Surveilling Suitability: How AI Hiring Interviews Impact Job Seekers with Disabilities

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Abstract

AI hiring interviews, asynchronous video recording platforms that use AI to assess candidate suitability, are increasingly used by employers to streamline hiring processes. These platforms often promise to standardize assessments and mitigate subjective biases in hiring decisions. Yet, little is known about how these technologies are perceived and experienced by people with disabilities, a group historically underrepresented in the workforce and particularly vulnerable to injustices perpetuated by technology. To address this gap, we conducted focus groups and semi-structured interviews with 19 people with disabilities. We found that people with disabilities perceive and experience discrimination by AI hiring interviews that: 1) center normative characteristics, 2) exacerbate information asymmetries, 3) undermine autonomy, and 4) intrude on privacy. We use the analytical frame of surveillance to interrogate the role of AI in reconfiguring social relations between job seekers and employers. We discuss implications of our work for design and policy.

CCS Concepts

• **Human-centered computing** → *Empirical studies in HCI*; *Empirical studies in accessibility*; *HCI theory, concepts and models.*

Keywords

Disability, Surveillance, AI, Artificial Intelligence, Fairness, Bias, AI Hiring, Automated Video Interviews

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1 Introduction

People with disabilities (PwD) make up the largest minority group globally [13], encompassing a wide range of physical, sensory, cognitive, developmental, and mental health impairments. Historically, PwD have faced systemic marginalization and discrimination, especially in the area of employment [148], which restricts their full participation in society. In the workplace, PwD encounter restricted job opportunities due to many physical, social, and attitudinal barriers. For instance, many workplaces lack essential accommodations, such as wheelchair accessibility or assistive technologies, making it difficult for some groups of PwD to work effectively [103, 108]. Societal attitudes further compound these employment barriers. PwD are frequently viewed as less productive or as costly hires because of perceived accommodation needs [21, 57], which can prevent hiring despite qualifications and capabilities. PwD are also too often seen as dependent or in need of constant assistance [21, 57, 91], reinforcing discriminatory stereotypes that hinder acceptance in workplace environments. These persistent barriers perpetuate a cycle of marginalization that limits PwD's economic independence [82, 90] and reduces their representation in the workforce [111]. Indeed, the unemployment rate for PwD is disproportionately high - nearly twice that of non-disabled individuals [111]. It is critical to study and address workplace barriers to ensure that *all* individuals have equal opportunities to participate in society.

Artificial Intelligence (AI) technologies, which refer to "systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals" [3], have been heralded for their potential to revolutionize society. AI promises to enhance efficiency and productivity by automating routine tasks, streamlining workflows and processes, and enabling data-driven insights [41]. In the domain of employment and hiring, AI technologies are becoming increasingly prevalent. AI systems are now used throughout the hiring process, including for job ad placements, resume screenings, and interview assessments. It is estimated that 88% of companies use some form of AI in the hiring process [39]. Of particular interest to this paper are automated video interviews, technologies which we refer to as *AI hiring interviews*. AI hiring interviews utilize AI to assess candidate suitability based on factors such as facial expressions, voice, and behavioral cues [54]. Proponents argue that such AI technologies allow organizations to enhance the efficiency of the hiring process by quickly screening a large number of job seekers, reducing time and resource costs (e.g., [26, 74]). These technologies are also stated to make hiring processes more equitable by standardizing assessments and eliminating subjective biases (e.g., those related to race and gender) [74, 99].

Yet, the proliferation of AI systems has been accompanied by significant concerns about AI perpetuating systemic biases. AI has been shown to amplify existing structural inequalities and reinforce discriminatory practices, producing unintended social consequences [26]. For instance, facial recognition software, often used in the domain of policing, has been shown to produce higher error rates for Black individuals, leading to increased misidentifications and arrests, widening pre-existing racial inequalities [20]. Similar forms of discrimination have been uncovered within broader AI hiring technologies. For instance, AI used for resume screening has been found to exhibit biases that disadvantage Black, Hispanic, and female candidates, favoring profiles that align with traditionally dominant demographics [37]. Similarly, AI hiring interviews have been shown to be biased against women and racial minorities, as they misinterpret and penalize behaviors that do not conform to stereotypical expectations of professionalism [5]. These biases disproportionately harm individuals from marginalized groups by limiting their chances of employment while also perpetuating a cycle of inequality in the workforce, creating a systemic barrier hidden behind the facade of "objective" technology.

In this paper, we extend and deepen emerging conversations around the social impact of AI technologies by focusing on the perceptions and experiences of people with disabilities with AI hiring interviews. In HCI, studying both perceptions and experiences provides complementary insights into how people interact with technology. Perceptions, i.e., what users think or expect as they learn about a technology, even before using it, help us understand intent to use and potential adoption barriers (e.g., [97, 145]). Experiences, i.e., what users actually encounter when interacting with the technology, reveal usability challenges and needs that can guide practical design improvements to make technologies more effective (e.g., [109]). We ask the following research questions:

- RQ1: How do people with disabilities perceive and experience AI hiring interviews?
- RQ2: What are their perceived and experienced barriers with AI hiring interviews?
- RQ3: What are the socio-technical implications for mitigating these barriers and supporting more equitable AI-based hiring for people with disabilities?

To answer these research questions, we conducted a qualitative study consisting of focus groups and semi-structured interviews with a broad group of people with disabilities. We use literature from surveillance studies in Human-Computer Interaction (HCI) as an analytical frame to explain the disparate impacts of AI hiring interviews on people with disabilities. Surveillance is an appropriate frame for multiple reasons. Firstly, it allows us to build on a rich body of work in HCI that has established the intimate connections between surveillance, technology, and the workplace, demonstrating how technologies function as mechanisms of control within organizational settings. Secondly, surveillance is rooted in concerns about power; hence, it enables us to foreground how the technical affordances of AI hiring interviews interact with social and organizational logics to shape power relations, in our case, between employers and job seekers with disabilities. Thirdly, surveillance tools, historically, have been used to monitor and control people with disabilities, reproducing prejudicial ideas about risk and worthiness [106] - mechanisms that, as we demonstrate in our work, persist in AI hiring interviews and help explain the marginalization of disabled job seekers when they encounter these systems. Finally, the surveillance framing helps us arrive at holistic considerations for supporting equitable AI-based hiring (e.g., through design and policy), given that prior work has shown surveillance to be a complex phenomenon that requires a multi-dimensional approach to mitigate its effects. We find that people with disabilities perceive and experience discrimination by AI hiring interviews that: 1) center normative characteristics, 2) exacerbate information asymmetries, 3) undermine autonomy, and 4) intrude on people's sense of privacy. These findings make the following contributions to the Human-Computer Interaction (HCI) literature:

(1) We report on rich empirical findings that detail people with disabilities' perceptions, experiences, and interactions with AI systems (RQ1 and RQ2). Although prior work has examined how AI affects many marginalized communities, little is known about how people with disabilities perceive and experience these systems [143, 150]; a critical gap that this paper addresses.
(2) We frame AI hiring interviews as a form of surveillance technology. In conjunction with our examination of the barriers people with disabilities encounter in navigating AI hiring interviews, this framing allows us to bring to light the role of AI in reconfiguring social relations by shifting power dynamics, and recognizes that those at the weaker end of power relations are often best positioned to reveal the injustices embedded within technologies [16] (RQ1 and RQ2).
(3) We draw from the data to propose design, policy, and community engagement considerations to inform the design of equitable AI systems (RQ3).

Through these contributions, this research enriches HCI's understanding of AI's impact on marginalized groups while also informing the design of more equitable AI technologies that work in the service of society.

2 Related Work

2.1 Disability, Fairness and AI

Research in Human-Computer Interaction (HCI) and accessibility highlights both the promise and perils of AI for people with disabilities. AI has been shown to improve the status quo of people with disabilities by easing burdensome tasks in low-stakes contexts [48], providing social support ([76]), allowing them to circumvent normative expectations [46], and enabling self-care and advocacy [11]. Novel AI capabilities have also been leveraged to build new accessible tools that allow people with disabilities to accomplish previously impossible tasks or perform existing tasks more efficiently (e.g., [113, 144, 154]). This thread, in particular, extends a long tradition of research in HCI and Accessibility that explores how technology can enhance the quality of life for people with disabilities and enable their equitable participation in everyday life.

Despite these promises, emerging research has begun to show how AI perpetuates ableism and reinforces harms against disabled people, raising broader questions about the fairness of AI [58, 98]. AI has been shown to erase disabled identities [43] (e.g., where people with disabilities are absent in training data), privilege normative expectations [48], and encode stereotypes that reflect dominant societal values [43, 84, 112]. Large Language Models (LLMs) have been found to perpetuate toxic and ableist language (e.g., [114, 146]). The heterogeneity of disability means that these harms are not experienced uniformly but vary across contexts and identities [61]. To address these key concerns, many solutions have been proposed. Technical strategies have emphasized incorporating diverse values, building representative training datasets [70, 80], and ensuring that training data portrays people with disabilities positively to mitigate AI bias. Additionally, the meaningful inclusion of people with disabilities throughout the AI development lifecycle [147], along with community oversight [84], can address concerns that technical fixes alone cannot resolve.

Research has begun to examine disability and fairness issues with the use of AI in hiring (e.g., [47]), including with AI hiring interview platforms [25, 117], uncovering how these platforms are likely to disadvantage people with disabilities. We build on this work by contributing rich, in-depth empirical evidence from a diverse group of people with disabilities, revealing a holistic set of barriers (RQ2) as well as perceived and experienced harms arising from people's encounters with these platforms (RQ1 and RQ2).

2.2 Surveillance in HCI Research

Surveillance, broadly defined as the "close watching over" of a person or group [19], has emerged as a significant area of interest within Human-Computer Interaction (HCI) (e.g., [15, 45, 50, 52, 128, 128, 132]). In this work, surveillance is understood as an adversarial practice [19], which foregrounds the power dynamics between the 'surveillant' and the 'surveilled'. Building on this perspective, studies examine how digital technologies enable and shape surveillance practices. Scholars agree that technologies intensify dynamics between the surveillant and surveilled [88], making surveillance more "focused and routine" [138], "limitless" [6], "intimate and perpetual" [4], and "expansive" [53]. Within this broader landscape, workplace environments, where technological and organizational practices converge to manage workers, have emerged as a key site for the study of technology-mediated surveillance.

2.2.1 The Workplace as a Site of Surveillance. Surveillance practices in workplaces date back to at least the 1920s, when employers gauged worker productivity through personality assessments, surveys, and lie detector tests [63]. The introduction of digital technology, often presented as a mechanism to benefit workers (e.g., by improving their work–life balance [4, 73, 131, 151]), in reality, only expanded these practices, allowing employers to exert greater control over workers. These technologies allow for the "continuous, pervasive, and constant capture" [124] of diverse forms of work-related data (e.g., workers' emotional states [124]). They are also notoriously opaque and render the employer's oversight invisible [4, 79, 120, 153]. Technology, thus, facilitates the creation of a truly panoptic workplace, where the disciplining gaze of management is omnipresent [49, 88]. We next turn to the two key topics of inquiry in HCI research on workplace surveillance: (1) the multifaceted effects of surveillance, and (2) approaches to mitigating these effects.

2.2.1.1 The Multifaceted Effects of Surveillance: HCI research has extensively studied the effects of technology-mediated surveillance in workplaces at both worker - and organizational-levels. At the worker level, surveillance is often entangled with privacy issues [129, 139], and many studies have used privacy as a lens to examine the nature of harms perpetuated by surveillance technologies (e.g., [124]). Technology-mediated monitoring has been shown to produce emotional harms and erode workers' sense of personhood and autonomy [4]. Surveillance also shapes worker-employer relationships in damaging ways. Surveillance technologies in the workplace create information asymmetries [30, 120] by allowing employers to gather extensive information about workers. Such practices exacerbate power imbalances while also making workers more vulnerable to exploitation [30, 121]. Such harms underscore how surveillance technologies reinforce hierarchical social control [53]. At the organizational level, surveillance has been shown to negatively affect work culture, creativity, and productivity [12], while also undermining worker trust in employers [56]. Surveillance has also been shown to magnify existing social inequalities [12]. The effects of this surveillance, however, are not homogeneous, i.e., not experienced equally [152, 155]. Research has begun to uncover how marginalized groups are disproportionately affected by surveillance in the workplace (e.g., gender minorities [10]), resulting in discrimination and exploitation. Yet, despite this emergent work, fewer studies (e.g., [129]) have studied the effects of surveillance on people with disabilities, a disadvantaged community, who have historically been marginalized in all avenues of everyday life, such as employment - this is a critical gap we address in this paper.

2.2.1.2 Approaches to Mitigate Effects of Surveillance: In response to the negative effects of surveillance, HCI scholarship has uncovered how design and policy can provide pathways to mitigate surveillance-induced harms. HCI work on design has called for facilitating "sousveillance" [87], i.e., empowering workers with novel technologies to make their work more visible and monitor employers [35, 126]) and fostering practices of resistance to counteract the negative effects of surveillance [139]. Participatory processes and frameworks such as adversarial design [33] are viewed as key mechanisms to empower the surveilled by surfacing issues concerning power imbalances. Critical and reflexive approaches [36, 49] have been highlighted as a means to question normative assumptions embedded in surveillance technologies [36], identify harms preemptively [49], and ultimately, cultivate more inclusive technologies. Alongside design, HCI work has emphasized the importance of centering ethics and values to reshape power dynamics. For instance, justice-oriented frameworks which prioritize the autonomy and agency of workers [101] are seen as tangible ways to address key surveillance-related concerns (e.g., invasion of privacy) [62]. However, there is agreement that design is insufficient and that there is a need for policy regulations and community intervention approaches to build accountability into surveillance technologies. In line with this sentiment, policy recommendations such as enhancing the rights of workers [124], building the power of worker collectives [23, 24], and restricting data collection and use [49, 124] have been proposed as ways to restrict the reach of the employer. Community-based strategies, including public awareness campaigns [7] and grassroots organizing efforts [138], are also crucial for pushing back against the increased proliferation of surveillance technologies. Ultimately, surveillance is a sociotechnical and political phenomenon, addressing which necessitates organizations, policymakers, and civil society to work together.

In this study, we focus on AI hiring interviews, which *surveil* job seekers to make decisions about their suitability for a job. The stakes in this pre-employment setting are tangible: surveillance via AI hiring interviews directly affects who gets the opportunity to enter a job and under what conditions, making it an important context to examine the real-world impact of AI systems. We use insights from this section on workplace surveillance to: 1) highlight the effects of AI hiring interviews on people with disabilities, a marginalized group who experience innumerable barriers to finding employment (RQ1 and RQ2); a focus which will provide a *lens of magnification* to understand the role of AI in (re)configuring power relations and 2) consider ways to mitigate the disparate impacts of AI hiring interviews (RQ3).

3 Methods

We conducted a qualitative study with people with disabilities to understand their perceptions and experiences with AI hiring interviews. This study was approved by our institution's IRB.

3.1 Participant Recruitment

Participants were recruited through online communities (e.g., Reddit), disability advocacy groups, personal contacts, and snowballing [102] - a technique used to reach out to hard-to-access marginalized groups like people with disabilities. In contrast to many studies in accessibility research that focus on one specific group of people with disabilities (e.g., people with visual impairments), our study design intentionally included participants with diverse disabilities in order to get a holistic and comprehensive understanding of the barriers people encounter with AI hiring interviews. To assess the eligibility of potential participants, we distributed a screener survey that collected information on demographics (e.g., race, gender, geographic location) and job-seeking experiences. Eligible participants needed to be: 1) 18 years or older, 2) U.S. residents, and 3) have participated in the job-seeking process at least once in the last 3 years. The screener survey description communicated the study's purpose, and all responses were treated confidentially.

3.2 Data Collection

We used both focus groups (5 focus groups with 11 participants in total) and semi-structured interviews (8 participants) to understand people's perceptions and experiences with AI hiring interviews. The study was centered around focus groups to 1) encourage participants to share diverse perspectives and build on each other's insights and 2) create a space for the discussion of both shared challenges and unique experiences. However, with focus groups, we encountered scheduling difficulties, and when we did, we conducted semi-structured interviews with individual participants.

The focus group and semi-structured interview protocol elicited narratives [77] of people's perceptions and experiences with AI hiring interviews. The focus groups and interviews included open-ended prompts (e.g., tell us about the last time you had an accessible interview experience), scenario-based questions (e.g., AI like HireVue analyze facial expressions, vocal cues and behavioral data to assess suitability. Tell us about your thoughts.), and conceptual questions (e.g., what does fairness mean to you in the context of hiring?). Overall, we covered several topics in the protocol, including 1) recent experiences with hiring (e.g., with traditional and AI interviews), 2) perceptions of fairness, accessibility, and bias in the job-seeking process, including with AI assessments, and 3) challenges with disability disclosure during hiring processes. Additionally, we had an "incremental reveal" section, where we incrementally opened the AI hiring interview black box based on findings from [104, 105]. The steps included showing them: 1) an accessible version of the marketing video from the popular AI hiring company HireVue, 2) how AI measurements work (e.g., facial expressions, vocal cues), and 3) how candidate suitability scores are drawn from AI measurements (e.g., excitement). We stopped between each stage to probe participants' thoughts and feelings.

Focus groups lasted between 75 and 90 minutes, and interviews lasted between 45 and 60 minutes. Both were conducted online via Zoom. Conversations were video and audio-recorded, for which consent was sought before the start of the focus group and interview sessions. We continued participant recruitment until we reached data saturation [42]. Consistent with saturation reporting practices in HCI (e.g., [32, 55, 116, 118, 122]), the first author, present in all focus groups and interviews, determined that data saturation had been reached based on "informational redundancy" [130] evidenced by the repetition of participant responses and the observation that no new empirical findings emerged from the data [100]. We stopped data collection at a sample size of 19 participants. This sample size is in line with qualitative research guidelines, which indicate that saturation often occurs within 12–20 interviews [51] and with the average sample size reported in published HCI studies [22]. We generated transcripts verbatim from the audio recordings for analysis. Participants were compensated $50 for their time.

3.3 Data Analysis

To analyze our transcripts, we used thematic analysis [142]. The first author, having participated in all focus groups/interviews and thus being closest to the data [89], conducted an initial pass through the transcripts and developed a set of 16 preliminary codes through open coding [125]. These codes were refined through discussions with the second and third authors. For example, the code on AI enforcing normative standards was elaborated and clarified to capture not just how AI sets criteria for how an ideal candidate should look and sound, but also how this enforcement generates subtle pressures to conform to organizational expectations (e.g., requiring masking one's disability) in order to get hired. A detailed description of the codes is provided in the supplementary materials. The codes broadly aligned with four overarching themes: 1) AI centers normative characteristics, 2) AI exacerbates information asymmetries, 3) AI undermines autonomy, and 4) AI intrudes on privacy. During the coding process, the first and last authors met regularly to discuss

ID	Age	Gender	Race/Ethnicity	Employment Status	Disability	AI Interview Experience
P1	21	Non-binary	White	Employed	Mobility or motor disability, Chronic condition, Mental health	Yes
P2	22	Non-binary	White	Student	Neurodivergent	No
P3	23	Non-binary	White	Employed	Neurodivergent, Mobility or motor disability	Yes
P4	24	Non-binary	White	Unemployed	Chronic condition, Mobility or motor disability	No
P5	24	Woman	White	Unemployed	Learning disability, Mobility or motor disability	Yes
P6	25	Woman	Black or African-American	Employed	Learning disability, Mobility or motor disability	Yes
P7	30	Woman	White	Employed	Blind or low vision	No
P8	30	Woman	White	Employed	Mobility or motor disability, Speech-related disability	Yes
P9	30	Woman	Hispanic or Latino	Employed	Neurodivergent, Mental health	Yes
P10	32	Woman	White	Employed	Neurodivergent, Chronic condition	Yes
P11	32	Woman	White	Employed	Mobility or motor disability	No
P12	36	Woman	White	Employed	Blind or low vision	No
P13	37	Man	Asian	Employed	Mobility or motor disability	No
P14	44	Woman	White	Employed	Blind or low vision	No
P15	54	Woman	Black or African-American	Employed	Mobility or motor disability, Mental health	No
P16	46	Man	White	Employed	Blind or low vision	No
P17	24	Man	Black or African-American	Employed	Mobility or motor disability	Yes
P18	24	Man	Black or African-American	Unemployed	Mobility or motor disability	Yes
P19	27	Woman	Black or African-American	Employed	Mobility or motor disability, Chronic condition	No

Table 1: Participant demographics.

insights emerging from the data. In discussions, the last author highlighted how the themes resonated with concepts in workplace surveillance in HCI (e.g., workplace surveillance and impact on worker privacy [124, 129, 139], workplace surveillance and power asymmetries [10, 30, 120]), which led us to adopt surveillance as an analytical frame to situate and interpret our findings.

To analyze our transcripts, we used thematic analysis [142]. The first author led coding efforts as they were closest to the data and developed an initial set of 16 codes by open coding [125] the data. We refined these codes during several meetings between the first three authors. For example, the code 'AI creates data privacy issues' initially only captured participants' concerns about how AI hiring interviews collected, stored, and used their video data. Through team discussions, we refined the code to also include participants' proposed strategies for addressing these data privacy risks. We then organized these codes around four themes: 1) AI centers normative characteristics, 2) AI exacerbates information asymmetries, 3) AI undermines autonomy, and 4) AI intrudes on privacy, which we explicate in this paper. These themes aligned with dimensions of technologically-mediated surveillance, which led us to situate our work within the HCI surveillance discourse. We provide descriptions of the final codes and themes in the supplementary materials.

3.4 Participant Demographics

We summarize key demographics in Table 1. A majority of participants (n=15) were employed at the time of the study. Three participants identified as unemployed, while one identified as a student. Most participants (n=10) identified with multiple disabilities. Nine participants had prior experience with AI hiring interviews.

4 Context: AI Hiring Interviews

In AI hiring interviews, candidates usually log into an online platform to answer a fixed set of pre-recorded or text-based questions. They have a short preparation window before each prompt and a strict time limit for video recording their answers. The questions primarily focus on personality traits and include situational and hypothetical scenarios. AI hiring interviews work by using a combination of data points, including facial and behavioral (e.g., eye contact), audio (e.g., pitch), and text-based data (e.g., words) to assess a candidate's suitability. AI conflates these signals to qualities such as levels of engagement and excitement based on previously collected data of successful candidates (e.g., [104, 105]). Platforms like HireVue also have automated disability detection features [60]. Although it is unclear how these platforms exactly detect disability, they likely do so by flagging facial expressions or speech features that fall outside statistical norms in their training data. By treating statistical differences as anomalies, the platforms operationalize disability without explicitly labeling it as such. The use of AI to infer disability follows a long line of research that demonstrates how user-generated data (e.g., mouse movements [8]) can be used to detect disability-related characteristics [150].

5 Findings

Overall, participants in the study viewed AI hiring interviews very negatively. Participants consistently described their perceptions of AI hiring interviews as unsettling and alienating, often using words such as *"messed up," "creepy," "dehumanizing,"* and *"weird."* They resented what felt like the hollow act of *"talking to themselves"* in front of a screen. They worried that AI could not get to know them as people. While a few participants acknowledged limited positives of these interviews - such as the flexibility of completing the interview at a convenient time and from a familiar and accommodating environment - these advantages were outweighed by significant drawbacks. Below, we describe how participants believed AI hiring interviews might discriminate against them.

5.1 AI Centers Normative Characteristics

5.1.1 Algorithmic Construction of the "Ideal" Candidate. AI hiring interviews particularly troubled respondents because of the way AI systems seemed to codify normative and narrow ideas of what a *good* candidate looked and sounded like. By normative, we refer to traits that align with socio-culturally dominant or typical standards [31], which implicitly establishes the default notion of an ideal candidate. Participants perceived standardized assessments to be inherently disabling for people whose impairments affected those behaviors. P3, upon being shown the AI marketing video, immediately remarked,

> *The perfect candidate [for AI] is likely a non-disabled person... It's going to have a bias against disabled people. My tone doesn't always sound how I'm meaning it to. I struggle with eye contact and looking at a camera... AI would dock me points for those autistic traits.* - P3 (Experienced with AI hiring interviews)

Like P3, others were also worried that the AI would unfairly penalize them for non-normative behaviors. In their view, AI systems would fail to recognize the diversity of communicative styles and reify standards that worked against people with disabilities. Faced with these normative expectations, some participants described how they would mask their disabilities during interviews. Masking typically involved closely monitoring one's gestures, modulating tone, and rehearsing answers to mimic non-disabled norms. While masking felt like a necessary strategy to get hired, it also required substantial physical and emotional work. Others noted that learning and performing normative communicative patterns felt like a forced assimilation that denied a central part of their disabled identity. As P16 questioned: *"Why should someone who is disabled have to accommodate the norms of non-disabled?"*

Standardized AI assessments were also perceived to have differential effects across different groups of people with disabilities. The use of facial expressions, behavioral data, and vocal cues to assess suitability meant that individuals whose impairments directly shaped how they registered on these criteria (e.g., someone with a speech impairment would fare poorly on vocal cues assessments) were likely to be viewed more negatively than those whose disabilities did not (e.g, a wheelchair user with no communication-related impairments). Others brought up how other intersectional aspects of one's identity, such as age, gender, and race, could challenge standardized assessments. P8, when told about how AI generates candidate suitability scores from measurements, mentioned,

> *Excitement or friendliness are very nebulous and terrible to assess with AI... Across cultures, everybody has a different level of acceptability... I also have some friends that have speech impediments, and so their speech is not always clear. AI would have to be very good [to work for them].* - P8 (Experienced with AI hiring interviews)

Many participants were also particularly skeptical of automated disability detection features. Disability, they stressed, was a complex phenomenon. Not only was disability a spectrum, but impairments, too, were likely to manifest differently among people with the same disability. Automated detection risked flattening this complexity, and participants' perceived doubts about the potential of these features to capture the nuances of disabled experiences also left them vulnerable to being *"misjudged"* (P13). Some noted that detection errors could also harm non-disabled candidates, who might be mistakenly labeled as disabled. Moreover, participants felt that automated disability detection features foregrounded their disability - an all too familiar feeling for people with visible disabilities in traditional (non-AI) interview settings, where, upon being identified with a disability, it became the defining lens through which their candidacy was evaluated. This experience was echoed by P13, a person with a mobility disability, who had encountered this feeling of their disability being foregrounded several times with traditional (non-AI) interviews.

> *In the conversation, it's about the job. I don't want my disability being the focus. If they're focusing on, 'What is going on with your back?' I say 'You're not hiring me for my disability. You're hiring me for what I bring, like my brain'. When I say that, the conversation starts steering differently, or I leave.* - P13

5.1.2 Algorithmic Misrecognition and Disability. Participants described a mismatch between what AI systems seemed to capture during interviews and what they believed to be relevant for assessing their job suitability. Rather than evaluating skills through qualifications and past experiences, these systems were perceived as disproportionately focused on personality or behavioral traits. Many likened the process to traditional personality tests, which they regarded as both inaccurate representations of candidates' qualities and have historically been shown to be ableist [92, 136]. Moreover, they noted that personable qualities did not always manifest in normative ways. Yet AI appeared to privilege narrow and rigid expressions of them. AI interviews were seen as one-size-fits-all solutions that ignored the requirements of specific jobs; while personable traits were valuable for some roles, they were not universally relevant. As one participant explained, the AI interviews felt as though organizations were simply *"looking for a warm body,"* (P14) rather than evaluating meaningful competencies. As P16, a blind participant, when asked about what constituted a fair hiring procedure, articulated that the emphasis on skills also, to some extent, helped combat stereotypes about disability in the interview.

> *The social and relational skills has no bearing on the actual job. A fair hiring procedure? There's no one-size-fits-all all... Hiring practices that put job skills as primary. [The focus on skills allows me to emphasize] I would be able to do tasks as well or better than sighted competitors... I have confidence in using the skills, and I am as competent as anyone else.* - P16

Alongside these frustrations, participants expressed uncertainty about what AI could truly capture about their personality and whether such assessments could ever be reliable. While this disconnect between what AI captures and assesses (personality and behavioral traits) and what participants deemed relevant (job skills) to performing a job effectively is problematic for all candidates, the effects of this mismatch are exacerbated for people with disabilities, whose impairments were seen to shape the ways they were evaluated under the restrictive criteria enforced by AI.

Participants also emphasized that AI interviews stripped away any opportunity to provide context for their answers. Unlike in-person interviews, where interviewers could situate responses within a broader frame (e.g., consider how a candidate's disability might shape their answers), AI systems did not seem to offer any such flexibility. Those who had experienced AI hiring interviews, in particular, believed that the affordances of AI, such as the short response time, made it difficult for them to convey the nuance of their experiences and provide explanations or additional context for their responses, leaving them vulnerable to misinterpretation and unfair assessment. In stripping this context, AI hiring interviews, in our participants' view, were unempathetic as they removed these important *human aspects* of an interview. AI was seen to evaluate their answers in isolation and demanded that people be at their best at all times. P1, when asked about what qualities they would want AI to measure in an ideal world, said,

> *[AI should] pick up on my facial expressions, but also why it's presenting that way? If I'm having a rough day... or doing bad mentally or physically, it'll be harder for AI to pick up... There are days when it's painful for me to make eye contact.... I don't see how AI can figure out my reasoning compared to a person, who could ask me.* - P1 (Experienced with AI hiring interviews)

5.2 AI Exacerbates Information Asymmetries

5.2.1 Algorithmic Affordances and the Loss of Mutuality. AI hiring interviews were characterized as one-directional assessments where the employer retained all control over interpretation and judgment over one's candidacy. While this observation was voiced most strongly by people who had prior experience with AI hiring interviews, it was also echoed to a lesser extent by participants without experience, like P11 below, who sought additional clarifications from the research team about the affordances of AI hiring interviews and how they worked (e.g., if job seekers could ask the AI questions). This characterization was in contrast to traditional (non-AI) interviews, which were very much understood as a two-way street where job seekers and employers made decisions about each other's fit and suitability. As P11 said, *I guess [I prefer the] physical interview, because then I could see a lot more about the company, the position, the person, what it's like to see, also, if it's a good fit for me. I could read certain cues and things that you can't see virtually.*

For many of our participants, traditional (non-AI) interviews were a way to gauge workplace inclusivity, a key consideration that determined whether people ultimately chose to pursue employment in an organization. In their experiences, conversations with interviewers and in-person workplace visits provided insight into the *"vibes"* of a workplace, i.e., the more intangible aspects of workplace culture, including whether an organization had prior experience with disabled employees, if they would be flexible and adaptive to their disability-specific needs and open to providing accommodations if they chose to work there. As P8, a person with cerebral palsy, said,

> *[I try to understand] The physical environment. Do they have an elevator? Can I get into the bathroom?... The culture around disability.. People's [interviewers] attitudes and how accommodating the company is... If they don't mention your disability or are subtly accommodating. Because I walk with a limp, [interviewers] would be like, 'We can take the stairs or the elevator.' It shows you they're willing to be accommodating.* - P8 (Experienced with AI hiring interviews)

Despite the risks of being stereotyped and judged, a few even strategically disclosed their disability during interviews to gauge the reactions of the interviewer. Positive interviewer responses, such as matter-of-factly treating their disability and engaging with participants' strengths rather than limitations, served as an indicator of organizational openness to disability, i.e., whether people could bring up their disability without the fear of being stigmatized or negative consequences (e.g., promotions). On the other hand, signs of rigidity or discomfort with their disability, explicit messages about workplace inflexibility and ableism, or uncomfortable questions about one's disability served as *"red flags,"*, shaping decisions about whether to pursue the role further.

> *I gauge reactions. How are they reacting to me describing my background? How are they reacting to my guide dog, my disability..? I feel for the vibes, how accommodating they seem, and how the workplace seems to be run. I've interviewed with some [and felt] I don't want to work here. This seems chaotic.* - P7

Finally, participants noted that interviews were important to assess their worth and whether the organization/workplace would recognize and value them as individuals. Again, being treated with respect, viewed as capable, and engaged with thoughtfulness during interviews helped signal that they would be valued beyond their disability. For people with disabilities who were used to being perceived as incapable and less competent than their non-disabled colleagues, this sense of worth was just as important as the job itself. In all, AI hiring interviews, by reducing the interview process to a one-directional assessment, seemed to remove this mutuality and the chance for participants to gather critical insights about whether a workplace would be supportive and safe.

5.2.2 Algorithmic Opaqueness and Rigidity. Participants with direct experience with AI hiring interviews also observed how AI changed how they engaged in interviews by shifting the focus from demonstrating emergent and adaptive capabilities to simply delivering prepared responses. For them, a good interviewee could respond flexibly in real time - reading the interviewer's reactions, interpreting subtle cues like tone or body language, and adjusting answers accordingly. Good interviewing was also about establishing a rapport and a relationship with the interviewer, as it was an indication of a person's personable qualities. AI hiring interviews, though, left many participants feeling as though they were speaking into a void. They noted that the AI systems were opaque and would offer no insight into what counted as a good response; again, something that cues from the interviewer helped establish, and was critical to participants being able to put their best foot forward. They were unsure of how they would be evaluated and whether they would meet the unstated evaluation criteria to be a successful job candidate. For P1, a participant with a cognitive disability, the opportunity to ask for clarifications from the interviewer was a critical accommodation.

> *[In AI interviews] I can't see somebody else reacting to what I'm saying. It doesn't give me much of an idea of how good I did... If it's another person, I can ask for clarification or just expand on certain things... When I have really bad brain fog or lower comprehension, it's really important that I can get that clarification.* - P1 (Experienced with AI hiring interviews)

Good interviewers brought the best out of participants. Indeed, people in our study counted on interviewers to be flexible, understanding, and accommodating. Many participants recalled instances of accommodating experiences in interviews (e.g., when interviewers asked them about any specific needs without participants bringing up their disability, gave them additional resources and time to answer), which enabled them to do well while making the interview experience enjoyable.

AI hiring interviews were also thought to necessitate producing polished answers within strict time limits. This emphasis on preparation within small time frames limited some people's ability to organize and deliver responses on the spot. This format was particularly disabling for some groups of people with disabilities (e.g., those with learning and cognitive disabilities) for whom strict time limits were anxiety-inducing, stressful, and a limitation to doing well. P6, while recalling her experiences with AI hiring interviews, articulated these challenges while also highlighting a previous inclusive experience that accommodated their disability.

> *It's [AI interviews] very hard, especially with dyslexia, because there might not be the opportunity to correct [answers]... [An inclusive non-AI interview] They gave me questions in advance, so I was able to come up with responses through the week... not on the spot... Having enough time, five minutes between each question, and having the ability to take breaks if needed.* - P6 (Experienced with AI hiring interviews)

Finally, participants noted that AI interviews also limited their ability to frame their disability as an asset; a strategy that many in our study used to preemptively address disability-related stereotypes. In traditional (non-AI) interviews, people noted how they could explain behaviors that might fall outside normative expectations and emphasized how their experiences and skills could benefit the organization. People spoke at length about finding ways to interject with such explanations during interviews, even when the questions were unrelated. People with visible disabilities, in particular, sought and appreciated explicit ways to demonstrate competence and skills directly related to the job, to counteract stereotypes that framed their disability as limiting. As P7, a teacher mentioned *"I liked having a model lesson as an opportunity to show that I am capable as a teacher. It gave me an opportunity to head off any preconceived notions about my abilities because I am blind."* Again, AI interviews removed this possibility by focusing on a standardized set of mostly personality-related questions.

5.3 AI Undermines Autonomy

Autonomy, in the context of people with disabilities, refers to their ability to make informed decisions about their lives and bodies [96], and is central to their self-determination, especially given the long history of their choices being constrained by paternalistic societal attitudes and ableist institutional norms [59]. Although participants acknowledged certain advantages of AI hiring interviews that supported or even enhanced their sense of autonomy (e.g., completing interviews remotely from the comfort of an accessible home environment), these benefits were considerably offset by affordances that undermined them. The shift from two-way interactions to one-way interactions, which meant people had no opportunities to ask questions (e.g., about the workplace), limited their ability to make an informed choice about whether the organization was a good fit for them. P2, for instance, was particularly proactive in assessing the workplace in traditional (non-AI) interviews, an approach they wanted to replicate in AI interactions.

> *[In traditional non-AI interviews] one question I ask is, what's your policy on sick leave [as a disability accommodation]? If they're like, no sick leave, that's not a place where I want to work. It demonstrates a certain amount of intolerance. I'd want the AI to have to provide an opportunity for you to ask questions as well. If it's like loaded with all the information from the company handbook, you should be able to ask questions and get those answers.* - P2

Autonomy was understood to be further undermined by automated disability detection features. Participants explained that such features would foreground their disability and limit their ability to choose when, how, and to whom they disclosed their disability. Disclosure was described as a personal and deliberate decision, central to the ways people with disabilities exercised autonomy and control over how they were perceived by potential employers. As P12 said, *I prefer not to disclose. The idea that AI is taking away my own autonomy [through automated disability detection] is highly concerning. I think it would lead to a lot of false assumptions about my disability and my capabilities.* Participants noted that disclosure decisions were often shaped by several factors, including the nature of their disability, the evolving dynamics of the interview, and prior experiences with disclosure. For individuals with visible disabilities, even when their disability was the focus in traditional (non-AI) interviews, they retained the agency to guide and shape the conversation (e.g., by suggesting alternative ways to accomplish tasks that might otherwise be seen as constrained by their disability) - something they were unable to do in AI hiring interviews.

As we stated earlier, the opacity of AI hiring interviews limited participants' understanding of the interview's purpose and how they were being evaluated. In traditional (non-AI) interviews, this understanding, to some degree, allowed people with disabilities to preserve their autonomy by exercising control over interactions and managing how they were perceived. Importantly, the opacity also curtailed their awareness of bias and discrimination in the hiring process and their ability to act on it. In traditional (non-AI) interviews, hiring participants noted being able to determine whether ableism shaped their hiring outcomes - for instance, whether an interviewer dismissed, minimized, or stigmatized disability, and if so, to pursue recourse and ensure fairness in the recruitment process. For instance, P15 noted how on one occasion she pursued recourse by filing complaints and escalating her case to relevant authorities when she felt that a hiring decision was impacted by her disability. However, such actions were no longer possible with AI hiring interviews, where the increased lack of transparency was seen to be disempowering.

5.4 AI Intrudes on Privacy

Participants consistently expressed privacy concerns related to their personal identity and data in AI hiring interviews. People with disabilities face heightened data-privacy risks with AI systems because the data these systems capture can increase risks of identifiability for some groups of people with disabilities and inadvertently reveal sensitive disability-related information, which may be stored, used, or shared in ways that lead to profiling and discrimination [86, 150]. Participants viewed aspects of their identity, especially those concerning their disability, as deeply private and sought to exercise control over when and how such information was disclosed. Needless to say, this apprehension in sharing disability-related information was challenged by automated disability detection features, which were perceived by participants to be intrusive as they seemed to collect this information without their consent. As P3 put it, *"[Automated disability-detection features] have privacy concerns, because not every disabled person wants to disclose that they're disabled, and in a hiring process that would take away their option to disclose."*

Concerns about data privacy surfaced in parallel. While a few participants were inherently wary of what data organizations collected and how this data might be used by them, others only reflected on the implications of data capture and use when the issue was raised during the incremental reveal portion of the focus groups and interviews. Across discussions, participants highlighted the lack of transparency around data use as a serious issue. They questioned how, where, and when their data might be stored and used, as well as how it would feed into AI models. A few even questioned whether their information would be managed securely, while others articulated broader risks - such as how unethical data practices could perpetuate systemic marginalization of people with disabilities in the job market and beyond. P4, when shown the AI hiring marketing video, highlighted their data privacy concerns by likening AI hiring interviews to more familiar facial recognition systems.

> *[AI hiring interviews] is like facial recognition without consent. I don't like that. It's not transparent, and they're not like, asking you, is this okay? They're likely gonna use your data for their training, for the model. That's what's creepy - you don't get to choose.* - P4

As we described above, while these data-privacy risks are likely not unique to people with disabilities, the potential impact of privacy violations is magnified for them, given the sensitive nature of disability-related information.

The incremental reveal section in the focus groups and interviews prompted participants to (re)consider what disability-related information they would be willing to share in AI hiring interviews and heightened awareness of data capture and use practices of organizations. Several expressed that they would become more guarded, even though they recognized that withholding certain kinds of information (e.g., employment and education experiences that could suggest that they are disabled) would ultimately be detrimental to their chances of employment. Others emphasized how the interview context was fraught with stress and vulnerability, given the high stakes of securing long-term work. Indeed, many of our participants described in detail their struggles in finding long-term employment. In this context, lingering doubts about their data privacy would likely amplify their feelings of anxiety and precarity. As a result, for participants like P5, data privacy was non-negotiable. They felt that any disability-related information they disclosed would be reduced to a demographic data point that could be used to potentially discriminate against them.

> *[Questions like] Do you have a disability? People are using this for demographics... They're going to use my info [against me]. [Data capture] It's invasive. I'm vulnerable going to the interview. You're trying to open up my can of worms of personal feelings. I would not work for them. I am eerie about sharing my data.* - P5

Although participants offered a few suggestions for mitigating data privacy risks - such as financial compensation to legitimize consent, formal agreements outlining data use (like P2 who said *"I need a legal agreement that my data will not be used to paint or view people like me negatively."*), or technical data anonymization techniques - most acknowledged that they would have little agency in the data capture and use process. This sense of resignation also underscored the power asymmetry in AI-mediated hiring.

6 Discussion

AI hiring technologies are touted for their potential to improve organizational hiring processes by enhancing efficiency and scalability while also providing a fair, standardized, and more objective experience for job seekers. However, our engagement with job seekers with disabilities reveals risks and concerns not well addressed by current systems. Participants with disabilities are concerned that rather than creating a level playing field, these technologies seem to center normative characteristics [117], exacerbate information asymmetries, undermine autonomy, and intrude on privacy (RQ1 and RQ2). While these risks are not limited only to job seekers with disabilities, they are magnified for this group, who are underrepresented in the labor market and contend with several physical, social, cultural, and attitudinal barriers to finding employment. In the next section, we discuss what it means for AI hiring technologies to constitute a surveillance infrastructure. By profiling and sorting people with disabilities, these systems not only surveil, but they also potentially impede access to employment. Through this framing, we contribute to conversations about the role of AI in reconfiguring social relations and its social impacts on marginalized groups (RQ1 and RQ2). We conclude with implications of our findings for design, policy, and research (RQ3).

6.1 AI Hiring Technologies as Surveillance Infrastructures

Writing about surveillance infrastructures in the age of digital technology, Lyon [83] introduced the concept of "surveillance as sorting" [83] to foreground "sorting" as a defining characteristic of technologies that monitor and control people. Such technologies operate by profiling individuals and then sorting them into distinct social groups. The purpose of this sorting, Lyon argues, is to assess levels of risk across populations, with those deemed "high risk" disproportionately subjected to discrimination [83]. Yet, he observes that less is known about the implications of these sorting technologies on everyday people and how this warrants interdisciplinary engagement [83]; an important gap that this paper addresses by examining how AI hiring interviews enact sorting to seemingly shape job seekers with disabilities' access to employment.

Hiring AI technologies, in our view, represents an instance of surveillance infrastructures that rely on "sorting" to profile and classify job seekers to determine organizational fit. Central to the functioning of sorting surveillance systems are abstracted data and the codes used to organize them [83]. In our context, abstract data includes video interview recordings, while codes take the form of standardized assessments that seem to privilege normative characteristics and, in doing so, position people with disabilities as atypical or abnormal. Here, we echo claims by prior HCI scholars that AI that quantifies personality and behavioral traits is indeed disabling [28, 143, 150]. A second feature of sorting-surveillance systems is that their outcomes have tangible consequences for individuals' life chances [83]. While we cannot make definitive claims about how AI hiring interviews shaped people's job prospects, a couple of things were true: all participants perceived the systems negatively, and those who had experiences with them did not have any success with interviewing. The affordances of AI hiring technologies, which privileged normative characteristics [117], shifted dynamics to one-way assessments, created mismatches between what the technology measured and what was deemed relevant to the job [25], constrained the format, which limited how much information interviewees could gather and share, meant that the odds were stacked against our participants; they had little to no opportunity to succeed. For a group struggling in the labor market, AI hiring interviews seemingly function as "doors that impede" [83] access to employment, potentially exacerbating existing inequities.

Hiring AI technologies also appears to operate as what Saltes terms "disability surveillance infrastructures" [127]. Saltes extends Lyon's notion of sorting to examine how surveillance technologies look to sort disabled people out by implicitly labeling them as economic risks [127]; a framing that could very well apply to our participants. People with disabilities are stereotyped as unproductive and burdensome, requiring disproportionate resources to contribute effectively; these stereotypes are consistent with both our participants' hiring experiences and prior work [21, 57, 91]. This framing of people with disabilities as unproductive aligns with long-standing critiques of capitalism in disability studies, which argue that capitalist societies deploy the concept of productivity as a normative standard to marginalize and discriminate against disabled bodies (e.g., [93]). Beyond this, disability surveillance infrastructures also diminish the personhood of people with disabilities by reducing individuals to their impairments. Participants saw AI as reducing them to data points or demographics that strayed from normative standards. AI also deprived people of opportunities to contextualize their disability and counter stereotypes. Automated disability detection features undermined their autonomy to disclose at their convenience. In essence, these affordances reproduce ableist norms, further exemplifying how technology systems like AI can reinforce the marginalization of people with disabilities.

How are AI hiring interviews similar or different to other surveillance infrastructures discussed in HCI? Like emotion AI [124], passive sensing [30], or monitoring software [139], AI hiring interviews also reduce people to measurable, quantifiable criteria to assess them. These quantifiable criteria are misaligned with people's conceptions of criteria that are essential to being a good worker or, in our case, who *can be* a good worker [115]. For job seekers with disabilities, this reduction to data points is particularly damaging, as it emphasizes impairments, stripping them of their humanity [107]. The surveillance systems also rely on standardized assessments that penalize deviations from the norm, reinforcing normative expectations. Power asymmetries in both cases emerge from information asymmetries [30]: employers retain privileged access to data and decision criteria invisible to the employee/job seeker. With hiring, the transformation of interviews to one-way assessments, which constrain the ability of job seekers to demonstrate their competence and emergent abilities, enables these asymmetries. Other similarities include autonomy harms [124], as job seekers, like workers, had little agency how they were characterized and evaluated by the systems (e.g., with automated disability detection features and one-way assessments) and intrusions into their sense of privacy (e.g., with how data was collected and used), which too are central to how surveillance infrastructures operate.

While similar in the above regards, AI hiring interviews differ from other workplace surveillance technologies in how they exert control over the surveilled. Unlike other surveillance technologies, which have been shown to enforce control over employees through regulation, i.e., continuous compliance shaping conduct and resulting in disciplinary surveillance [40], AI hiring interviews seem to enact surveillance through gatekeeping, determining who is even allowed to enter the workforce. These systems give the impression that they use sorting to exercise "differential control" [95], i.e., actively construct differences between groups of job seekers which result in disparate outcomes. Algorithmic functioning can amplify these differential effects [95], enabling what has been described as the "algorithmic management" [79, 120] of job seekers, where opaque systems allow a few to control who gets a job. AI hiring interviews also appear to constitute a more overt form of surveillance: job seekers are acutely aware they are being observed and recorded, though the criteria are opaque. Finally, participation is arguably very much coerced; job seekers are not under any contractual obligation with employers and surrender personal data without any guaranteed return, rendering this surveillance a uniquely extractive form of gatekeeping. In all, it seems like AI hiring interviews work in conjunction with other forms of surveillance infrastructures to intensify control and reproduce structural challenges.

AI hiring interviews reconfigure relationships between job seekers and employers: what was once an interactive exchange where job seekers could demonstrate skills and competence, build rapport with interviewers, and challenge implicit perceptions has seemingly become a one-sided, opaque evaluation in which algorithms dictate worthiness based on personality traits. These technologies also undermine autonomy by constraining how job seekers present themselves and intrude on privacy by extracting personal data under coercive conditions. These shifts redistribute power away from job seekers, narrowing the terms under which they are recognized as employable. For HCI, paying attention to these evolving dynamics of surveillance systems is crucial as it: 1) challenges HCI to expand its analytic lens beyond the workplace, to understand how surveillance infrastructures reshape access to work itself, and 2) foregrounds how socio-technical systems reproduce structural inequities in ways that design and policy must contend with.

6.2 Design and Policy Implications

6.2.1 Participation as a bottom-up requirement to address technical AI challenges. Increased public participation in the AI design and evaluation process is often seen as necessary to address the more harmful outcomes of surveillance systems [95]. This participation should include marginalized groups, like people with disabilities, to steer AI technologies towards fairer outcomes. In much AI research, however, this imperative of enhancing participation of marginalized groups is frequently reduced to a technical call for more 'diverse' datasets. In theory, this approach can foster greater fairness by de-centering normative attributes and improving the accuracy of model predictions to ensure that people with disabilities are evaluated like anyone else [70, 71]. However, in reality, such narrow abstractions sidestep the broader issues of power and other structural challenges that underlie discriminatory hiring practices (e.g., [9, 134]), introduce new ethical concerns (e.g., about data ownership and management), and heighten the risk of over-surveillance of marginalized groups. Thus, countering the adverse effects of surveillance necessitates that meaningful participation be grounded in participatory AI processes and community-led audits.

Participatory AI: Participatory AI processes have the potential to account for the needs of marginalized job seekers like people with disabilities in the design of AI systems, like hiring interviews, and address harms they encounter preemptively by making them equal stakeholders in the design process [17, 18]. Prior research in HCI and labor has stated how participatory design methods that center workers' rather than employer perspectives [23, 24] can address harms associated with surveillance systems in the workplace (e.g., erosion of privacy [124]). While extending such considerations to AI hiring interviews and job seekers would also move them towards fair(er) outcomes, it also raises an important question: *Which* workers (or job-seekers) should be centered? Workers (or job-seekers) are not a monolithic group, and marginalized groups such as our participants face disparate challenges in the labor market. Centering their needs and critical perspectives [36, 49] throughout, right from problem formulation to system deployment [85, 147] can reveal systemic inequities (e.g., how disability stereotypes perpetuate inequity in hiring), surface normative concerns embedded in technologies (e.g., challenges with standardized assessments) and preemptively anticipate harms (e.g., with data privacy). Calacci goes a step further, asserting that such participatory processes should be 'led' by those most affected by surveillance systems [23], to avoid their involvement being tokenized [17].

Simultaneously, these participatory processes should include other stakeholders of AI hiring technologies, like human resource professionals (HR). Preliminary research with these stakeholders shows both overlaps (e.g., concerns over transparency) and divergences (e.g., perceived value in automating routine interviewing tasks) in how these groups and the likes of our participants understand and use such systems [81]. Although prior work has highlighted the challenges of finding alignment between worker and management interests in the context of surveillance [23], we believe otherwise; bringing these stakeholders to the same table is a critical starting point to surface their distinct values and needs, which can then guide the design of equitable AI systems. Here, initiatives such as WeBuildAI provide a model for designing AI systems in more participatory ways that reflect diverse stakeholder interests [78].

Community-led Audits: Routine community-led audits of AI systems, using tools like model cards [94] and auditing frameworks such as [119], can serve as a form of sousveillance [87], allowing the likes of our participants to scrutinize the AI-driven decisions and hold surveillance technologies, such as AI hiring interviews, accountable. These audits can surface some of the key concerns perceived and experienced by our participants, including issues with their representation in training data, disparities in model performance across groups of people with disabilities, and the ways AI data points (e.g., facial expressions) and measurements (e.g., excitement) may disadvantage them. These audits can be complemented by HR involvement in ongoing monitoring and feedback loops of AI hiring interviews, where tools like the TARAI index [133] can provide a transparent view of AI decisions, enabling the timely correction of biases.

Community-led audits should not only evaluate AI from a technical standpoint, but also examine their use from a broader socio-technical and organizational standpoint - an approach which has been proposed even in the context of hiring AI previously [135]. Bias and fairness encoded in AI systems are only one part of the issue; the broader issue lies in how they are deployed and used by organizations. Evaluating AI within the context of its use can surface broader social and structural concerns (e.g., organizational culture to address disability stereotypes) that also need to be addressed to ultimately create meaningful participation for groups like people with disabilities in society.

To ensure these audits are genuinely community-led, organizations deploying AI hiring systems should be required to establish and collaborate with community oversight boards composed of diverse groups of people with disabilities. These boards could partner with organizations to 1) conduct routine audits and evaluations and 2) advise on how to enhance meaningful participation of people with disabilities in addressing issues surfaced by those audits. For instance, the community board, through audits, could flag issues in how candidate suitability is scored - a key concern raised by our participants - and work with companies to develop more inclusive assessments. Simultaneously, building the independent auditing capacity of community-led advocacy organizations is essential for supporting collective resistance [23, 24] and anti-surveillance initiatives [44] that will contest the growing use of surveillance technologies in hiring; an avenue for academic-community partnerships. Academia, here, can contribute technical expertise (e.g., audit training through the use of tools like the Algorithmic Equity Toolkit [72]), which both benefits community organizations and fosters novel intellectual directions with real-world community impact like [149]. The University of Michigan's Community Partnerships model offers one example of how such collaborations can be structured from within academia [29]. In the arena of technology and digital accessibility, such collective resistance efforts would extend a long lineage of social movements that have reshaped equity and access for underserved groups (e.g., [123, 141]).

6.2.2 Policy as a top-down necessity to promote fair AI use. Policy regulations are necessary to hold employers accountable and limit the deployment of surveillance systems that exploit job seekers and workers. For instance, prior work in HCI has discussed at length how policy can protect workers' right to privacy [30, 124, 139]. Similar protections are necessary for job seekers, who face even greater vulnerabilities since they lack contractual protections and risk losing opportunities if they refuse to consent to data capture. For job seekers with disabilities in the USA, we believe that the Americans with Disabilities Act (ADA), which protects the civil rights of people with disabilities, [1] can play a vital role in guaranteeing privacy protections and limiting AI harms preemptively.

ADA & Privacy: Among the specific privacy concerns raised by our participants were issues related to the automatic detection of their disability. Although the ADA [1] recognizes legal issues related to privacy, including those involving AI [2], it does not yet provide specific guidance on automated disability detection features, a necessary first step that will recognize the seriousness of the problems posed by these features. As our participants noted, automated disability detection features impinge on their autonomy and privacy. As such, guidance here should ban the development and implementation of these features, given their capacity to discriminate against people with disabilities and non-disabled people. Participants also expressed apprehension about data privacy, i.e, their data being recorded and used to train AI models. To address these concerns, regulation could push employers to implement mechanisms that provide job seekers with more control over their data [49]. Job seekers should have the right to control their data and withhold it from organizations without fear of retribution. Another option is for platforms to set up data exchange as a negotiation [49], where people can consent to some of their data being used by organizations (e.g., verbal but not facial data).

ADA & AI in Employment settings: The ADA should include more provisions to preemptively protect people with disabilities from AI-related harms. At present, ADA guidance on AI implementation in the workplace is in its nascent stages [2]. To develop this guidance, policymakers could look to the European Union (EU) to develop robust preemptive measures. EU regulations classify the use of automated decision-making tools in employment contexts as high-risk while explicitly prohibiting sorting and categorization of job seekers [38]. For non-decision-making AI tools, EU law requires full transparency of the AI model and explanations of decisions [38]. Implementation of both of these measures can drastically improve the hiring experiences of job seekers with disabilities, including participants in our study who perceived discrimination by black-box algorithms. Here, community oversight boards (Section 6.2.1) could also offer policy guidance that could ensure that organizations are not penalized (like with ADA violations that resulted in fiscal and reputational damage for corporations like Domino's [123]).

Broader policy regulations that govern AI use should include disability as a protected category. In the US context, legislation that seeks to regulate the use of AI in employment settings has begun to emerge [110]. For example, New York State recently established a policy around the use of automated decision-making tools in workplaces that prohibit discrimination based on race, ethnicity, and sex [110]. As is evident, these measures lack explicit protections against disability discrimination [34]. Expanding the scope of such policies to include disability alongside other recognized demographic categories represents a crucial step in establishing more equitable protections for people with disabilities.

Ultimately, while design and policy interventions are crucial for mitigating the harms of surveillance technologies like AI hiring interviews, they may be insufficient to fully address the structural inequities [140] these technologies perpetuate. It is vital that we HCI researchers go beyond developing these interventions and actively contest the acceptance of these technologies in order to reject their exploitative practices. Here, recognizing when not to design [27], advocating for refusal [7, 14] (e.g., opposing AI adoption in organizational contexts [124]), and shaping public discourse about the inequities produced by AI systems [7] can challenge the legitimacy and proliferation of surveillance technologies [137].

7 Limitations

This study has several limitations. First, our participants were people with disabilities based in the United States who were recruited through personal contacts and snowball sampling; consequently, the sample is not representative of the broader population of people with disabilities, even within the U.S. In addition, our results are based on focus groups and interviews with a relatively small number of participants, as is common in qualitative research. Future work that incorporates larger qualitative samples, as well as quantitative studies, will be important for generating more generalizable insights and informing efforts to address barriers associated with surveillance technologies, such as AI hiring interviews. Moreover, our focus on a diverse group of people with disabilities meant that we were unable to examine the specific and distinct concerns of individual disability groups (e.g., deaf people) - an important step toward designing inclusive AI hiring interview platforms. Our methodological choices also introduce limitations. While focus groups and interviews are valuable for understanding participants' broad experiences and perceptions with technology, they have inherent limitations that other methods could address. For instance, using AI hiring interviews as design probes combined with think-aloud protocols can reveal more detailed, nuanced, and moment-to-moment interactions, while technical analyses of AI systems could help identify systematic patterns of bias within these platforms. Research involving additional stakeholders (e.g., HR professionals and organizational leaders) will be crucial for understanding both shared and divergent experiences, needs, and values - insights that are essential for guiding the design of equitable, multi-stakeholder technologies like AI hiring interviews. Finally, our study's U.S. context is a limitation, given that most people with disabilities reside in the Global South [65–68]. As AI systems continue to proliferate worldwide, it will be essential to investigate situated experiences in these contexts, where distinct socio-cultural-political conditions (e.g., differing perceptions of objectivity and authority) will shape how people engage with AI-based hiring platforms (e.g., [64, 69, 75]).

8 Conclusion

Our study surfaces how job seekers with disabilities perceive and experience discrimination with AI hiring interviews, which: 1) center normative characteristics, 2) exacerbate information asymmetries, 3) undermine autonomy, and 4) intrude on privacy. We conceptually reframe AI hiring interviews as surveillance infrastructures to shine light on how AI technologies reconfigure social relationships by shifting power dynamics, thus altering life chances for a marginalized group. We offer suggestions for how design and policy could mitigate the discriminatory effects of AI.

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