Even though it says in every application that people don’t discriminate based on race and aspects of your identity, with an AI program, it would be interesting to see how they deal with that.

Here, P5 connects the distributive injustice of “*not getting the job*” to emotion AI’s exacerbation of vague, potentially discriminatory assessments of “cultural fit.” She suggests that while companies are compelled to take stances against employment discrimination, emotion AI use might facilitate less overt forms of discriminatory decision-making.

Taken together, our analysis demonstrates how participants perceived that emotion AI-enabled asynchronous interviews could make 1) (in)accurate references about them that hinge upon their social identity, and/or 2) discriminatory inferences that could result in their loss of job opportunities, signifying distributive injustice.

Data Security/Privacy Implications. Participants perceived that emotion AI’s generation of emotional data could harm job-seekers by increasing their risk of exposure to security and privacy violations. Participants raised concerns that identifiable, sensitive emotional inferences could be sold, shared with, or leaked to third parties. For instance, P11 (white, man, finance industry, AEA) shared:

You wouldn’t want that [emotional] data out there. I’m not even a fan of being reported by AI, but obviously, you wouldn’t want that data to be shared [with] third parties. Or maybe you wouldn’t want it to send to other companies out there... maybe your interview gets put into a big place of data, and maybe other companies can tap into [it and] say, “Oh, person X... they don’t have good AI scores.”

Here, P11 expresses concern that the very creation of job-seekers’ inferred emotional data creates the possibility for it to be shared with “*third parties*,” a practice which may restrict his future job opportunities, implicating distributive injustice, as records of “poor” emotional performances in one interview would be stored and potentially accessed by potential employers, precluding future opportunities. Moreover, participants, including P11, reported worrying about the potential for these inferences to be aggregated, sold, or used for profiling purposes. These concerns apply even if data were re-used internally (i.e., *not* shared by third-party vendors). For example, if a candidate were profiled on a hiring platform’s database, in the absence of oversight and regulation, it could

be used by multiple companies to which the same candidate applied. As P12 (Asian American, East Asian, & white, woman, disabled, finance industry, AEA) reported:

I know with Pymetrics, the actual game one, you only need to take it once, and it shares with all the companies that require it for a year or something or half a year... It makes it almost feel like you have one shot once you're in the system... If you perform differently in different interviews, I wonder if it could compare... I don't think this is great because people grow even in a short time. You can have an experience that changes your outlook or your ambitions.

Sharing her experience with Pymetrics' assessments, P12 provides an example of concerning data-sharing practices that violate job-seekers' privacy in the context of emotion AI-enabled asynchronous interviews. Notably, many emotion AI-enabled asynchronous interview platforms' privacy policies allow for data retention, repurposing, and sharing (e.g., [2, 13, 14]), making participants' concerns over privacy and security especially salient. Unlike AI-enabled cognitive games, however, sharing emotional inferences could have more drastic implications for job-seekers' privacy.

One implication of privacy intrusions is that they enable commodification of job-seekers' emotional inferences. As P5 (Hispanic or Latino/a/x, woman, film/TV industries, AA) notes:

I think maybe the first thing that comes to mind is where the information is used for commercial use... if my likeness is shared with certain companies where I start getting emails or things like that, my number is released [or] something.

Here, P5 notes distinct concerns about the sale of job-seekers' emotion inferences, particularly if shared with personal identifiers. Associated distributive justice implications could include loss of job opportunities and other indirect consequences (i.e., spam, unwanted targeted advertising) from the trading of identifiable emotion inferences on the data marketplace.

Moreover, sharing job-seekers' emotion inferences could damage their reputation. Exemplifying this point, P1 (Hispanic or Latino/a/x, man, IT/administrative industries, AA) notes:

But even if you don't have something to hide, even if there aren't any stigmas associated [with] whatever is going on in your personal life, you're never going to get back that level of separation between you and everyone else. Because if that kind of [emotional] information is hacked and put out onto the internet, your entire life is a Google search away... Employers and bosses can use it to abuse their employees... If someone else got their hands on that information somehow, they can use it to abuse you... if that information is available to your boss or your coworkers, you're never going to have the comfort of that bubble around you. You're never going to have that personal space between you and them. You're always going to be judged.

While the possibility of privacy and security breaches exists with any data-collecting technology, these quotes highlight the sensitive nature of one's emotions and the heightened risk associated with having one's emotional information available to unwanted parties. Ultimately, our analysis demonstrates how participants perceived that sensitive, identifiable emotional inferences could be leaked or sold, enabling emotion inferences generated from candidates' participation in automated asynchronous job interviews to be repurposed and (mis)used by buyers on the data marketplace. As such, using emotion AI-enabled asynchronous interviews was perceived to be distributively unjust in precluding job-seekers from career opportunities in the short and long term and facilitating consequences for one's reputation and personal privacy.

4.2.2 Perceived Procedural Injustices. In addition to outcomes, participants perceived the *process* of evaluation in emotion AI-enabled asynchronous interviews to be harmful and unjust due to the

perceived rigidity of interview platforms' underlying algorithms and how the *process* of automated inferences of interviewees' emotions could invoke identity-related bias.

Rigid Algorithm(s). Participants expressed concerns that a rigid set of algorithms underpinning emotion AI-enabled asynchronous interview platforms could be unjust in failing to adequately account for diverse identities and experiences. For instance, P8 (Hispanic or Latino/a/x, man, medical/aerospace industries, AA) notes:

It's just set in stone like, "Oh, this is what it looks for at all times. This is what the algorithm's going to consistently keep looking for." And there's no way to change that. Unless they redo the algorithm... It doesn't feel like it's really tailoring towards people's different features or maybe different flaws that they might have, with just different little quirks that they might have.

The perceived lack of "tailoring" shared by P8 demonstrates concern about algorithmic processes that presume emotions can be inferred through the same features for all applicants and that all applicants' emotional expressions would be uniform. This rigid, universalizing conception of emotions is aligned with the heavily critiqued [16, 143] Basic Emotion Theory [51] that forms the basis for leading emotion recognition/AI models which classify emotion families into discrete categories. Although P8's concerns are speculative, they are supported by criticisms of applying limited inferences in real-world contexts. Further, participants perceived emotion AI to be unable to consider individual differences adequately based on rigid and contested emotion theories [16] to comprehend the holistic capabilities of candidates, as rigidly encoding what constitutes a "desirable" applicant along emotional dimensions filters out qualities that fail to meet those rigid parameters. P12 (Asian-American, East Asian & White, woman, disabled, finance Industry, AEA) illustrates this point:

Once AI has these characteristics and these assumptions on you, I feel like it might put a little bit less emphasis on actually what you're saying as opposed to who you are... [and] there's no human oversight to say, "Okay, well, that person said 'like' 70 times in three minutes. That's excessive. But they said something really profound and really intelligent." They might not get that opportunity because AI would just be like, "No. This person has this, this, this, this [emotional characteristic] all against them" even if they have really good ideas or show really great intuition or creativity... AI just can be like, "Nope. Doesn't meet three of the five [emotional] characteristics".

In P12's view, emotion AI's automatic assessment of applicants using proxies of applicants' "emotion" may come at the expense of assessing *what* applicants directly and intentionally convey in an interview, especially without "*human oversight*." Further, participants perceived emotion AI's reliance upon a limited set of modalities to potentially overlook even desirable qualities like "*intuition*" or "*creativity*," which humans may more readily infer, in ways that could prevent applicants from obtaining employment through opaque decision-making processes justified under the guise of AI legitimacy and "objectivity." While some aspects of participants' concerns (i.e., repeatedly saying "like", and other common disfluencies) are likely handled in the pre-processing stage, meaning they may ultimately be ignored in the feature selection process, it is unclear to what extent highly opaque commercial emotion AI applications actually do this, despite technical capabilities and vendor claims around technical de-biasing mechanisms [114]. Importantly, though, we do know that some commercial emotion recognition applications do not perform well for marginalized groups, including youth on the Autism Spectrum [75, 76], suggesting that existing technical de-biasing efforts may be insufficient to prevent identity-based harm.

Concerns about the opacity of emotion AI underscore such risks. P11 (white, man, finance industry, AEA) says:

How many qualified applicants are being screened out through that AI process before it can even reach a human? What I'm gathering [is that] obviously AI's not looking at your answers, your quality of answers, how well you fit the position. All they're looking for is these certain metrics it's being trained to do... eye contact, voice inflection, [and] maybe posture.

Here, P11 expresses doubt and concern over the (in)ability of rigid algorithms to holistically evaluate applicants beyond narrow analyses of emotional expression according to some opaque standard(s) for "*certain metrics*" that participants recognize must exist but to which they do not have access. P11's concerns extend to the perceived insufficiency of human-in-the-loop processes, as applicants are already screened out, losing out on job opportunities before a human enters the decision-making loop.

Identity-related Bias in the Process of Automated Emotion Inferences. Participants perceived that the *process* of making automated inferences about interviewees' emotions could involve identity-related bias. For instance, P12 (Asian-American, East Asian, & white, woman, disabled, finance industry, AEA) notes:

I feel like [emotion AI] could confirm biases that it already has in place. If it repeatedly gets applicants of a certain race or gender that behave a certain way... that would integrate into its future judgments, so being more inclined to categorize someone in that way who has those same characteristics, even if the behavior is... weak at best in terms of affirming that characteristic or category... I think it puts you in a box and then says, "Alright, how do you compare in relation to this box?" and not in relation to the entire talent pool... If you're put in that box, and you're compared against other highly successful people but within your own race, it might say, "Oh okay, well, they're not that smart for an Asian. Compared to the other Asians, they're middle of the pack".

In P12's view, emotion AI may engage in the *process* of evaluating asynchronous interviews differently depending on applicants' identities and learn to associate social identity and emotional expression in ways that impact "*future judgments*" of applicants. P12 notes that race and ethnicity can also play a role, with both emotional inferences and applicant characteristics (e.g., intelligence) perceived to be assessed with respect to an applicant's race (perceived based on phenotype) in the process of automated emotion recognition. P12, who is mixed-race (Asian and Caucasian), also points out the flaws in assuming identity based on phenotype, as "*the AI could be expecting me to give that correlate much more with culturally Asian households or upbringings that I would not correspond with because I was basically raised in a white household.*" Again, participants like P12 point to canonical fairness-accuracy and bias-variance tradeoffs, expressing concern about emotion AI's fairness for marginalized groups *and* concern that their emotional expressions could be evaluated according to group-level differences in emotional expression that are inappropriate for their individual-level identities and circumstances. Regardless of these technologies' actual functionality, these quotes also demonstrate how social identity, including race, ethnicity, gender, age, and intersections thereof, inform people's perceptions of them.

In addition, P2 (white, non-binary, disabled, restaurant industry, AEA) speaks to the identity-laden implications stemming from the training of emotion classification models on data that may not be diverse and representative of the potential range of people's emotional expression:

There should be training with the AI that is specifically focusing on those types of people that express and see emotions differently, like neurodivergent people... because there's such a range in how people express emotions.

By noting that there should be more diverse training data in future iterations of emotion AI, P2, who is neurodivergent, exposes a perception that emotion AI may be trained by narrow, skewed data

sets that may inadequately represent the full range of emotional expression, especially expression by neurodivergent individuals and others who may not express emotion in normative ways. Here, P2 demonstrates that disability can inform job-seekers' emotion AI perceptions (though we do not claim that disability monolithically shapes all disabled individuals' emotion AI perceptions in the same way; future work with larger sample sizes can ascertain differences across types and experiences of disability).

Moreover, as P4 noted when discussing racial bias in emotion AI, this software can be imbued with the biases of the programmers developing it. Thus, the data sources and programming decisions that inform emotion AI may facilitate procedural injustice in hiring contexts. As prior work shows, commercial emotion AI tools do not work for all sub-groups equally [75, 76], suggesting that de-biasing techniques, including diversified training datasets, may be insufficient for achieving procedural justice. These quotes demonstrate how participants' perceptions that the process of emotion AI evaluation could differ based on their social identity and that training data may not encompass an adequate range of identities and emotional expressions are emblematic of procedural injustice concerns.

4.2.3 Perceived Interactional Injustices. Participants also referenced how emotion AI-enabled asynchronous interviews could be unjust in an interactional sense, as candidates perceived that they were denied dignity and respect, namely via 1) emotional harm [32], 2) mandates to perform emotional labor [70], and 3) withheld information about how and by whom/what they will be evaluated in employment interviews. Our analysis mapped these perceptions to Citron and Solove's privacy harms taxonomy [32].² Concerning information about emotion AI evaluations, several of the eight participants who were aware of emotion AI referenced how they developed this awareness. Primarily, awareness stemmed from receiving emails from the employing organization that stated that AI would automatically analyze the interviews, and participants presumed that this included automatic emotional inferences.

Emotional Harms. Participants noted that emotion AI-enabled asynchronous interviews may be emotionally harmful, which we interpret as constituting both interactional justice and a subset of psychological privacy harms, according to Citron and Solove [32]. As a type of psychological privacy harms, emotional harms – or emotional distress – encompasses “annoyance, frustration, fear, embarrassment, anger, and various degrees of anxiety” [32]. Most notably, this form of interviewing exacerbated candidates' frustration and pressure when going into the interview process. As P6 (Indigenous & First-Nations, white, non-binary, disabled, healthcare industry, AA) who acknowledged having anxiety, noted, “*Well, I think it would make me even more anxious about what my face is doing and what my facial expressions are. But then, because of that, I would try even more to look really happy and enthusiastic.*” Echoing P6's feelings of anxiety, P8 (Hispanic or Latino/a/x, man, medical/aerospace industries, AA) recalled:

It just feels like an extra weight because I start getting even more nervous. I start just trying to focus a lot more on it and then trying to keep maybe eye contact, just trying to focus on the question as well for the interview... to the point I might just freeze for a second, just trying to think about everything and just trying to manage it all in one go.

While nervousness is unsurprising in interviews, P6 and P8 describe how this nervousness is exacerbated by the need to express emotions in a specific way and constantly monitor their

²While we note that emotional harms may overlap with emotional labor harms, categorizing emotional labor harms as emotional harms per Citron and Solove's taxonomy [32] inadequately describes the depth of harm that can result from increased demands for emotional labor, such as alienating people from their own felt emotions, as past work demonstrates [126]. Thus, we dedicate separate subsections to *emotional harms* and *emotional labor harms*.

emotional expression. As P8 notes, this constant self-monitoring and feeling that one needs to perform emotional labor during the interview can result in a freeze response that signals intense fear, anxiety, and, in some cases, a traumatic experience. Thus, P8 experiences distinct emotional harms stemming from emotion AI-enabled asynchronous interviews, and as such, his dignity and “respect for persons” as an applicant are compromised.

Trust in employing organizations can also be eroded by experiences with emotion AI-enabled asynchronous interviews, as P12 (Asian-American, East Asian, White, woman, finance industry, disabled, AEA) notes, saying:

I feel like I hold some resentment. I was pretty jaded by the 10th one... I felt really out of control, kind of powerless. There's nothing I can do. It's just if the computer software says yes at that point. It makes me a little bit skeptical about all of their corporate statements... their DEI initiatives.

This quote demonstrates a combination of resentment, mistrust, fear, and frustration that ultimately colors the reputations of employing organizations that deploy emotion AI-enabled hiring platforms. Taken together, these quotes demonstrate how participants' perceptions that emotion AI-enabled asynchronous interviews could be emotionally harmful are emblematic of the interpersonal dimension of interactional justice and that emotional harms were perceived across those with and without prior awareness of the emotion AI component of asynchronous hiring platforms.

Emotional Labor Harms. In addition to purely emotional harms, participants reported harms related to increased and uneven demands for emotional labor, which constitute emotional labor harms that do not evenly map to Citron and Solove's privacy harms taxonomy [32], as explored in recent work on emotion AI's implications in workplace monitoring [126].

Participants perceived that emotion AI-enabled asynchronous interviews may mandate job-seekers to express emotion unnaturally to be rated favorably by emotion AI and obtain employment. P1 (Hispanic or Latino/a/x, man, disabled, IT/administrative industries, AA) notes:

If I was doing an asynchronous interview with an organization that I know does this kind of thing, that I know has emotion-sensing AI, I would probably change my personality and demeanor to fit the job that I'm trying to apply to. So, if I'm applying to be an HR manager, I would lower my voice. I would speak like a very approachable [person] and a good listener. And if I were a business manager, I'd puff my chest out to project my voice more and be leaderly. Be someone that feels reliable.

Rather than focusing on emphasizing the skills and qualities that make him an ideal candidate for the job, P1 reports that emotion AI would instead coerce him into changing the tone and volume of his voice (thus engaging in emotional labor [70]) to be received positively by the emotion AI-enabled asynchronous interview platform. While people selectively present themselves in all job interview scenarios, we argue that it can be particularly uncomfortable for applicants to be expected to simultaneously change their demeanor and focus on this aspect of self-presentation to be rated highly by the emotion AI while also focusing on portraying the job-relevant skills one brings as a candidate.

Moreover, emotion AI-enabled asynchronous interviews introduce a high degree of information asymmetry wherein job-seekers may assume the kinds of (potentially discriminatory) expectations they must meet to “game” the algorithm and obtain employment. For instance, P10 (Hispanic or Latino/a/x, man, retail, AEA) recalled:

It made me feel that whatever I tried to place over myself, whatever hypothetical armor I tried to shield myself with would be... impenetrable based on the power of AI. So with that, I try to adjust how I presented myself... I still tried to stay stoic and professional but didn't want my stoicism to be confused for almost robotic monotony.

This quote demonstrates how perceptions of AI’s “*impenetrable*” power shape the degree to which job-seekers attempt a deep form of emotional labor to convey the emotions they think are requested. Interestingly, perceptions of emotional labor harms persisted across those with and without prior awareness of emotion AI-enabled features.

Autonomy Harms. Not only is emotional labor encouraged by emotion AI-enabled asynchronous interviews, but the performance of emotional labor is coerced given the power asymmetries in hiring, signaling autonomy harms [32]. While one could argue that participants opt into experiences with emotion AI-enabled asynchronous interviews, this choice is heavily constrained by one’s need to obtain employment and the power imbalances between organizations and applicants combined with the way new technologies can “concretize social relations of coercion and consent at work” [5]. As such, while participants may “opt-in”, they may not be consenting in a meaningful and affirmative way, which requires that consent is freely given in ways that may not be possible in the workplace or hiring contexts [31]. To this point, P6 (Indigenous or First Nations & white, non-binary, disabled, healthcare industry, AA) who acknowledged having anxiety, describes the annoyance of emotion AI-enabled asynchronous interviews, saying:

It’s really annoying. I feel like being made to do something that I’m not comfortable with, but then having to do it is really frustrating. I feel like I don’t have much choice or freedom. It just makes me anxious knowing that I don’t have any choice. I have to do this if I want to get a job or have the chance to get a job.

Autonomy and emotional labor harms, like those mentioned by P6, induced by emotion AI demand unique consideration, as their risks involve not only acute emotionally harmful feelings but deeper negative changes to how one perceives oneself and interacts with others [70]. Similarly, P3 (white, man, disabled, recruiting industry, AEA) recalled his experience with emotion AI-enabled asynchronous interviews, saying:

I was pissed. And it was just really, once it started, it was like, “Why the fuck am I doing this?” I was like, “I don’t want to work for this company.”... It [emotion AI] forced me to put on a front and to wear a mask that I don’t want to wear. A mask of, “I’ve got it all together, I’ve got it figured out, I’ve got an answer for you, I got this blah, blah, blah”. That’s all bullshit. I hate wearing masks... So things like [emotion AI] kind of force you to just be something that you’re not.

On the one hand, P3 felt compelled to “*wear a mask*” to pass the emotion AI’s assessment, signaling threats to his autonomy, while dealing with the emotional ramifications of doing so and presenting oneself in a way that felt inauthentic to him for a job opportunity.

In sum, the tension between being emotionally monitored, having emotional labor demanded of job-seekers, and not feeling like one has full autonomy compromises applicants’ dignity and undermines “respect for persons,” signaling interactional injustice. These findings were consistent across participants with and without awareness.

Lack of Meaningful Transparency and Contestability. Finally, participants noted that emotion AI-enabled asynchronous interviews were not made meaningfully transparent to them, compromising interactional justice by making it difficult (if not impossible) to effectively contest emotion AI-enabled hiring decisions.

Participants reported not being notified that the interview would be conducted asynchronously, such as P2 (white, non-binary, disabled, customer service industries, AEA) who said:

I think I didn’t realize [it was an asynchronous interview] until I had gotten actually into the app... I don’t think I knew it was until I started the interview process because I didn’t know what the app was. I didn’t recognize the name. And then I got into the interview process and the questions, and I’m like, “Oh, there’s nobody here.”

P2 was not notified of the asynchronous virtual interview format nor about how the interview would be evaluated. Others, like P3 (white, man, disabled, recruiting industry, AEA), reported that he was told he would be doing an asynchronous interview in “a two to three-sentence email” saying “here’s your link, record these things”, but that he did not receive further information. Despite there being some degree of transparency, at least where the asynchronous virtual format of the interview was concerned, P3 mentioned that there was little information about how it would work or how the interview would be evaluated (i.e., through emotion AI), making him feel disrespected as an applicant, signaling interactional injustice.

In addition to a lack of meaningful transparency, P3 highlighted the lack of mechanisms for contestability [93] or one’s ability to dispute algorithmic decision-making. When asked what forms of contestability he would like to see with respect to emotion AI in one-way interviews, P3 described:

So at least give someone a chance to explain themselves and explain where they’re coming from and where they’re at... [it] at least allows the human being the dignity to explain maybe what’s going on in their internal world or external world at the moment.

P3 argues for redesigning emotion AI-enabled asynchronous interviews to incorporate opportunities for job-seekers to contextualize their responses and the emotional inferences AI makes about them.

For other participants, like P8 (Hispanic or Latino/a/x, man, medical/aerospace industries, AA), the hiring organization provided some level of detail about *what* would be inferred, although too vague to be meaningful and contestable:

They just said, “We’ll assess your skills”. I don’t know what they meant by ‘we’ or who or what will assess it. And then it says, “We’ll get back to you if we are interested in your position with another interview”... There wasn’t any way to let the algorithm know there may be a technical issue. I definitely wish if they do use AI, they might have an option where they can let the AI know, “Oh, I’m having a technical issue... just keep this under consideration.”

P8’s experience exemplifies how cosmetic transparency (i.e., giving a short explanation to make the process appear transparent and avoid scrutiny) does not necessarily translate into meaningful transparency that makes applicants feel respected and taken seriously in the interview process. While P8 was given some information, he still did not understand the mechanisms (i.e., emotion AI) by which his interview would be evaluated and the specific information inferred. Additionally, like P3, P8 notes that contestability mechanisms could involve more communication between the job-seeker and the hiring company to contextualize their responses and emotional inferences about them. P8 later described in more depth the contestability mechanisms that he would like to see if emotion AI-enabled asynchronous interviews were to be used:

Maybe they have an option that if you feel the AI misrepresented you, you could at least have some specific email or specific direction in the company to communicate this to. Just because I could understand that some people might have specific reasonings or concerns or just understandable situations about them that they might feel that the AI’s feedback was inaccurate or biased or something was wrong.

P8 notes that transparency and contestability are linked, as the mechanisms for contestability must be made transparent to be meaningful and address manifold interactional injustice concerns. Importantly, while these mechanisms could jointly increase transparency and contestability, the question remains as to whether and/or to what extent inferences of one’s emotions are relevant in assessing a job-seeker’s ability to perform in the workplace, to begin with.

Thus, opacity or cosmetic transparency, combined with few existing mechanisms for effective contestability, failed to make participants – both with and without prior awareness – feel respected as applicants, exemplifying interactional injustice.

5 Discussion

Despite acknowledging the potential benefits of asynchronous interviews for employing organizations stemming from both the asynchronous, virtual format and emotion AI-enabled features, our results show job-seekers perceive no benefit to themselves from emotion AI use and instead perceive harms to applicants involving distributive, procedural, and interactional injustices (RQ1). Additionally, our findings indicate that social identities, namely race/ethnicity, gender, disability status, age, and socio-economic status, can inform job-seekers' perceptions (RQ2). The following discussion elaborates on:

- How a relational ethics approach and representing marginalized groups reveals the relevance of identity in organizational justice perceptions of emotion AI-enabled asynchronous interviews
- How emotion AI-enabled asynchronous interviews may (re)configure emotional labor [70] in hiring
- Whether emotion AI in its current iterations should be used in hiring, and how to design and deploy (via policy considerations) future iterations of these technologies (with or without emotion AI) to be more meaningfully transparent, contestable, and privacy-preserving

5.1 Identity Informs Injustice Perceptions of Emotion AI-Enabled Asynchronous Interviews

By representing marginalized identities, our relational ethics [18] approach centers job-seekers who occupy vulnerable positions in the hiring context and are best positioned to identify injustices associated with this technology. Our analysis uncovers that identity *can* inform applicant reactions to hiring processes, at least those that are mediated by emotion AI. Specifically, race, gender, disability status, and socio-economic status partly shaped participants' perceptions of emotion AI-enabled asynchronous interviews, which mapped to organizational justice dimensions [61, 121]. We note that in the present study, emotion AI-enabled asynchronous interviews were perceived to be unjust across *all* organizational justice dimensions.

The present study shows that emotion AI in hiring is perceived to enable flawed or unjust automatic emotional inferences to preclude marginalized social groups from attaining employment in the first place, with perceived downstream implications on their livelihood and holistic well-being. The aforementioned body of work on “applicant reactions” often does not consider identity attributes [1, 60, 88], or asserts that social identity is not relevant to applicants' reactions to hiring processes [65, 95]. When social identity is considered, it is often confined to race [134], ignoring other social identities (e.g., socio-economic status, disability, etc.), or the intersections of these identities, that can shape applicant reactions. The present study's findings suggest that we should reconsider the role of identity in informing perceptions and reactions to hiring processes, particularly given the shifts in these processes that emerging technologies like emotion AI facilitate.

5.2 Emotion AI's Reconfiguration of Emotional Labor in Hiring

Highlighting the unique implications stemming from the use of AI technologies in hiring that automatically analyzes emotions, we situate our findings on emotional and emotional labor harms perceived by job-seekers in the extant literature on emotional labor, arguing that the use of emotion AI-enabled asynchronous interviews reconfigures the role and implications of emotional labor

in the hiring process in three important ways: 1) by demanding unpaid emotional labor before attaining employment, 2) by heightening the prevalence of deep acting over surface acting, and 3) by rendering emotional labor performed in one interview potentially influential to future interviews and employment opportunities.

First, rather than confining emotional labor to the workplace, emotion AI necessitates more (unpaid) emotional labor before job-seekers attain employment. For instance, participants felt they must mold their emotional expressions to what they think the algorithm expects of them, sometimes in problematic and stereotypical ways. While job-seekers may already engage in emotional labor by managing their emotional expressions during conventional in-person interviews, the asynchronous interview format and automatic emotional inferences amplify the emotional labor required of them and deny candidates the opportunity to leverage the interviewers' dynamic feedback of their performance in situ, which interviewees may use to their advantage (i.e., negotiating higher pay once they perceive a positive emotional response by the interviewer [120]). Our findings indicate that without this feedback, power asymmetries between the candidate and the employing organization widen, requiring additional emotional labor for candidates to navigate. Increased demand for emotional labor is interesting given recent work suggesting that emotion AI in the workplace may shift human workers *away* from technical and cognitive labor and toward emotional labor, which *may* be constructive in some domains where emotional labor may be more justified [83]. Whether this shift is desirable is an open question, but necessitating greater amounts of unpaid emotional labor from job candidates to attain employment still carries the risk of harm, as we show, and is worth problematizing.

Second, emotion AI heightens the prevalence of “deep acting” over “surface acting” in asynchronous interviews. Emotion AI-enabled asynchronous interview platforms purport to accurately infer a candidate's “true” inner emotions [125]. Because emotion AI-enabled asynchronous interviews use external (i.e., physiological) markers to purportedly infer one's “true” feelings, increased demands for job-seekers' emotional labor are problematic not only for its requirement before they even obtain employment but also for its implied expectation that job-seekers' internal feelings mirror the emotions they display. This aspect of emotional labor, known as “deep acting,” can be troublesome in rendering the ability to distinguish between one's “authentic” and displayed emotions more difficult, diminishing one's ability to “turn off” deeply ingrained yet inauthentic emotional self-presentation on and off the job, and leading to harms by inducing feelings like exhaustion and alienation [70], as evidenced, for example, by P3 who was “*pissed*” at how he felt AI “*force[s] you to just be something that you're not.*”

Third, we find that emotional labor during emotion AI-enabled asynchronous interviews is not necessarily confined to a single interview. Instead, one's (in)ability to effectively engage in emotional labor during one asynchronous interview may have implications for future employment opportunities. Unlike traditional emotional labor in which evaluations of an employee's performance of emotional labor are limited to a particular workplace and/or interaction, identifiable inferences generated by emotion AI can carry longer-term implications based on unregulated and opaque [40] data handling practices. If the inferences generated about applicants are not ephemeral, job-seekers' acts of emotional labor in emotion AI-enabled asynchronous interviews are made higher stakes, more exploitable, and more commodifiable.

In sum, this section highlights how job-seekers perceived emotion AI-enabled asynchronous interviews to (unevenly) reconfigure demands for emotional labor in hiring interviews, widening the existing power differentials between job-seekers and employing organizations.

5.3 Considerations around Design and Deployment of Emotion AI-Enabled Asynchronous Interview Platforms

Given our findings on the trade-offs between perceived benefits to employing organizations and injustices to job-seekers, we suggest that it is ethically imperative for employing organizations to critically reflect upon whether emotion AI-enabled asynchronous interview technologies, in their current state, should be deployed for hiring purposes. While emotion AI-enabled asynchronous interviews may be alluring for employing organizations looking to preserve organizational resources, recent work has suggested that the claims made by emotion AI vendors in hiring exaggerate its technological capabilities and obfuscate its potential to facilitate discriminatory hiring decisions [125]. The present study builds on this prior work by surfacing tensions between the exaggerated claims of emotion AI vendors and job-seekers' perceptions. Additionally, many of the benefits job-seekers perceived in the present study were not germane to emotion AI-enabled features but to the asynchronous, virtual interview mode. Therefore, if the technology itself does not work as claimed [125], the benefits of asynchronous interviews can be retained without emotion AI. Additionally, as job-seekers perceive emotion AI as harmful, it is likely futile for employers to adopt and deploy existing emotion AI asynchronous interview platforms if they desire a workforce that trusts them as an employer.

Beyond ethical imperatives, continuing to deploy invasive existing emotion AI platforms that job-seekers find unjust can create problems for employing organizations' reputations. Organizational reputation can inform who and how many job-seekers apply for jobs within an organization. For instance, 76% of Americans reported not wanting to apply to an organization using automated hiring platform [141]. That said, we acknowledge that the luxury of opting out is not available to all job-seekers, as tensions around consent and agency are magnified for job-seekers who embody historically marginalized identities.

Accordingly, we identify ways that future iterations of emotion AI-enabled asynchronous interviewing platforms could be redesigned to address job-seekers' concerns and may help organizations avoid reputational harm from deploying controversial hiring technologies. In the following subsections, we outline how developers can create more meaningfully transparent and contestable emotion AI-enabled asynchronous interview platforms and engage in bias mitigation techniques. We also highlight policy considerations and trade-offs in deciding whether asynchronous interview platforms should continue incorporating emotion AI *at all*.

5.3.1 Meaningful Transparency and Contestability. Participants surfaced concerns related to the (lack of) transparency and contestability in current iterations of emotion AI platforms used to evaluate asynchronous interviews, facilitating interactional injustices. If emotion AI-enabled asynchronous interview platforms are designed and deployed, we argue that they ought to be imbued with meaningful transparency mechanisms from both emotion AI developers and employing organizations, with consideration of impacted groups' perspectives like those we surface. Adding clearly visible black-box and white-box explanations (i.e., explanations that reveal the existence of algorithmic decision-making mechanisms and describe algorithms' basic inputs and outputs, respectively [89]) could be ways forward since, as our findings demonstrate, participants do not always know what a hiring platform does with their data. Another way to improve transparency involves making inputs, outputs, and models more explainable via easily accessible, personalized feedback provided directly to job-seekers rather than obscuring this information (i.e., on a website which will likely rarely be accessed [89, 133] or only providing it via the employing organization). Adding these transparency mechanisms can also aid job-seekers' ability to effectively contest hiring decisions mediated by emotion AI. P3, for instance, wanted the opportunity for job-seekers to "explain themselves" and "what's going on in their internal world or external world at the moment",

while P8 desired “an option where they can let the AI know, “Oh, I’m having a technical issue... just keep this under consideration”. These reported concerns suggest the need for, at minimum, a form field for job-seekers to write or otherwise explain circumstantial information to submit along with their recorded interviews. How additional information should be incorporated into an assessment is an open question for future work.

Additionally, meaningful transparency must be implemented not just with respect to the inputs and outputs used but also its data policies [89] as participants shared concerns about the privacy and security of their identifiable emotion inferences. Greater transparency over data sources, procedures, and handling practices may assuage concerns about distributive injustices resulting from potential privacy and security breaches.

While we uncover some design-related preferences in our study, future work may use participatory design methods [123, 140, 142, 160] to uncover what specific mechanisms for transparency, explainability, contestability, and meaningful consent would be most valuable for a diverse set of job-seekers. If these systems ought to be used, future work may investigate how to make existing emotion AI tools that evaluate asynchronous interviews more privacy-preserving or may devise technical and/or regulatory solutions to improve data security.

5.3.2 Bias Mitigation Techniques. Grounded in participants’ perceptions, we argue that bias mitigation techniques like diversifying training datasets can address some distributive injustice (but not other injustice) concerns. Since emotion AI vendors note that they often collect training data from high-performing employees and these employees are overwhelmingly cisgender men (owing to past biases in recruitment and assessments), current training datasets are likely insufficient at encompassing a range of emotional expression across demographic differences [3, 4], as our participants also note. While prior work [46, 58, 127] has identified and problematized the lack of demographic diversity in AI training datasets, this problem may be even more acute for emotion AI training datasets, as emotional expression is highly contextual, varying across cultures, shaped by sexist and racist expectations of emotional expression, and intimately intertwined with disability status. Moreover, while some companies, such as HireVue, may claim they use diverse training datasets [69, 114], these companies’ algorithms and data practices are opaque and largely unregulated, so nothing is ensuring that companies follow through with these claims in our current regulatory landscape.

However, we echo past work’s skepticism that technical algorithmic de-biasing efforts and diversified training datasets are likely insufficient at addressing the structural biases embedded in the development of emotion AI-enabled asynchronous interview platforms [4]. In addition, diversifying datasets is not always a step toward fairness or justice, especially given that datasets are often constructed without data subjects’ knowledge [41], and some marginalized communities may not wish to be represented in these datasets, as this can facilitate greater surveillance and *discursive violence* [71]. Moreover, technical de-biasing efforts may aid in achieving “group-level” fairness [87, 97, 158] but may nonetheless spark concerns, like those mentioned by participants in this study, about being evaluated according to group-level norms and differences, and how these evaluations 1) may reward emotional expression that imitates group-level stereotypes, and 2) may be inappropriately applied to evaluate individuals who may differ from expectations of group differences. Lastly, technical de-biasing efforts can potentially assuage job-seekers’ concerns with distributive injustices, not procedural and/or interactional injustices.

5.3.3 Policy Considerations. In the U.S. context where this study is situated, policy change and adoption, like the adoption of the proposed AI Bill of Rights [159], may ensure company follow-through where issues of data representativeness, transparency, contestability, and disparate outcomes are concerned. Combined with other organizational initiatives like the Equal Employment Opportunity

Commission's (EEOC) initiative on algorithmic fairness and the Federal Trade Commission's (FTC) focus on representative training data, continuous testing, outcome explainability, and accountability and governance mechanisms, emotion AI hiring vendors will be incentivized to make their technologies *meaningfully* explainable, transparent, and contestable [7].

Participants perceived one crucial benefit of emotion AI, specifically, to employing organizations: emotion AI's supposed ability to gauge job-seekers' honesty and passion for the job. Notably, vendors deceptively exaggerate their products' capabilities [125]. *If* emotion AI truly possesses these capabilities, then emotion AI-enabled asynchronous interview platforms may violate the Employee Polygraph Protection Act (EPPA), which prohibits most private employers from using lie-detector tests in pre-employment assessments and during one's employment. The Department of Labor, which oversees the EPPA, may also consider developing stronger, more up-to-date protections that prohibit the use of emotion AI/technologies that claim to infer emotions and affective phenomena, specifically, as opposed to more traditional polygraph tests that are already somewhat regulated.

5.3.4 Removing vs. Preserving Emotion AI-Enabled Features. Finally, that participants' perceived benefits of emotion AI-enabled asynchronous interviews stemmed from the asynchronous, virtual format and not the emotion AI component itself calls into question the need to preserve emotion AI-enabled features in future iterations of asynchronous hiring interview platforms. Perceived benefits of efficiency for employing organizations and convenience and reduced pressure for job-seekers stem from the asynchronous virtual format, while perceived injustices hinged upon automated emotional inferences, specifically. Thus, developers may consider creating asynchronous, virtual interview platforms that are *not* emotion AI-enabled, retaining benefits of organizational efficiency and the few perceived benefits to job-seekers that participants identified – and mitigating associated harms with their emotion AI components. Recent work has found that job-seekers who use features of asynchronous video interviewing platforms, such as unlimited re-recording attempts and preparation time, fared better in the interview [129] and that job-seekers using asynchronous video interview platforms are rated as appearing less stressed by external observers [86], highlighting their potential to be used constructively in the absence of emotion AI-enabled features. However, even asynchronous interview platforms that do not harness emotion AI must also meaningfully contend with transparency, contestability, and privacy concerns such as those raised by participants in the present study.

On the other hand, removing the emotion AI component from interview platforms would also do away with one perceived benefit to employing organizations that participants identified – the ability for emotion AI to allegedly uncover who is “authentically” passionate about the job. However, this alleged ability to judge authenticity maps to vendors' claims about emotion AI-enabled asynchronous interview platforms [125], which have been critiqued for being deceptive and hyperbolic. Moreover, if true, as previously discussed, these claims warrant concerns about job-seeker privacy and emotional labor harms that suggest the need for design and policy changes.

In sum, whether vendors redesign emotion AI or move toward the development of asynchronous interview platforms that are *not* emotion AI-enabled, they must meaningfully contend with the perceived benefits and injustices raised by job-seekers in the present study to develop and/or deploy these technologies ethically and justly. The decision to retain or remove emotion AI-enabled features raises an open ethical question – do we want to promote the design of technologies that infer private, sensitive information about job-seekers that has little to do with their job-related qualifications? While we acknowledge the likelihood that emotion AI-enabled asynchronous interview platforms will continue to be developed and deployed – likely until regulation steps in – we advocate that such a future of work would be unjust.

6 Conclusion

We interviewed U.S. job-seekers ($n = 14$) to explore their perceptions of emotion AI-enabled asynchronous virtual hiring interviews. Using a relational ethics approach and seeking representation of marginalized job-seekers (along dimensions of disability, race/ethnicity, and gender), we find that while participants perceived potential benefits of emotion AI-enabled asynchronous interviews to employing organizations, they highlighted potential harms to job-seekers that mapped to distributive, procedural, and interactional injustices. Importantly, while we note some perceived benefits to job-seekers, these perceived benefits correspond to the asynchronous virtual format of the interviews and not emotion AI-enabled features. In contrast, perceived harms *were* specific to emotion AI-enabled features. Additionally, we find that participants' social identities (especially disability, race/ethnicity, gender, and socioeconomic status) intimately informed these perceptions. Considering our findings, we discuss emotion AI's role in reconfiguring emotional labor in organizational contexts and question the design and deployment of emotion AI asynchronous interview platforms. We note how redesigning these platforms to implement transparency, contestability, and privacy-preserving mechanisms and/or retaining the asynchronous virtual interview format while removing emotion AI components, along with relevant policy considerations, may be promising avenues to rectify *some* of the injustices participants identified. However, we assert that these and other technical fixes to emotion AI harms may attend to some distributive injustices but fail to address the procedural and interactional injustices we uncover.

Acknowledgments

We appreciate the ACs' and reviewers' constructive feedback on this work. We are grateful to Joanna Kroll at the University of Michigan School of Information's Career Development Office for circulating our screening survey to their membership to aid our recruitment efforts. This work was sponsored by NSF award 2020872 and CAREER award 2236674. The authors wish to acknowledge the contributions of each as follows:

- **Data curation** was led by the second author with support from the third author.
- **Formal analysis** was led by the first author with support from second and third authors.
- **Funding acquisition** was led by the third author with support from the second author.
- **Investigation** was led by the second author with support from the third author.
- **Methodology** was led by the first author with support from the second and third authors.
- **Project administration** was equally shared by the first and second authors with support from the third author.
- **Validation** was led by the first author with support from the second and third authors.
- **Visualization** was led by the first author with support from the second and third authors.
- **Writing - original draft** was led by the first author with support from the third author.
- **Writing - review and editing** was led by the first author with support from the second and third authors.

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 (Dec. 2020), 399–416. <https://doi.org/10.1111/ijsa.12306>
- [2] Agnya by Culturo. 2019. Agnya | Privacy Policy. <https://www.agnya.co/#/privacyPolicy>
- [3] Ifeoma Ajunwa. 2021. An Auditing Imperative for Automated Hiring Systems. *Harvard Journal of Law and Technology* 34, 2 (2021), 622–699. <https://doi.org/10.2139/ssrn.3437631>
- [4] Ifeoma Ajunwa. 2021. Automated Video Interviewing as the New Phrenology. <https://doi.org/10.15779/Z38RX93F1Q>
- [5] Ifeoma Ajunwa and Daniel Greene. 2019. Chapter 3 Platforms at Work: Automated Hiring Platforms and Other New Intermediaries in the Organization of Work. In *Research in the Sociology of Work*, Steve P. Vallas and Anne

- Kovalainen (Eds.). Vol. 33. Emerald Publishing Limited, Bingley, England, 61–91. <https://doi.org/10.1108/S0277-283320190000033005>
- [6] Rahaf Alharbi, Robin N. Brewer, and Sarita Schoenebeck. 2022. Understanding Emerging Obfuscation Technologies in Visual Description Services for Blind and Low Vision People. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW2 (Nov. 2022), 469:1–469:33. <https://doi.org/10.1145/3555570>
 - [7] Alston & Bird. 2022. AI Regulation in the U.S.: What’s Coming, and What Companies Need to Do in 2023 | News & Insights | Alston & Bird. <https://www.alston.com/en/insights/publications/2022/12/ai-regulation-in-the-us>
 - [8] Tawfiq Ammari, Sarita Yardi Schoenebeck, and Meredith Ringel Morris. 2014. Accessing Social Support and Overcoming Judgment on Social Media among Parents of Children with Special Needs. In *Eighth International AAAI Conference on Weblogs and Social Media*, Vol. 8. AAAI Conference on Weblogs and Social Media, Ann Arbor, MI, USA, 22–31. <https://www.aaai.org/ocs/index.php/ICWSM/ICWSM14/paper/view/8032>
 - [9] Nazanin Andalibi. 2021. Symbolic annihilation through design: Pregnancy loss in pregnancy-related mobile apps. *New Media & Society* 23, 3 (March 2021), 613–631. <https://doi.org/10.1177/1461444820984473> Publisher: SAGE Publications.
 - [10] 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 (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–16. <https://doi.org/10.1145/3313831.3376680>
 - [11] Lori Andrews and Hannah Bucher. 2022. Automating Discrimination: Ai Hiring Practices and Gender Inequality. *Cardozo Law Review* 44, 1 (Oct. 2022), 145–202. <https://search.ebscohost.com/login.aspx?direct=true&db=a9h&AN=160188845&site=ehost-live> Publisher: Benjamin N. Cardozo School of Law of Yeshiva University.
 - [12] Larisa Antonisse, Rachel Garfield Published: Aug 07, and 2018. 2018. The Relationship Between Work and Health: Findings from a Literature Review. <https://www.kff.org/medicaid/issue-brief/the-relationship-between-work-and-health-findings-from-a-literature-review/>
 - [13] Aon Assessment Solutions. 2022. Aon’s Assessment Solutions Online Privacy Notice. <https://assessment.aon.com/en-us/sites/privacy-statement>
 - [14] AQai Adaptability Assessments. 2019. Terms of Use and Privacy Policy. <https://www.aqai.io/company/terms-of-services>
 - [15] Lisa Feldman Barrett. 2006. Are Emotions Natural Kinds? *Perspectives on Psychological Science* 1, 1 (March 2006), 28–58. <https://doi.org/10.1111/j.1745-6916.2006.00003.x> Publisher: SAGE Publications Inc.
 - [16] 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 (July 2019), 1–68. <https://doi.org/10.1177/1529100619832930> Publisher: SAGE Publications Inc.
 - [17] Rewina Bedemariam and Jennifer L. Wessel. 2023. The roles of outcome and race on applicant reactions to AI systems. *Computers in Human Behavior* 148 (Nov. 2023), 107869. <https://doi.org/10.1016/j.chb.2023.107869>
 - [18] Abeba Birhane. 2021. Algorithmic injustice: a relational ethics approach. *Patterns* 2, 2 (Feb. 2021), 100205. <https://doi.org/10.1016/j.patter.2021.100205>
 - [19] Abeba Birhane, Elayne Ruane, Thomas Laurent, Matthew S. Brown, Johnathan Flowers, Anthony Ventresque, and Christopher L. Dancy. 2022. The Forgotten Margins of AI Ethics. In *2022 ACM Conference on Fairness, Accountability, and Transparency (FAccT '22)*. Association for Computing Machinery, New York, NY, USA, 948–958. <https://doi.org/10.1145/3531146.3533157>
 - [20] Karen 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, 1 (2023), 1–37. <https://doi.org/10.1145/3579528>
 - [21] Virginia Braun and Victoria Clarke. 2012. Thematic analysis. In *APA handbook of research methods in psychology, Vol 2: Research designs: Quantitative, qualitative, neuropsychological, and biological.*, Harris Cooper, Paul M. Camic, Debra L. Long, A. T. Panter, David Rindskopf, and Kenneth J. Sher (Eds.). American Psychological Association, Washington, 57–71. <https://doi.org/10.1037/13620-004>
 - [22] Grace Brennan. 2020. Emotion Analytics Used in AI Recruitment Tools Are Not Only Unethical But Incorrect. <https://sociable.co/technology/emotion-analytics-ai-recruitment-tools-incorrect/>
 - [23] Robin N. Brewer and Vaishnav Kameswaran. 2018. Understanding the Power of Control in Autonomous Vehicles for People with Vision Impairment. In *Proceedings of the 20th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '18)*. Association for Computing Machinery, New York, NY, USA, 185–197. <https://doi.org/10.1145/3234695.3236347>
 - [24] Jed R. Brubaker, Lynn S. Dombrowski, Anita M. Gilbert, Nafiri Kusumakaulika, and Gillian R. Hayes. 2014. Stewarding a legacy: responsibilities and relationships in the management of post-mortem data. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '14)*. Association for Computing Machinery, New York, NY,

- USA, 4157–4166. <https://doi.org/10.1145/2556288.2557059>
- [25] Sarah A. Burgard and Katherine Y. Lin. 2013. Bad Jobs, Bad Health? How Work and Working Conditions Contribute to Health Disparities. *The American behavioral scientist* 57, 8 (Aug. 2013), 10.1177/0002764213487347. <https://doi.org/10.1177/0002764213487347>
- [26] Heather Cairns-Lee, James Lawley, and Paul Tosey. 2022. Enhancing Researcher Reflexivity About the Influence of Leading Questions in Interviews. *The Journal of Applied Behavioral Science* 58, 1 (March 2022), 164–188. <https://doi.org/10.1177/00218863211037446> Publisher: SAGE Publications Inc.
- [27] Rafael A. Calvo and Sidney D'Mello. 2010. Affect Detection: An Interdisciplinary Review of Models, Methods, and Their Applications. *IEEE Transactions on Affective Computing* 1, 1 (Jan. 2010), 18–37. <https://doi.org/10.1109/T-AFFC.2010.1> Conference Name: IEEE Transactions on Affective Computing.
- [28] Lara Carminati. 2018. Generalizability in Qualitative Research: A Tale of Two Traditions. *Qualitative Health Research* 28, 13 (Nov. 2018), 2094–2101. <https://doi.org/10.1177/1049732318788379>
- [29] Priya Chakriswaran, Durai Raj Vincent, Kathiravan Srinivasan, Vishal Sharma, Chuan-Yu Chang, and Daniel Gutiérrez Reina. 2019. Emotion AI-Driven Sentiment Analysis: A Survey, Future Research Directions, and Open Issues. *Applied Sciences* 9, 24 (Jan. 2019), 5462. <https://doi.org/10.3390/app9245462> Number: 24 Publisher: Multidisciplinary Digital Publishing Institute.
- [30] Hyesun Choung, John S. Seberger, and Prabu David. 2023. When AI is Perceived to Be Fairer than a Human: Understanding Perceptions of Algorithmic Decisions in a Job Application Context. *International Journal of Human-Computer Interaction* 0, 0 (2023), 1–18. <https://doi.org/10.1080/10447318.2023.2266244> Publisher: Taylor & Francis _eprint: <https://doi.org/10.1080/10447318.2023.2266244>.
- [31] Shreya Chowdhary, Anna Kawakami, Mary L. Gray, Jina Suh, Alexandra Olteanu, and Koustuv Saha. 2023. Can Workers Meaningfully Consent to Workplace Wellbeing Technologies?. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency (FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 569–582. <https://doi.org/10.1145/3593013.3594023>
- [32] Danielle Keats Citron and Daniel J. Solove. 2022. Privacy Harms. *Boston University Law Review* 102 (2022), 793. <https://heinonline.org/HOL/Page?handle=hein.journals/bulr102&id=815&div=&collection=>
- [33] Adele E. Clarke. 2003. Situational Analyses: Grounded Theory Mapping After the Postmodern Turn. *Symbolic Interaction* 26, 4 (2003), 553–576. <https://doi.org/10.1525/si.2003.26.4.553> _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1525/si.2003.26.4.553>.
- [34] Jason A. Colquitt. 2001. On the dimensionality of organizational justice: A construct validation of a measure. *Journal of Applied Psychology* 86 (2001), 386–400. <https://doi.org/10.1037/0021-9010.86.3.386> Place: US Publisher: American Psychological Association.
- [35] Jason A. Colquitt and Jessica B. Rodell. 2015. Measuring justice and fairness. In *The Oxford handbook of justice in the workplace*. Oxford University Press, New York, NY, US, 187–202. <https://doi.org/10.1093/oxfordhb/9780199981410.013.8>
- [36] Deondra S. Conner. 2003. Socially Appraising Justice: A Cross-Cultural Perspective. *Social Justice Research* 16, 1 (March 2003), 29–39. <https://doi.org/10.1023/A:1022922010184>
- [37] Karen S. Cook and Karen A. Hegtvædt. 1983. Distributive Justice, Equity, and Equality. *Annual Review of Sociology* 9 (1983), 217–241. <https://www.jstor.org/stable/2946064> Publisher: Annual Reviews.
- [38] Shanley Corvite, Kat Roemmich, Tillie 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, 1 (2023), 1–38. <https://doi.org/10.1145/3579600>
- [39] Nick Couldry and Ulises A. Mejias. 2020. The Costs of Connection: How Data Are Colonizing Human Life and Appropriating It for Capitalism. *Social Forces* 99, 1 (Aug. 2020), e6. <https://doi.org/10.1093/sf/soz172>
- [40] Kate Crawford. 2021. Artificial Intelligence Is Misreading Human Emotion. <https://www.theatlantic.com/technology/archive/2021/04/artificial-intelligence-misreading-human-emotion/618696/> Section: Technology.
- [41] Kate Crawford and Trevor Paglen. 2021. Excavating AI: the politics of images in machine learning training sets. *AI & SOCIETY* 36, 4 (Dec. 2021), 1105–1116. <https://doi.org/10.1007/s00146-021-01162-8>
- [42] Kimberle Crenshaw. 1989. Demarginalizing the Intersection of Race and Sex: A Black Feminist Critique of Antidiscrimination Doctrine, Feminist Theory and Antiracist Politics. *University of Chicago Legal Forum* 1989 (1989), 139–168. <https://heinonline.org/HOL/P?h=hein.journals/uchclf1989&i=143>
- [43] Russell Cropanzano, Zinta S. Byrne, D. Ramona Bobocel, and Deborah E. Rupp. 2001. Moral Virtues, Fairness Heuristics, Social Entities, and Other Denizens of Organizational Justice. *Journal of Vocational Behavior* 58, 2 (April 2001), 164–209. <https://doi.org/10.1006/jvbe.2001.1791>
- [44] 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 (Sept. 2002), 324–351. <https://doi.org/10.1177/1059601102027003002>

- [45] Mira Crouch and Heather McKenzie. 2006. The logic of small samples in interview-based qualitative research. *Social Science Information* 45, 4 (Dec. 2006), 483–499. <https://doi.org/10.1177/0539018406069584> Publisher: SAGE Publications Ltd.
- [46] Roxana Daneshjou, Mary P. Smith, Mary D. Sun, Veronica Rotemberg, and James Zou. 2021. Lack of Transparency and Potential Bias in Artificial Intelligence Data Sets and Algorithms: A Scoping Review. *JAMA Dermatology* 157, 11 (Nov. 2021), 1362–1369. <https://doi.org/10.1001/jamadermatol.2021.3129>
- [47] Michael Ann DeVito. 2021. Adaptive Folk Theorization as a Path to Algorithmic Literacy on Changing Platforms. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (Oct. 2021), 1–38. <https://doi.org/10.1145/3476080>
- [48] Michael Ann DeVito. 2022. How Transfeminine TikTok Creators Navigate the Algorithmic Trap of Visibility Via Folk Theorization. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW2 (Nov. 2022), 380:1–380:31. <https://doi.org/10.1145/3555105>
- [49] Artem Donnich and Gholamreza Anbarjafari. 2021. Responsible AI: Gender bias assessment in emotion recognition. <https://doi.org/10.48550/arXiv.2103.11436> arXiv:2103.11436 [cs].
- [50] Paul Ekman. 1992. Are there basic emotions? - PsycNET. *Psychological Review* 99, 3 (1992), 550–553. <https://psycnet.apa.org/doiLanding?doi=10.1037%2F0033-295X.99.3.550>
- [51] Paul Ekman. 1992. An argument for basic emotions. *Cognition and Emotion* 6, 3-4 (May 1992), 169–200. <https://doi.org/10.1080/02699939208411068> Publisher: Routledge _eprint: <https://doi.org/10.1080/02699939208411068>.
- [52] Paul Ekman and Wallace V. Friesen. 1978. Facial Action Coding System. *Environmental Psychology & Nonverbal Behavior* (1978). <https://doi.org/doi/10.1037/t27734-000>
- [53] Sandra L. Faulkner and Stormy P. Trotter. 2017. Theoretical Saturation. In *The International Encyclopedia of Communication Research Methods*. John Wiley & Sons, Ltd, Hoboken, NJ, USA, 1–2. <https://doi.org/10.1002/9781118901731.iecrm0250> _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/9781118901731.iecrm0250>.
- [54] Ronald Fischer. 2016. Justice and Culture. In *Handbook of Social Justice Theory and Research*, Clara Sabbagh and Manfred Schmitt (Eds.). Springer, New York, NY, 459–475. https://doi.org/10.1007/978-1-4939-3216-0_25
- [55] Elizabeth Ford, Keegan Curlewis, Akkapon Wongkoblap, and Vasa Curcin. 2019. Public Opinions on Using Social Media Content to Identify Users With Depression and Target Mental Health Care Advertising: Mixed Methods Survey. *JMR Mental Health* 6, 11 (Nov. 2019), e12942. <https://doi.org/10.2196/12942>
- [56] Kelsey Gee. 2017. In Unilever’s Radical Hiring Experiment, Resumes Are Out, Algorithms Are In. <https://www.wsj.com/articles/in-unilevers-radical-hiring-experiment-resumes-are-out-algorithms-are-in-1498478400>
- [57] Maria Gendron and Lisa Feldman Barrett. 2009. Reconstructing the Past: A Century of Ideas About Emotion in Psychology. *Emotion Review* 1, 4 (Oct. 2009), 316–339. <https://doi.org/10.1177/1754073909338877> Publisher: SAGE Publications.
- [58] Judy Wawira Gichoya, Kaesha Thomas, Leo Anthony Celi, Nabile Safdar, Imon Banerjee, John D Banja, Laleh Seyyed-Kalantari, Hari Trivedi, and Saptarshi Purkayastha. 2023. AI pitfalls and what not to do: mitigating bias in AI. *British Journal of Radiology* 96, 1150 (Oct. 2023), 20230023. <https://doi.org/10.1259/bjr.20230023>
- [59] Denny Gioia. 2021. A Systematic Methodology for Doing Qualitative Research. *The Journal of Applied Behavioral Science* 57, 1 (March 2021), 20–29. <https://doi.org/10.1177/0021886320982715> Publisher: SAGE Publications Inc.
- [60] Manuel F. Gonzalez, Weiwei Liu, Lei Shirase, David L. Tomczak, Carmen E. Lobbe, Richard Justenhoven, and Nicholas R. Martin. 2022. Allying with AI? Reactions toward human-based, AI/ML-based, and augmented hiring processes. *Computers in Human Behavior* 130 (May 2022), 107179. <https://doi.org/10.1016/j.chb.2022.107179>
- [61] Jerald Greenberg. 2002. *Advances in Organizational Justice*. Stanford University Press, Stanford, CA, USA. <https://www.sup.org/books/title?id=1335> Google-Books-ID: KQU_nqwIjv4C.
- [62] 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 (April 2022), 78:1–78:35. <https://doi.org/10.1145/3512925>
- [63] Foad Hamidi, Morgan Klaus Scheuerman, and Stacy M. Branham. 2018. Gender Recognition or Gender Reductionism? The Social Implications of Embedded Gender Recognition Systems. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–13. <https://doi.org/10.1145/3173574.3173582>
- [64] Roxanna Harlow. 2003. "Race Doesn’t Matter, but...": The Effect of Race on Professors’ Experiences and Emotion Management in the Undergraduate College Classroom. *Social Psychology Quarterly* 66, 4 (2003), 348–363. <https://doi.org/10.2307/1519834> Publisher: [Sage Publications, Inc., American Sociological Association].
- [65] John P. Hausknecht, David V. Day, and Scott C. Thomas. 2004. Applicant Reactions to Selection Procedures: An Updated Model and Meta-Analysis. *Personnel Psychology* 57, 3 (2004), 639–683. <https://doi.org/10.1111/j.1744-6570.2004.00003.x> _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1744-6570.2004.00003.x>.
- [66] Karen A. Hegtvædt. 2018. *Justice frameworks*. Stanford University Press, Stanford, CA, USA. <https://psycnet.apa.org/record/2006-07094-003>

- [67] Andrew C. High, Anne Oeldorf-Hirsch, and Saraswathi Bellur. 2014. Misery rarely gets company: The influence of emotional bandwidth on supportive communication on Facebook. *Computers in Human Behavior* 34 (May 2014), 79–88. <https://doi.org/10.1016/j.chb.2014.01.037>
- [68] Crosby Hipes, Jeffrey Lucas, Jo C. Phelan, and Richard C. White. 2016. The stigma of mental illness in the labor market. *Social Science Research* 56 (March 2016), 16–25. <https://doi.org/10.1016/j.ssresearch.2015.12.001>
- [69] HireVue. 2023. Our Science | HireVue Online Interviewing & Recruiting Platform. <https://www.hirevue.com/our-science>
- [70] Arlie Russell Hochschild. 2012. *The Managed Heart: Commercialization of Human Feeling*. University of California Press, Berkeley, CA, USA. <https://www.ucpress.edu/book/9780520272941/the-managed-heart> Google-Books-ID: whi61UWpoj4C.
- [71] Anna Lauren Hoffmann. 2021. Terms of inclusion: Data, discourse, violence. *New Media & Society* 23, 12 (Dec. 2021), 3539–3556. <https://doi.org/10.1177/1461444820958725> Publisher: SAGE Publications.
- [72] Anna Lena Hunkenschroer and Alexander Kriebitz. 2023. Is AI recruiting (un)ethical? A human rights perspective on the use of AI for hiring. *AI and Ethics* 3, 1 (Feb. 2023), 199–213. <https://doi.org/10.1007/s43681-022-00166-4>
- [73] Sarah E. Igo. 2018. *The Known Citizen: A History of Privacy in Modern America*. Harvard University Press, Cambridge, MA, USA. <https://www.hup.harvard.edu/catalog.php?isbn=9780674737501> Google-Books-ID: CrNyDwAAQBAJ.
- [74] Nicholas Jenkins, Michael Bloor, Jan Fischer, Lee Berney, and Joanne Neale. 2010. Putting it in context: the use of vignettes in qualitative interviewing. *Qualitative Research* 10, 2 (April 2010), 175–198. <https://doi.org/10.1177/1468794109356737> Publisher: SAGE Publications.
- [75] Haik Kalantarian, Khaled Jedoui, Kaitlyn Dunlap, Jessey Schwartz, Peter Washington, Arman Husic, Qandeel Tariq, Michael Ning, Aaron Kline, and Dennis Paul Wall. 2018. *The Performance of Emotion Classifiers for Children With Parent-Reported Autism: Quantitative Feasibility Study (Preprint)*. preprint. JMIR Mental Health. <https://doi.org/10.2196/preprints.13174>
- [76] Haik Kalantarian, Khaled Jedoui, Kaitlyn Dunlap, Jessey Schwartz, Peter Washington, Arman Husic, Qandeel Tariq, Michael Ning, Aaron Kline, and Dennis Paul Wall. 2020. The Performance of Emotion Classifiers for Children With Parent-Reported Autism: Quantitative Feasibility Study. *JMIR Mental Health* 7, 4 (April 2020), e13174. <https://doi.org/10.2196/13174> Company: JMIR Mental Health Distributor: JMIR Mental Health Institution: JMIR Mental Health Label: JMIR Mental Health Publisher: JMIR Publications Inc., Toronto, Canada.
- [77] Brittany Kammerer. 2021. Hired by a Robot: The Legal Implications of Artificial Intelligence Video Interviews and Advocating for Greater Protection of Job Applicants. *Iowa Law Review* 107 (2021), 817. <https://heinonline.org/HOL/Page?handle=hein.journals/ilr107&id=841&div=&collection=>
- [78] Asli Kandemir and Richard Budd. 2018. Using Vignettes to Explore Reality and Values With Young People. *Forum : Qualitative Social Research* 19, 2 (2018), 23. <https://doi.org/10.17169/fqs-19.2.2914> Place: Berlin, Germany Publisher: Freie Universität Berlin Section: Single Contributions.
- [79] Miliann Kang. 2003. The Managed Hand: The Commercialization of Bodies and Emotions in Korean Immigrant-Owned Nail Salons. *Gender & Society* 17, 6 (Dec. 2003), 820–839. <https://doi.org/10.1177/0891243203257632> Publisher: SAGE Publications Inc.
- [80] 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 (CHI ’22)*. Association for Computing Machinery, New York, NY, USA, 1–18. <https://doi.org/10.1145/3491102.3517453>
- [81] Simran Kaur and Richa Sharma. 2021. Emotion AI: Integrating Emotional Intelligence with Artificial Intelligence in the Digital Workplace. In *Innovations in Information and Communication Technologies (IICT-2020) (Advances in Science, Technology & Innovation)*, Pradeep Kumar Singh, Zdzislaw Polkowski, Sudeep Tanwar, Sunil Kumar Pandey, Gheorghe Matei, and Daniela Pirvu (Eds.). Springer International Publishing, Cham, 337–343. https://doi.org/10.1007/978-3-030-66218-9_39
- [82] Kate Kaye. 2022. Class tests Intel AI to monitor student emotions on Zoom - Protocol. <https://www.protocol.com/enterprise/emotion-ai-school-intel-edutech>
- [83] Angeliki Kerasidou. 2020. Artificial intelligence and the ongoing need for empathy, compassion and trust in healthcare. *Bulletin of the World Health Organization* 98, 4 (April 2020), 245–250. <https://doi.org/10.2471/BLT.19.237198>
- [84] Os Keyes. 2018. The Misgendering Machines: Trans/HCI Implications of Automatic Gender Recognition. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (Nov. 2018), 88:1–88:22. <https://doi.org/10.1145/3274357>
- [85] Youngmoo E Kim, Erik M Schmidt, Raymond Migneco, Brandon G Morton, Patrick Richardson, Jeffrey Scott, Jacquelin A Speck, and Douglas Turnbull. 2010. Music Emotion Recognition: A State of the Art Review. In *11th International Society for Music Information Retrieval Conference (ISMIR 2010)*, Vol. 11. International Society for Music Information Retrieval, Utrecht, Netherlands, 12. <https://archives.ismir.net/ismir2010/paper/000045.pdf>

- [86] Emmanuelle P. Kleinlogel, Marianne Schmid Mast, Dinesh Babu Jayagopi, Kumar Shubham, and Anaïs Butera. 2023. “The interviewer is a machine!” Investigating the effects of conventional and technology-mediated interview methods on interviewee reactions and behavior. *International Journal of Selection and Assessment* 0, 0 (2023), 17. <https://doi.org/10.1111/ijsa.12433> _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/ijsa.12433>.
- [87] Alina Köchling, Shirin Riazzy, Marius Claus Wehner, and Katharina Simbeck. 2021. Highly Accurate, But Still Discriminatory. *Business & Information Systems Engineering* 63, 1 (Feb. 2021), 39–54. <https://doi.org/10.1007/s12599-020-00673-w>
- [88] Markus Langer, Cornelius J. König, and Maria Papathanasiou. 2019. Highly automated job interviews: Acceptance under the influence of stakes. *International Journal of Selection and Assessment* 27, 3 (2019), 217–234. <https://doi.org/10.1111/ijsa.12246> _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/ijsa.12246>.
- [89] Siddique Latif, Hafiz Shehbaz Ali, Muhammad Usama, Rajib Rana, Björn Schuller, and Junaid Qadir. 2022. AI-Based Emotion Recognition: Promise, Peril, and Prescriptions for Prosocial Path. <https://doi.org/10.48550/arXiv.2211.07290> arXiv:2211.07290 [cs].
- [90] B C Lee and B Y Kim. 2021. Development of an AI-Based Interview System for Remote Hiring. *International Journal of Advanced Research in Engineering and Technology* 12, 3 (2021), 654–663.
- [91] Kwok Leung and Michael W. Morris. 2001. Justice through the lens of culture and ethnicity. In *Handbook of justice research in law*. Kluwer Academic Publishers, Dordrecht, Netherlands, 343–378. <https://psycnet.apa.org/record/2001-00118-006>
- [92] Jacqueline Low. 2019. A Pragmatic Definition of the Concept of Theoretical Saturation. *Sociological Focus* 52, 2 (April 2019), 131–139. <https://doi.org/10.1080/00380237.2018.1544514> Publisher: Routledge _eprint: <https://doi.org/10.1080/00380237.2018.1544514>.
- [93] Henrietta Lyons, Eduardo Velloso, and Tim Miller. 2021. Conceptualising Contestability: Perspectives on Contesting Algorithmic Decisions. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (April 2021), 1–25. <https://doi.org/10.1145/3449180>
- [94] Peter Mantello, Manh-Tung Ho, Minh-Hoang Nguyen, and Quan-Hoang Vuong. 2021. Bosses without a heart: socio-demographic and cross-cultural determinants of attitude toward Emotional AI in the workplace. *AI & SOCIETY* 0, 0 (Nov. 2021), 23. <https://doi.org/10.1007/s00146-021-01290-1>
- [95] Julie M. McCarthy, Talya N. Bauer, Donald M. Truxillo, Neil R. Anderson, Ana Cristina Costa, and Sara M. Ahmed. 2017. Applicant Perspectives During Selection: A Review Addressing “So What?,” “What’s New?,” and “Where to Next?“. *Journal of Management* 43, 6 (July 2017), 1693–1725. <https://doi.org/10.1177/0149206316681846> Publisher: SAGE Publications Inc.
- [96] Andrew McStay. 2018. *Emotional AI: The Rise of Empathic Media*. SAGE, Thousand Oaks, CA, US. <https://uk.sagepub.com/en-gb/eur/emotional-ai/book251642>
- [97] Ninareh Mehrabi, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. 2021. A Survey on Bias and Fairness in Machine Learning. *Comput. Surveys* 54, 6 (July 2021), 115:1–115:35. <https://doi.org/10.1145/3457607>
- [98] Emma Mishel. 2016. Discrimination against Queer Women in the U.S. Workforce: A Résumé Audit Study. *Socius: Sociological Research for a Dynamic World* 2 (Jan. 2016), 237802311562131. <https://doi.org/10.1177/2378023115621316>
- [99] 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 (March 2022), 203–211. <https://doi.org/10.1007/s11920-022-01330-7>
- [100] Susan Moore. 2018. 13 Surprising Uses For Emotion AI Technology. <https://www.gartner.com/smarterwithgartner/13-surprising-uses-for-emotion-ai-technology>
- [101] Agnes Moors, Phoebe C. Ellsworth, Klaus R. Scherer, and Nico H. Frijda. 2013. Appraisal Theories of Emotion: State of the Art and Future Development. *Emotion Review* 5, 2 (April 2013), 119–124. <https://doi.org/10.1177/1754073912468165> Publisher: SAGE Publications.
- [102] Bonnie Moradi. 2017. (Re)focusing intersectionality: From social identities back to systems of oppression and privilege. In *Handbook of sexual orientation and gender diversity in counseling and psychotherapy*. American Psychological Association, Washington, DC, US, 105–127. <https://doi.org/10.1037/15959-005>
- [103] Mordor Intelligence. 2022. Emotion Detection And Recognition (EDR) Market Share, Size | 2022 - 27 | Report, Trend. <https://www.mordorintelligence.com/industry-reports/emotion-detection-and-recognition-edr-market>
- [104] Janice M. Morse. 2015. “Data Were Saturated . . .”. *Qualitative Health Research* 25, 5 (May 2015), 587–588. <https://doi.org/10.1177/1049732315576699> Publisher: SAGE Publications Inc.
- [105] Haley Moss. 2021. Screened Out Onscreen: Disability Discrimination, Hiring Bias, and Artificial Intelligence. *Denver Law Review* 98, 4 (2021), 31. <https://doi.org/10.2139/ssrn.3906300>
- [106] Jeff Nagy. 2022. Autism and the making of emotion AI: Disability as resource for surveillance capitalism. *New Media & Society* 00, 0 (July 2022), 146144482211095. <https://doi.org/10.1177/14614448221109550>

- [107] Devah Pager and Lincoln Quillian. 2005. Walking the Talk? What Employers Say Versus What They Do. *American Sociological Review* 70, 3 (June 2005), 355–380. <https://doi.org/10.1177/000312240507000301>
- [108] Devah Pager and Bruce Western. 2012. Identifying Discrimination at Work: The Use of Field Experiments. *Journal of Social Issues* 68, 2 (2012), 221–237. <https://doi.org/10.1111/j.1540-4560.2012.01746.x> _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-4560.2012.01746.x>.
- [109] Deborah Powell, Maria Kavanagh, Bethany Wiseman, and Audrey Hodgins. 2023. Effects of Background Cues on Videoconference Interview Ratings. *Personnel Assessment and Decisions* 9, 1 (May 2023). <https://doi.org/10.25035/pad.2023.01.003>
- [110] Cassidy Pyle, Lee Roosevelt, Ashley Lacombe-Duncan, and Nazanin Andalibi. 2021. LGBTQ Persons' Pregnancy Loss Disclosures to Known Ties on Social Media: Disclosure Decisions and Ideal Disclosure Environments. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery, New York, NY, USA, 1–17. <https://doi.org/10.1145/3411764.3445331>
- [111] Lincoln Quillian, John J Lee, and Mariana Oliver. 2020. Evidence from Field Experiments in Hiring Shows Substantial Additional Racial Discrimination after the Callback. *Social Forces* 99, 2 (Nov. 2020), 732–759. <https://doi.org/10.1093/sf/soaa026>
- [112] Lincoln Quillian and Arnfinn H. Midtbøen. 2021. Comparative Perspectives on Racial Discrimination in Hiring: The Rise of Field Experiments. *Annual Review of Sociology* 47, 1 (2021), 391–415. <https://doi.org/10.1146/annurev-soc-090420-035144> _eprint: <https://doi.org/10.1146/annurev-soc-090420-035144>.
- [113] Lincoln Quillian, Devah Pager, Ole Hexel, and Arnfinn H. Midtbøen. 2017. Meta-analysis of field experiments shows no change in racial discrimination in hiring over time. *Proceedings of the National Academy of Sciences* 114, 41 (Oct. 2017), 10870–10875. <https://doi.org/10.1073/pnas.1706255114> Publisher: Proceedings of the National Academy of Sciences.
- [114] 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 (FAT* '20)*. Association for Computing Machinery, New York, NY, USA, 469–481. <https://doi.org/10.1145/3351095.3372828>
- [115] Carl Ratner. 1989. A Social Constructionist Critique of The Naturalistic Theory of Emotion. *The Journal of Mind and Behavior* 10, 3 (1989), 211–230. <https://www.jstor.org/stable/24859883> Publisher: Institute of Mind and Behavior, Inc..
- [116] Stefan Reindl. 2021. Emotion AI in education: a literature review. *International Journal of Learning Technology* 16, 4 (Jan. 2021), 288–302. <https://doi.org/10.1504/IJLT.2021.121366> Publisher: Inderscience Publishers.
- [117] Lauren Rhue. 2018. Racial Influence on Automated Perceptions of Emotions. <https://doi.org/10.2139/ssrn.3281765>
- [118] Lauren Rhue. 2019. Emotion-reading tech fails the racial bias test. <http://theconversation.com/emotion-reading-tech-fails-the-racial-bias-test-108404>
- [119] Meghan Rimol. 2020. 6 Digital Workplace Trends on the Gartner Hype Cycle for the Digital Workplace, 2020. <https://www.gartner.com/smarterwithgartner/6-trends-on-the-gartner-hype-cycle-for-the-digital-workplace-2020>
- [120] Lauren A. Rivera. 2015. Go with Your Gut: Emotion and Evaluation in Job Interviews. *Amer. J. Sociology* 120, 5 (March 2015), 1339–1389. <https://doi.org/10.1086/681214> Publisher: The University of Chicago Press.
- [121] Lionel P. Robert, Casey Pierce, Liz Marquis, Sangmi Kim, and Rasha Alahmad. 2020. Designing fair AI for managing employees in organizations: a review, critique, and design agenda. *Human-Computer Interaction* 35, 5–6 (Nov. 2020), 545–575. <https://doi.org/10.1080/07370024.2020.1735391> Publisher: Taylor & Francis _eprint: <https://doi.org/10.1080/07370024.2020.1735391>.
- [122] Robert Wood Johnson Foundation. 2013. How Does Employment, or Unemployment, Affect Health? <https://www.rwjf.org/en/insights/our-research/2012/12/how-does-employment--or-unemployment--affect-health-.html>
- [123] Samantha Robertson and Niloufar Salehi. 2020. What If I Don't Like Any Of The Choices? The Limits of Preference Elicitation for Participatory Algorithm Design. <https://doi.org/10.48550/arXiv.2007.06718> arXiv:2007.06718 [cs].
- [124] Kat Roemmich and Nazanin Andalibi. 2021. Data Subjects' Conceptualizations of and Attitudes Toward Automatic Emotion Recognition-Enabled Wellbeing Interventions on Social Media. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (Oct. 2021), 308:1–308:34. <https://doi.org/10.1145/3476049>
- [125] 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 (April 2023), 109:1–109:28. <https://doi.org/10.1145/3579543>
- [126] 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 (CHI '23)*. Association for Computing Machinery, New York, NY, USA, 1–20. <https://doi.org/10.1145/3544548.3580950>
- [127] Drew Roselli, Jeanna Matthews, and Nisha Talagala. 2019. Managing Bias in AI. In *Companion Proceedings of The 2019 World Wide Web Conference (WWW '19)*. Association for Computing Machinery, New York, NY, USA, 539–544.

<https://doi.org/10.1145/3308560.3317590>

- [128] Nicolas Roulin, Eden-Ray Lukacik, Joshua S. Bourdage, Lindsey Clow, Hayam Bakour, and Pedro Diaz. 2023. Bias in the background? The role of background information in asynchronous video interviews. *Journal of Organizational Behavior* 44, 3 (2023), 458–475. <https://doi.org/10.1002/job.2680> _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/job.2680>.
- [129] Nicolas Roulin, Odelia Wong, Markus Langer, and Joshua S. Bourdage. 2023. Is more always better? How preparation time and re-recording opportunities impact fairness, anxiety, impression management, and performance in asynchronous video interviews. *European Journal of Work and Organizational Psychology* 32, 3 (May 2023), 333–345. <https://doi.org/10.1080/1359432X.2022.2156862> Publisher: Routledge _eprint: <https://doi.org/10.1080/1359432X.2022.2156862>.
- [130] Terry Rowlands, Neal Waddell, and Bernard McKenna. 2016. Are We There Yet? A Technique to Determine Theoretical Saturation. *Journal of Computer Information Systems* 56, 1 (Jan. 2016), 40–47. <https://doi.org/10.1080/08874417.2015.11645799> Publisher: Taylor & Francis _eprint: <https://doi.org/10.1080/08874417.2015.11645799>.
- [131] J. A. Russell, José-Miguel Fernández-Dols, Anthony S. R. Manstead, and Jane C. Wellenkamp. 2013. *Everyday Conceptions of Emotion: An Introduction to the Psychology, Anthropology and Linguistics of Emotion*. Springer Science & Business Media, Berlin, Germany. <https://books.google.com/books?id=j5tfBgAAQBAJ> Google-Books-ID: j5tfBgAAQBAJ.
- [132] Zlatka Russinova, Shanta Griffin, Philippe Bloch, Nancy J. Wewiorski, and Ilina Rosoklija. 2011. Workplace prejudice and discrimination toward individuals with mental illnesses. *Journal of Vocational Rehabilitation* 35, 3 (Jan. 2011), 227–241. <https://doi.org/10.3233/JVR-2011-0574> Publisher: IOS Press.
- [133] Roland T. Rust and Ming-Hui Huang. 2021. AI for Feeling. In *The Feeling Economy: How Artificial Intelligence Is Creating the Era of Empathy*, Roland T. Rust and Ming-Hui Huang (Eds.). Springer International Publishing, Cham, 151–162. https://doi.org/10.1007/978-3-030-52977-2_14
- [134] Ann Marie Ryan and Robert E Ployhart. 2000. Applicants’ perceptions of selection procedures and decisions: a critical review and agenda for the future. *Journal of Management* 26, 3 (Jan. 2000), 565–606. [https://doi.org/10.1016/S0149-2063\(00\)00041-6](https://doi.org/10.1016/S0149-2063(00)00041-6)
- [135] Johnny Saldaña. 2013. *The coding manual for qualitative researchers* (2nd ed ed.). SAGE, Los Angeles. <https://us.sagepub.com/en-us/nam/the-coding-manual-for-qualitative-researchers/book243616> OCLC: ocn796279115.
- [136] Klaus R. Scherer. 1993. Studying the emotion-antecedent appraisal process: An expert system approach. *Cognition and Emotion* 7, 3-4 (May 1993), 325–355. <https://doi.org/10.1080/02699939308409192> Publisher: Routledge _eprint: <https://doi.org/10.1080/02699939308409192>.
- [137] Phoebe Sengers, Kirsten Boehner, Michael Mateas, and Geri Gay. 2008. The disenchantment of affect. *Personal and Ubiquitous Computing* 12, 5 (June 2008), 347–358. <https://doi.org/10.1007/s00779-007-0161-4>
- [138] Behavioral Signals. 2022. Gartner’s Emotion AI Technologies Report Includes Behavioral Signals’ Voice Technology Overview. <https://www.prnewswire.com/news-releases/gartners-emotion-ai-technologies-report-includes-behavioral-signals-voice-technology-overview-301457052.html>
- [139] Pradeep Kumar Singh, Zdzislaw Polkowski, Sudeep Tanwar, Sunil Kumar Pandey, Gheorghe Matei, and Daniela Pirvu (Eds.). 2021. *Innovations in Information and Communication Technologies (IICT-2020): Proceedings of International Conference on ICRiHE - 2020, Delhi, India: IICT-2020*. Springer International Publishing, Cham. <https://doi.org/10.1007/978-3-030-66218-9>
- [140] Zoe Skinner, Stacey Brown, and Greg Walsh. 2020. Children of Color’s Perceptions of Fairness in AI: An Exploration of Equitable and Inclusive Co-Design. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems (CHI EA ’20)*. Association for Computing Machinery, New York, NY, USA, 1–8. <https://doi.org/10.1145/3334480.3382901>
- [141] Aaron Smith. 2017. *Automation in Everyday Life*. Technical Report. Pew Research Center. <https://www.pewresearch.org/internet/2017/10/04/automation-in-everyday-life/>
- [142] Logan Stapleton, Min Hun Lee, Diana Qing, Marya Wright, Alexandra Chouldechova, Ken Holstein, Zhiwei Steven Wu, and Haiyi Zhu. 2022. Imagining new futures beyond predictive systems in child welfare: A qualitative study with impacted stakeholders. In *2022 ACM Conference on Fairness, Accountability, and Transparency (FAcT ’22)*. Association for Computing Machinery, New York, NY, USA, 1162–1177. <https://doi.org/10.1145/3531146.3533177>
- [143] 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*. ACM, Virtual Event Canada, 782–793. <https://doi.org/10.1145/3442188.3445939>
- [144] Heather Stuart. 2006. Mental illness and employment discrimination. *Current Opinion in Psychiatry* 19, 5 (Sept. 2006), 522–526. <https://doi.org/10.1097/01.yco.0000238482.27270.5d>
- [145] Hung-Yue Suen, Mavis Yi-Ching Chen, and Shih-Hao Lu. 2019. Does the use of synchrony and artificial intelligence in video interviews affect interview ratings and applicant attitudes? *Computers in Human Behavior* 98 (Sept. 2019), 93–101. <https://doi.org/10.1016/j.chb.2019.04.012>

- [146] Javier Sánchez-Monedero, Lina Dencik, and Lilian Edwards. 2020. What does it mean to 'solve' the problem of discrimination in hiring? social, technical and legal perspectives from the UK on automated hiring systems. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency (FAT* '20)*. Association for Computing Machinery, New York, NY, USA, 458–468. <https://doi.org/10.1145/3351095.3372849>
- [147] Taryn M. Williams. 2022. The Intersection of Work and Wellbeing, for All Workers. <http://blog.dol.gov/2022/03/30/the-intersection-of-work-and-wellbeing-for-all-workers>
- [148] David R. Thomas. 2006. A General Inductive Approach for Analyzing Qualitative Evaluation Data. *American Journal of Evaluation* 27, 2 (June 2006), 237–246. <https://doi.org/10.1177/1098214005283748> Publisher: SAGE Publications Inc.
- [149] Shari Trewin, Sara Basson, Michael Muller, Stacy Branham, Jutta Treviranus, Daniel Gruen, Daniel Hebert, Natalia Lyckowski, and Erich Manser. 2019. Considerations for AI fairness for people with disabilities. *AI Matters* 5, 3 (Dec. 2019), 40–63. <https://doi.org/10.1145/3362077.3362086>
- [150] Margery Austin Turner, Michael Fix, and Raymond J. Struyk. 1991. *Opportunities Denied, Opportunities Diminished: Racial Discrimination in Hiring*. The Urban Institute, Washington, DC, US. <https://webarchive.urban.org/publications/204580.html#:~:text=Opportunities%20Denied%2C%20Opportunities%20Diminished,-Racial%20Discrimination%20in&text=A%20hiring%20audit%20in%20two,interview%20than%20their%20white%20counterparts>. Google-Books-ID: uetziCpmbNIC.
- [151] U.S. Office of Science and Technology Policy. 2021. Notice of Request for Information (RFI) on Public and Private Sector Uses of Biometric Technologies. <https://www.federalregister.gov/documents/2021/10/08/2021-21975/notice-of-request-for-information-rfi-on-public-and-private-sector-uses-of-biometric-technologies>
- [152] Kristen Vaccaro, Dylan Huang, Motahhare Eslami, Christian Sandvig, Kevin Hamilton, and Karrie Karahalios. 2018. The Illusion of Control: Placebo Effects of Control Settings. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–13. <https://doi.org/10.1145/3173574.3173590>
- [153] Elmira van den Broek, Anastasia Sergeeva, and Marleen Huysman. 2019. Hiring Algorithms: An Ethnography of Fairness in Practice. In *ICIS 2019 Proceedings*. Association for Information Systems, Munich, Germany, 9. https://aisel.aisnet.org/icis2019/future_of_work/future_work/6/?utm_source=aisel.aisnet.org%2Ficis2019%2Ffuture_of_work%2Ffuture_work%2F6&utm_medium=PDF&utm_campaign=PDFCoverPages
- [154] Elmira van den Broek, Anastasia Sergeeva, and Marleen Huysman. 2021. When the Machine Meets the Expert: An Ethnography of Developing Ai for Hiring. *MIS Quarterly* 45, 3 (Sept. 2021), 1557–1580. <https://doi.org/10.25300/MISQ/2021/16559>
- [155] Garima Vijh, Richa Sharma, and Swati Agrawal. 2021. The Heartfelt and Thoughtful Rulers of the World: AI Implementation in HR. In *Futuristic Trends in Network and Communication Technologies (Communications in Computer and Information Science)*, Pradeep Kumar Singh, Gennady Veselov, Valeriy Vyatkin, Anton Pljonkin, Juan Manuel Doderó, and Yugal Kumar (Eds.). Springer, Singapore, 276–287. https://doi.org/10.1007/978-981-16-1480-4_24
- [156] Ashley Marie Walker and Michael A. DeVito. 2020. "More gay" fits in better": Intracommunity Power Dynamics and Harms in Online LGBTQ+ Spaces. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–15. <https://doi.org/10.1145/3313831.3376497>
- [157] Qiaosi Wang, Shan Jing, David Joyner, Lauren Wilcox, Hong Li, Thomas Plötz, and Betsy Disalvo. 2020. Sensing Affect to Empower Students: Learner Perspectives on Affect-Sensitive Technology in Large Educational Contexts. In *Proceedings of the Seventh ACM Conference on Learning @ Scale (L@S '20)*. Association for Computing Machinery, New York, NY, USA, 63–76. <https://doi.org/10.1145/3386527.3405917>
- [158] Yuyan Wang, Xuezhi Wang, Alex Beutel, Flavien Prost, Jilin Chen, and Ed H. Chi. 2021. Understanding and Improving Fairness-Accuracy Trade-offs in Multi-Task Learning. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining (KDD '21)*. Association for Computing Machinery, New York, NY, USA, 1748–1757. <https://doi.org/10.1145/3447548.3467326>
- [159] White House Office of Science and Technology Policy. 2022. Blueprint for an AI Bill of Rights | OSTP. <https://www.whitehouse.gov/ostp/ai-bill-of-rights/>
- [160] Madisson Whitman, Chien-yi Hsiang, and Kendall Roark. 2018. Potential for participatory big data ethics and algorithm design: a scoping mapping review. In *Proceedings of the 15th Participatory Design Conference: Short Papers, Situated Actions, Workshops and Tutorial - Volume 2 (PDC '18)*. Association for Computing Machinery, New York, NY, USA, 1–6. <https://doi.org/10.1145/3210604.3210644>
- [161] Meredith Whittaker, Meryl Alper, Olin College, Liz Kazianas, and Meredith Ringel Morris. 2019. *Disability, Bias, and AI*. Technical Report. AI Now Institute at NYU. 32 pages. <https://disabilitystudies.nyu.edu/disability-bias-and-ai-report/>
- [162] Jill E Yavorsky. 2019. Uneven Patterns of Inequality: An Audit Analysis of Hiring-Related Practices by Gendered and Classed Contexts. *Social Forces* 98, 2 (Dec. 2019), 461–492. <https://doi.org/10.1093/sf/soy123>
- [163] Minda Zetlin. 2018. AI Is Now Analyzing Candidates' Facial Expressions During Video Job Interviews. <https://www.inc.com/minda-zetlin/ai-is-now-analyzing-candidates-facial-expressions-during-video-job-interviews.html>

- [164] Annuska Zolyomi and Jaime Snyder. 2021. Social-Emotional-Sensory Design Map for Affective Computing Informed by Neurodivergent Experiences. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (April 2021), 77:1–77:37. <https://doi.org/10.1145/3449151>

Received July 2023; revised January 2024; accepted March 2024