Navigating a Black Box: Students' Experiences and Perceptions of Automated Hiring

Lena Armstrong*
lena318@sas.upenn.edu
University of Pennsylvania
Philadelphia, PA, USA

Jayne Everson
University of Washington
Seattle, WA, USA

Amy J. Ko
University of Washington
Seattle, WA, USA

ABSTRACT

Automated hiring algorithms are increasingly used in computing job recruitment. Prior work has examined perceptions of algorithmic fairness and established bias in hiring algorithms, but there is limited work on the ability of computer science students, who are applying for their first computing job, to overcome new barriers posed by automated hiring. To investigate what challenges students face, how they work through them, and their perceptions of these systems, we conducted semi-structured interviews with post-secondary students who were first-time computing job applicants. Analyses revealed that participants had diverse knowledge of hiring algorithms; some people knew to use strategies, such as keywords in resumes, online assessment practice, and referrals to circumvent automated processes to progress to in-person interviews, but others were entirely unaware of the automation. Participants also expressed that current systems prevented them from demonstrating the full extent of their skills and attributed job offers to personal contacts within the company. While some deemed automation a "necessary evil" to combat scale, many struggled with the inequity automated hiring processes perpetuated. Understanding student experiences and perspectives with automated hiring has relevance for how current computer science curricula prepares students for the transition to computing jobs post-graduation. Our findings have implications for how to develop new practices to better support students in their transitions amid a changing hiring landscape.

CCS CONCEPTS

• **Social and professional topics** → **Computing education**; **Computing industry**; **Employment issues**; **Automation**.

KEYWORDS

automated hiring, applicant tracking system, job application, student

ACM Reference Format:
Lena Armstrong, Jayne Everson, and Amy J. Ko. 2023. Navigating a Black Box: Students' Experiences and Perceptions of Automated Hiring. In *Proceedings of the 2023 ACM Conference on International Computing Education Research V.1 (ICER '23 V1), August 7–11, 2023, Chicago, IL, USA.* ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3568813.3600123

ICER '23 V1, August 7–11, 2023, Chicago, IL, USA

ACM ISBN 978-1-4503-9976-0/23/08…$15.00
https://doi.org/10.1145/3568813.3600123

1 INTRODUCTION

As computer science students enter the job market, they face an ever-changing landscape as automation is increasingly used in the recruitment process. An important part of understanding computer science education includes examining student transitions to computing jobs post-graduation and how current pedagogy prepares students for this transition [4]. According to studies with human resource professionals, artificial intelligence (AI) is already prevalent in recruitment and used most frequently in earlier stages of the hiring process for sourcing and screening candidates [1, 44]. In 2016, it was estimated that up to 72% of resumes are never seen by a person [39]. As applicants progress in the hiring process, there are fewer automated hiring systems, more in-person interviews, and sometimes even in-company recruiters to help applicants through later hiring stages, which creates an initial automated hurdle for applicants to jump through with limited resources.

While previous work has focused on bias in automated hiring algorithms [2, 10, 11, 30, 37, 41, 45] and applicants' perceptions of automated hiring [7, 20, 31, 35, 51], there is limited work on computer science students in particular, who are entering the job market for the first time. The most relevant prior work is on professional software developer's experiences and perceptions of hiring, which revealed perceptions that automated hiring lacked relevance to the job and could increase anxiety [5]. Students, however, may face even greater challenges, as they may have fewer job seeking skills overall, may have a greater need to assess their own fit within the company, and may have smaller networks and more limited industry-specific knowledge [46]. This intersection between student experiences, perceptions of fairness, and career seeking may also play an important role in shaping students' sense of belonging in the field and their long term career goals.

To address these gaps, in this work we asked *what are CS students' experiences and perceptions of automated hiring algorithms?* To answer this question, we specifically focused on those seeking jobs in computing, both because computing job markets are particularly vibrant and competitive globally, but also because those seeking jobs in computing might have a unique perspective on the trade-offs of using algorithms to streamline hiring. We conducted semi-structured interviews with 15 post-secondary students to investigate what challenges students face, how they work through them, and their perceptions of these systems. We then qualitatively analyzed the interviews by inductively coding for significant statements and determining emerging themes. Our findings have implications for how current computing pedagogy prepares students for the hiring process and how to better support students in this evolving landscape. Our results suggest that there needs to be further work to mitigate opacity and inequity in the hiring process by developing new practices to reduce the gap in understanding of automated practices and support applicants throughout the process.

2 RELEVANT WORK

2.1 Bias in Automated Hiring Algorithms

Hiring professionals frequently rely on applicant tracking systems (ATS) to provide support throughout the recruitment process from identifying open positions, receiving and managing incoming applicants, checking and scoring resumes, and hiring a candidate [32]. One industry report estimated that over 98% of Fortune 500 companies use applicant tracking systems (ATS) [27]. For applicants trying to secure technical roles, such as software engineering positions, many face online coding assessments with problems designed by either the company or third party sources. In addition to ATS and automated technical interviews, behavioral interviews have been increasingly conducted without human interviewers through automated video interviews (AVI). Many AVI platforms have applicants record a video of themselves answering a series of questions for a predetermined amount of time, which are ranked by the applicant's word choice, facial expressions, and voice inflection among other traits. Using factors such as speech (fluency, prosody, pronunciation, language usage) and nonverbal behaviors (facial expressions, posture, and eye movements), some researchers have determined for online video-based interviews that algorithms can predict interviewees personality traits, flight risk for changing jobs, and job fit, which have been adopted by many of these AVI platforms [12, 13, 25, 36]. In response to the increasing number of applicants, companies have incorporated AVI as part of their hiring practices. While some companies use their own ATS and AVI software, many use third-party automated hiring companies' software to aid with job recruitment, which claim to reduce bias and discrimination in hiring [45]. However, other researchers have indicated the lack of auditing of these systems and bias in the models despite these claims [2, 11, 41, 45].

Previous work has shown that automated hiring algorithms have limited auditing and perpetuate issues with discrimination in hiring [2, 41]. After reviewing commonly used automated hiring algorithms, Sanchez-Monedero, Dencik, and Edwards found that many did not uphold the standards of US and EU non-discrimination laws, even when they claimed to reduce discrimination in hiring [45]. Despite advertisements claiming to prevent bias in hiring, algorithms learn bias similar to the way humans learn bias. Prior research by Caliskan, Bryson, and Narayanan used the Implicit Association Test to determine that machines learn word associations from text that mirrors human implicit bias [11]. One technology company recently stopped its use of an automated hiring system after determining that it gave preferential treatment to men, scoring resumes lower if they contained the word "woman" in a club name or mentioned a women's college [17]. Researchers have found this link between resume scanning software and gender bias prevalent across ATS where machine learning models differentiate between genders even when resumes are controlled for similar experience levels and job-relevant characteristics, such that women applying to the same job openings receive less callbacks than men [40]. Some algorithms are even excluding people from the hiring process before they apply, such as social networking sites allowing companies to send job advertisements to only certain age groups, excluding older workers [30]. Researchers have also found that many AI-driven hiring tools bias against people with disabilities [10, 37].

Even audits of bias in these automated hiring tools often fail to examine bias in the assumptions of these tools, according to Sloan, Moss, and Chowhury, who call for socio-technical audits [47]. Audits of AI Personality Prediction in Hiring that investigated the underlying assumptions in the models and found that there was persistent and frequently inaccurate data linkage where algorithmic personality tests were not stable across job-irrelevant input [42, 43]. For students who are navigating the computing hiring process for the first time, hiring practices and decisions may influence their sense of belonging in the field. While prior work suggests that automated hiring may be biased, there is limited work on applicants' experiences navigating automated hiring systems and decisions, and its impact on their self-efficacy in the hiring process.

2.2 Variance in Perceptions of Algorithmic Fairness

It is crucial to understand users' perceptions of algorithmic systems to ensure greater transparency [7]. As the capabilities of machine learning and the number of applicants continue to increase, algorithmic systems are making more complex decisions that have the potential to perpetuate or worsen inequality and social stereotypes [31]. While there has also been increasing research to develop frameworks to alleviate algorithmic bias, researchers have pointed out how current factors in these approaches do not guarantee user trust and perceived fairness [31]

In the context of hiring algorithms, past work has shown that perceptions of algorithms vary based on age, gender, race, income, level of education, and employment experience [7, 20, 51]. There are also different perceptions of algorithmic fairness based on the task and situation, which complicates decisions of where and how to apply automation. In Lee's work, participants deemed tasks more fair if they were more mechanical [33]. Previous work has also suggested that people prefer human-based or human and AI-based decisions as opposed to solely AI-based decisions [22]. A study of the perceptions of HR professionals who use AI in hiring for sourcing and assessment revealed that recruiters had distrust in data accuracy, held different views based on the hiring scenario and their company, and perceived a lack of control in algorithmic candidate matches [35]. Differences in algorithmic perceptions pose challenges to algorithmic bias audits. Wang, Harper, and Zhu determined that when an algorithm predicts in people's favor, they rate it higher, so evaluating algorithmic fairness through user feedback may be susceptible to outcome favorability bias [49]. Additionally, variance in perceptions of fairness can also impact human behavior. Previous qualitative analysis by Woodruff, Fox, Rousso-Schindler, and Warshaw determined that perceptions of algorithmic fairness impacted user trust in a company [50], which may have implications for applicants' self-perceived fit within a company.

Past work has also shown a disconnect between employers', teacher's and student applicants' perceptions of what is most important in the hiring process [18, 23, 26]. For students who are trying to break into the field of computing, automated decisions with limited feedback, transparency, and further career support may influence their sense of belonging in the field and perceived ability to find a computing job. This may lead to qualified applicants who have less knowledge of the system removing themselves from the computing hiring process to find work in a different field. Our work aims to better understand this by investigating student experiences with feedback, access to resources, and perceptions of transparency. While studies have assessed perceptions of algorithmic fairness in hiring, there is limited research on the impact of automated hiring on students and their perceptions of how to navigate current prevalent automated hiring practices amid infrequent audits [47].

2.3 Automation and Career-Seeking

Prior work based on Social Cognitive Career Theory (SCCT) emphasizes personal agency, identity, experiences, and environment in understanding career choices and experiences [9, 34, 38, 48]. Additionally, perceptions of success in the field of computing varies based on identity and impacts personal interest in pursuing computing jobs [3]. In particular, women and minorities are underrepresented in computer science education and careers, with environment and feedback influencing their desire to stay in the field [8, 19, 21]. Previous work has shown that students from different socioeconomic backgrounds have different experiences with hiring processes even for computer science students who have access to the same resources (social connections and insider knowledge about the hiring process), which may have implications for automated hiring [14].

Past research that tracked software developers in their first six months working at technology companies emphasized how the transition from school to a first computing job can be anxiety-provoking without sufficient support [4]. Other work has also examined the impact of the traditional hiring process on self-efficacy and social support for adjustment to organizations [28]. As automation increases in hiring, understanding computer science students' experiences with automated hiring can better aid those transitions.

There is also a link between social class background and bias in hiring and how recruiters at technology companies will assess applicants' on perceived industrial, organizational, and individual "fit" [15]. These explicit and implicit signals of "fit" are translated to automated contexts. In addition to bias within the models, studies have shown that applicants' face transparency and communication issues with online hiring. Prior work has shown that current hiring pipelines lose qualified candidates at various stages in the process, which impact the diversity and effectiveness of software teams [6]. One qualitative study of 10,000 reviews on 19 companies at Glassdoor revealed many companies ghosted candidates and did not adequately communicate hiring criteria [6]. There is a need for further work to gain insight into how first-time job seekers maneuver these automated practices and transparency issues and the impact of the process on their career-seeking.

3 METHODS

To investigate perceptions and experiences of automated hiring for first computing jobs, the first author conducted semi-structured one-on-one interviews over Zoom. The aim was to identify bias in recruitment, how the process impacts applicants, and whether automated hiring changes people's perceptions of computing jobs.

3.1 Participants

Participants included undergraduate and graduate students, as well as recent graduates who had graduated less than one year prior to the interview. All the participants had either gone through or were going through the job application process for their first full-time computing job. To reach students and first-time job seekers, we recruited participants from university student computer and information science clubs, Facebook groups, and LinkedIn networks based in the United States. During recruitment, the research team was described as interested in understanding challenges that first time tech job seekers face with automated hiring algorithms and asked for the perspectives of people who had applied or were applying for jobs in the past year. Participants were told it would be a 30 min interview as part of a study on perceptions and experiences with automated hiring algorithms, they would be given $10 for their time, and that the research team hoped to share what they learned to inform better hiring practices and career services support. The university institutional review board granted this study exemption, since it was deemed to be no more than minimal risk to participants.

Overall, 22 participants signed up for interviews within one week and 16 participated in the interviews. While 16 participants were interviewed, one participant's data was excluded, since they were in the process of applying for their second job out of university. Of the remaining 15 participants, 9 were undergraduate students, 2 had graduated from an undergraduate program within the past year, and 4 had graduated from a Masters program within the past year. Following the interview, participants were asked to describe their gender identity, ethnic identity, what language(s) they speak at home, and if they wanted to disclose any other aspects of their identity. All fields were optional and participants self-reported their answers. Table 1 shows participant demographic information using participants' self-descriptions.

3.2 Interviews

Interview questions were developed by the first and third author to investigate people's beliefs about themselves, their experiences, and automation as a crucial part of better understanding career behavior and hiring processes. Building off of SCCT to determine participant perceptions and experiences with automated hiring, the first two questions ask about participants' career goals and contexts for the hiring process and the last question asks participants to reflect on their job process and qualifications [34]. The remaining questions sought to determine what automated systems participants experienced during the process and their perceptions of fairness of these systems. The questions were piloted with six college students who were undergoing the application process to improve conversationality, order, and wording of the interview questions. The first author conducted 15 to 45 minute semi-structured interviews over Zoom

Table 1: Participant self-described demographics.

Participant	Gender	Race & Ethnicity	Languages	Other Identities
1	Female	East Asian	English, Mandarin Chinese	ADHD, Autistic
2	Cis Male	Indian American	English, Gujarati	Bisexual
3	Female	Asian (Indian)	English, Punjabi	N/A
4	Female	Asian	English	N/A
5	Female	White	English	N/A
6	Male	Asian	Chinese, English	N/A
7	Female	Asian	Gujarati	No
8	Female	Asian	English, Vietnamese	N/A
9	Male	Prefer Not to Say	English	None
10	Male	Asian & White	English, Japanese	N/A
11	Male	Seattle	English, Hindi, Bengali	Immigrant, International Student
12	Female	Chinese	English, Chinese (Mandarin)	Straight
13	Male	South Asian	Telugu, Kannada, English	N/A
14	She/her	Asian/Chinese	English	N/A
15	Female	Caucasian	Croatian, Albanian, and English	N/A

in English, with most around 30 minutes, guided by the following questions:

(1) Tell me the story of why you are applying for tech jobs and how you got to the point of applying for your first technology job?
(2) What are your current career goals?
(3) What job(s) have you applied for?
(4) Since there are many types of application processes, which have you gone through?
  - How fair did it seem?
(5) Describe your experiences with automated hiring algorithms in the recruitment process.
  - Did you send a resume, have online coding assessments, do an automated interview, or upload a video? How was that?
  - What do you know about how your data was used?
  - Did you receive any feedback? If so, what was it?
(6) How do you wish this process worked?
  - Should a computer make these decisions?
(7) Did you wind up getting a job?
  - Is it the one you wanted?
  - Why do you think you got the job?
(8) Is there anything else you would like to add?

The interviews were auto-transcribed by Zoom and then the transcripts were cleaned and verified before analysis.

3.3 Analysis

Our analysis was guided by the arguments of Hammer and Berland [24], who position qualitative thematic analysis as interpretative claims about data, not as structured data for quantification. Therefore, rather than reporting inter-rater reliability analyses and quantities, we followed the guideline of discussing our analysis process and the interpretative disagreements that emerged in building a shared interpretation. We used principles of phenomenological research as described by Creswell and Poth [16], which means identifying significant statements, grouping them into broader themes, interpreting those themes for what and how the experience happened.

Our analysis proceeded as follows: the first and second author independently read the same several interviews and identified significant statements, which included any quote that mentioned an experience or perception of automated hiring algorithms or other elements of the hiring process. They then met to compare the selection of significant statements and surface initial themes. After agreeing on themes (experiences with feedback, strategies, and knowledge of the system and perceptions of fairness, transparency, and acceptance), they each pulled significant statements from additional interviews and met again to confirm and clarify the initial themes. Most disagreements in codes in the initial themes arose from clarifications of which types of strategies applicants were using and how to include the spectrum of perceptions of whether a computer should make hiring decisions. These disagreements were easily resolved, however, with further discussion of themes. Once the two authors were able to apply at least one theme from a set of unique themes to each significant statement, they re-coded each of the transcripts with those set of themes (experience with strategies and perceptions of fairness with strategies, knowledge of the system through varying levels of feedback and transparency, perceptions of power, and perceptions of whether computers should make decisions), leading to an agreed-upon set of themes linked to data.

3.4 Positionality

For transparency in how the identities of the authors relate to the research topic, each author provided a positionality statement explaining their experiences, perspectives, and identities that may have impacted their research engagement.

The first author is a white computer science student who studies algorithmic fairness and how to create more equitable and meaningful experiences with technologies. She believes computers have the potential to make biased decisions and approached this study with the lens of uncovering who was advantaged and disadvantaged by current hiring practices. Part of her motivation for this study was based on past experiences as an applicant with computing job recruitment and automated hiring algorithms.

The second author is a white computer science graduate student who studies critical computer science and is skeptical about the ability of computers to make unbiased decisions. She was motivated to work on this study because of the inequity of power in the current workforce in the United States, and the systemic inequities in the current hiring process.

The third author is a multiracial woman professor who advises students on job searches, has formerly hired many computer science graduates as an engineering manager, and who had to decide whether to adopt automated hiring solutions to streamline recruiting and interviewing. She observes the anxiety that many first time job seekers face and approached the work curious how automated hiring algorithms might influence students' experiences.

4 RESULTS

Analyses of interviews with participants revealed that first-time job applicants held a diverse range of knowledge about hiring algorithms. While some people knew to use strategies, such as keywords in resumes, online assessment practice, and referrals to circumvent automated processes to progress to in-person interviews, others were entirely unaware of automated hiring practices. Participants seemed to perceive that automated hiring algorithms exacerbated power dynamics between applicants and companies, were a "black box," and prevented applicants from demonstrating the full extent of their skills. Many seemed to think that having personal contacts within the company was required to progress past automated hiring processes and obtain job offers. While some expressed that computers should make hiring decisions to combat the rising number of applicants, many struggled with the inequity perpetuated by automated hiring processes.

4.1 Strategies & Fairness

Participants used a variety of strategies to progress through the hiring process and reflected on the fairness of using those strategies to get through automated recruitment stages.

4.1.1 Strategies. To get job offers, participants employed strategies like modifying resumes, practicing online assessments, having experience with automated interviews, using referrals, connecting with recruiters, and mass-applying.

To get through automated resume readers, some participants used keywords or modified their resumes' formatting. Participant #10 mentioned how he had to reformat his resume before he received an interview, and Participant #2 mentioned how he checked his resume in an automated scanner, but struggled to get it to scan properly. Another participant noted her frustration with not having information about applicant tracking systems (ATS) explicitly stated during the application process:

> With ATS systems there's conflicting advice and whether or not parentheses mess up ATS systems or formatting a two column resume versus one column resume can also matter. There's just so much. Why would you not tell us that before we submit the application? — Participant #14

Based on advice from friends, a participant included keywords from the job description in her resume, but questioned the ability of an algorithm to assess all the aspects of a resume:

> When it comes to the hiring process, I was trying to use keywords that are related to the job itself because I heard it ranks better in the algorithmic process itself. But then when it comes to that, I don't know how good the algorithmic process is because it cannot judge some stuff that people can when they look at the resume. — Participant #15

Another method participants used was online coding assessment practice, since online assessments have become increasingly common in computing job recruitment. Many participants mentioned that they had been practicing with LeetCode (https://leetcode.com/) and other free practicing platforms to prepare for automated technical interviews. Participant #4 questioned whether or not online assessments allowed companies to see the actual abilities of applicants, since they seemed to require so much targeted practice beforehand:

> But really, to get past the LeetCode stage, you're just practicing LeetCode specifically. So I think that cuts out people that just aren't as well practiced in algorithms, but maybe they have a really solid set of thinking in other areas. — Participant #4

In addition to providing resumes and undergoing online assessments, some participants had undergone automated interviews where applicants are given a question and then a brief 2-3 minute window within which they can video record a response to behavioral questions. Some participants expressed how experience with automated interviews provided valuable practice for subsequent interviews. Participant #14 explained the benefit of gaining familiarity with the platform:

> The only good thing about those [automated] interviews are that you almost 100% knew that if you have had experience with this very odd format then you automatically have a leg up from the other people because I think most people get tripped up over the format." - Participant #14

Many participants found greater success in the job recruitment process once they had a human contact within the company, such as a recruiter or referral. After describing the difficulty of applying to jobs and not hearing back, Participant #11 described how they waited to apply until they get a referral, in order to sidestep automated hiring processes:

> These employees put your name into their internal system. This could take multiple different forms. Most commonly what happens is you get an email with a link to apply to that role. So they'll say oh this person has referred, you please apply to these roles... So always that's why I don't apply until I know that I might have a referral from this company, and then I go through that process. — Participant #11

Participants who did not have contacts had a different experience. Participant #6 described the waiting process after the initial application as hopeless unless they knew someone within the company:

> For the normal software engineering jobs, it's normally you send your resume and then you wait three weeks before you realize you are never going to hear back from them. And then, when you do hear back it's probably because you've got a referral from someone because that's the only jobs I ever hear back from. —Participant #6

Many participants resorted to mass-applying (applying to over 20 companies) to find jobs which required complicated tracking, time, and effort:

> I kept a spreadsheet for a list of all the companies I applied to. Sophomore year it was nearly 500. — Participant #2

Participants shared a variety of strategies they learned either from friends and family networks, or from classmates who were also applying. They applied these strategies to make it through the automated steps of the recruiting process, and sometimes these strategies were just trial and error.

4.1.2 Perceptions of Fairness and Equity with Strategies. Participants attributed success in recruitment to understanding strategies and perceived an unequal distribution of this information. Many expressed that automated hiring systems privileged applicants who had access to networks with insider knowledge. For example, Participant #10 worried about "potential gaming" with LeetCode questions and formatting resumes for automated readers and also expressed that:

> It just leaves people who haven't heard about that yet behind. — Participant #10

Participant #15 expressed how seeing a problem in practice during interview preparation might benefit an applicant, since current automated technical assessments use well-known problems. Participant #15 also mentioned that with automation there was less accountability:

> For example, if I'm doing a problem now, I'm sharing my screen with the recruiter himself or herself and then they can see that I'm the one who's actually doing the stuff. For example, when they send the HackerRank or some other automated coding interview like coding exercises, how do you know if I'm doing that and not someone else? How is that fair? — Participant #15

With automation, many perceived a greater potential to cheat the system. Some participants even mentioned they had cheated during aspects of the automated hiring process to progress to later in-person hiring stages.

In contrast, Participant #14 expressed how online coding assessments helped improve fairness in technology jobs as opposed to other sectors:

> It's so competitive and LeetCode coding is really hard and so on and so forth, but I do want to say, it is much better to have this LeetCode or [Online Assessments] and all of these ridiculous steps that you don't know about. At least you feel like you have a fighting chance — Participant #14

Participants attributed referrals as the reason that applicants moved to the next phase, got job offers, and bypassed automated rounds, which they deemed unfair and part of perpetuating a system of inequality. Participant #2 saw this inequity as part of the broader systemic inequity in the world:

> If you know people in the industry for a couple reasons they can just tell you where to look for these resources or they can help you get to interview. The second of which is like okay, that is a classic rich get richer situation there. — Participant #2

Many participants commented on the inequity of knowledge of these strategies and referrals, since they perceived that it contributed to getting past automated rounds and then getting interviews and job offers. Participants who did not have referrals or an inside connection, resorted to mass-applying and faced mass-rejections.

4.2 Diverse Knowledge of the System

Another theme was the varying amount of information each individual had about the automated hiring process before and while applying. Some participants had a deep understanding of many of the automated processes involved, and other participants had no idea any of the processes were automated.

4.2.1 Different Understandings of Automation. Participants shared experiences of applying and some were unsure which systems were automated. Several participants shared that they hadn't heard of automated hiring processes, but went on to share that they had experience with video interviews from HireVue (https://www.hirevue.com/), a third party platform designed to make scaling hiring easier with AI:

> I don't think I've actually come across any [automated hiring software]. I think the closest one that comes first is something called HireVue, and that asks you for recorded answers to their questions or prompts. I didn't know if there was an actual person behind those or just some kind of machine learning algorithm that is just parsing your answers and then giving the score — Participant #13

In addition to different understandings of automated interviews, other participants did not know if a human would even see their resume and made assumptions based on this uncertainty. These automated experiences seemed confusing and isolating to applicants who were already in the vulnerable position of applying to jobs. Participant #6 expressed how strange it felt to be talking to a system and not know if there was even a person on the other end to connect with. Other participants touched on how anxiety provoking this automated interview process can be when you do not know how you are being viewed:

> I think it's really stressful. It's because you don't know who's going to be watching it. — Participant #8

Alternatively, some participants had experience with more transparent automated hiring practices where companies shared public documents and resources:

> Well, I'll start from the top so [technology company] is so huge. I'll assume they've had 1000 lawsuits about unfair hiring practices, so everything they do is like there's subtext, there's footnotes... Here's the link to the 12 blog articles, where you can read more about this precise process. We use these eight different rubrics to measure you and here's the rubrics as well. It was just very transparent. — Participant #5

While some participants were given explicit information about automated hiring practices or learned of automated processes from company contacts, many seemed to be lost in the process, describing interactions where they would complete code sets, record interviews, submit applications, and not hear anything back from companies. For many, the lack of transparency and communication about what was automated made it hard to know what they were doing right, what they were doing wrong, and if a human even saw their work.

4.2.2 Different Amounts of Feedback Throughout the Process. While some participants had recruiters or automated systems that provided them feedback in the process, many participants expressed that they had no idea where they were in the process or if companies were even interested in their application. A common perception among participants was a lack of feedback and transparency:

> There's no feedback, no nothing. It's like I'm tossing a ball in the black hole and expecting it to bounce back. — Participant #6

Many mentioned how they felt ghosted by the process where they received no response after submitting their application:

> I'd say maybe 5% of the jobs I applied to actually get back to me with the next step, like an online exam or an interview. — Participant #7

Many participants seemed frustrated because they were not sure what companies were looking for and expressed that they wanted more feedback in the process. However, some mentioned how automated systems could provide more transparency and shared brief moments of feedback they received:

> I remember a few companies use something... that actually tells you when somebody looked at your resume or when different things happen... It doesn't really give you much more information, but it kind of makes it feel like things are actually happening. — Participant #10

Another participant, who just completed the application process, shared their experience of trying to create more transparent hiring procedures:

> It's inherently challenging because for me it's very vulnerable putting myself out there, trying to apply myself, both literally applying to all these jobs and then also being available and content with the amount that they're giving back... So this is kind of tangential, but where I'm currently working we are getting ready to launch a company that is going to help with tech recruiting. Pretty much giving especially engineers more transparency into that system, so that's something we're working towards launching, so I know that it can look better. — Participant #5

Some participants understood the difficulty of providing feedback to so many applicants, but remained frustrated by the inability to see how the automated system saw their application. Participant #14 suggested standardization of resumes to improve it:

> Yeah in terms of feedback, I mean, I understand that it's almost impossible for a recruiter to have that much time... and it's almost impossible for me to tailor 170 resumes to each job and even keep track of that. I wish there was a way to check the baseline things... One time I was reading in Korea, for example, you submit a resume and then they have a really particular format. It comes in this table format and it's basically you fill it out like a worksheet. And there's just so much less variability where you can mess up. — Participant #14

When participants did receive feedback or had a glimpse inside the "black box," it was usually when they connected with people within the company as opposed to through automated systems. Some participants were able to connect with recruiters later in the process who were able to provide more transparency. One participant expressed that a recruiter frequently checked in to see how they were feeling, which helped them feel connected with the company:

> A lot of times they will just contact you once through email, but every time [the company recruiter] called me, I had the number saved in my phone... Every time I'd be like oh, this is really awesome because there's a sense of familiarity and you can tell that they care about you. — Participant #12

Participants who were unable to connect with people inside of a company, frequently were unable to get feedback to figure out why they did not proceed to the next step. Participant #6 compared the process to online dating where after a date you never hear back:

> It's like going back on a dating scheme where nobody responds to you... it feels robotic almost and it almost discourages you to put stuff in without having a referral. — Participant #6

While many participants expressed an understanding that companies had a lot of applicants and it was difficult to get back to every applicant with feedback for various reasons, many continued to struggle with the lack of feedback to make sense of their communication with companies and how to succeed in the hiring process.

4.2.3 Lack of transparency in use of applicant data. In addition to a lack of transparency in the automation and the application process, many job seekers were also unclear about how companies used their data or what happened to their personal information after the application process was complete.

> I think they stored my resume in a huge database that's kind of a black hole, never to be seen again. There was very little transparency about how they were storing my data. — Participant #1

Often, these opaque processes meant that job seekers were left to guess at how their data was collected and how they were being tracked:

> I feel confident that the emails probably have some sort of thing to track how fast I opened it and if I forwarded it, did I reply to it in a certain amount of time, how much time did I spend drafting the email. I'm sure there's something that's recording all of that, and I assume that for the larger companies, they have more depth to that data than the smaller ones.
> — Participant #5

Participant #9 pointed out the inequity in the system where to apply for a job, you have to waive your rights to much of your personal information and do not know what companies will do with the data after you have applied:

> I think you have to... You waive your rights [for your data] to be used, but I don't know exactly how it's used. — Participant #9

4.3 Perceptions of Power

Participants did not feel that there was an equitable power dynamic when applying for jobs. They found it difficult to share their strengths and to assess their fit within the company with the current processes. Several participants mentioned how they were not able to advocate for a more fair system while applying for jobs because they needed the jobs.

4.3.1 Self-perception of qualification & representation. Many participants expressed that current practices did not allow them to represent their ability to do the job and did not account for a variety of skill sets and factors:

> I think, solving a LeetCode problem definitely shows your capability to some degree... But I think the main problem is that because that is the first baseline step, it cuts out people that probably excel in other areas.
> — Participant #4

Some participants mentioned that automated systems cannot capture how you solve problems or if you were close to solving it. Participant #15 pointed out that explaining how you solve the problem in an in-person technical interview shows a different side of your abilities and that an automated process is unable to catch those nuanced differences.

Several participants expressed that their perception of their own under-qualification was magnified in automated systems with the lack of feedback. Participant #3 mentioned how she did not apply for some jobs out of fear of that she did not meet all of the requirements:

> There is this common trend of how I read the job description versus how maybe a dude would read the job description… a lot of people like myself will say I don't meet this small qualification so I'm not going to apply, so I feel like there's a little bit of unfairness in that sense. — Participant #3

Participants expressed that automated hiring algorithms did not capture the full range of their abilities or talents, and perhaps favored applicants who had more traditional qualifications, but not the qualifications that would make the most successful employee.

4.3.2 One-way interactions. Traditional hiring practices with human decision makers and interviewers were a two-way decision where companies decided if an applicant is the best person for the job and also allowed applicants to assess if the company has the best job for their future. Participants expressed that the current automated processes seemed to create one-way interactions, since companies see many aspects of an applicant, but in turn job seekers were unable to assess their fit in the company. Due to automation and the lack of feedback, participants reported that they were not able to build a strong conception of the company. This perpetuated a divide and unequal power dynamics between themselves and company for some participants.

Participant #2 shared how the automated interview compared with in-person interviews:

> The biggest thing that made these automated hiring interviews worse or weird was I didn't get any feedback. With a nod and smile and things like that I can figure out if what I'm saying is making any sense... It felt like I'm talking to a two way mirror, or how does that work, one way mirror right. It just kind of felt like I was in the box and everyone's looking at me. It was really bizarre. — Participant #2

For larger companies, third party interviewers are often part of the initial steps of an application process. Participant #8 shared how that stilted their ability to build an understanding of the work environment and atmosphere at a prospective company:

> Usually they say interviews are a two way thing: the companies interview you, but you also interview the company, the employee that's there interviewing you. But with these third parties, it's just that they're solely interviewing your skills, without you making any judgment on them, so it's a very interesting one way street... it adds another layer of impersonality. It distances the interviewee from the company, even more. Already the applicant had to go through the online application, the coding assessment, now a third party interview? When are they actually gonna be able to see the company?
> — Participant #8

Many conversations touched on experiences with power differentials throughout the hiring process as applicants had to navigate presenting all of their skills to companies who provided little information about themselves in exchange.

4.4 Should Computers Make Hiring Decisions?

Participants held a variety of opinions about whether computers should be making hiring decisions. Some people understood why algorithms were making initial hiring decisions, while others did not think they should be part of the process. Other participants accepted automated hiring algorithms with hesitation, describing how it would be nearly impossible for a company to handle the vast number of applicants they had, but suggested there should be more transparency. As part of the group favorable to automated hiring, Participant #7 shared:

> I think a computer kind of has to make some of these decisions because I mean companies don't have an unlimited amount of people to keep just to look through millions of resumes that they're probably getting. Even if it weren't like that now, I think, in the future, it would kind of have to go that route, so much is just becoming automated. — Participant #7

Another participant seemed to believe computers were less biased or could become less biased more quickly than their human counterparts could:

> So the reason that the computer should be making these choices is because I think at the end of the day, it's easier to teach a computer to be fair than to teach a person to be fair. — Participant #13

Participant #5, who just underwent the hiring process and is working with an automated hiring start-up as part of her first full-time computing job, grappled with the complexity of looking at a high volume of applications and still providing transparency:

> I hear ads all the time on my podcasts for zip recruiter and it's like we'll find you a candidate in 12 hours or something and I'm like okay, so I know a computer is going through those processes, I think there's definitely a place for it... Maybe if it was more transparent like hey you're we're going to run your resume when you submit, it's going to go through our automated system, and here's a link to see how it's going to show up in our system. Maybe something like that would make it a little bit better.
> — Participant #5

Other participants commented on the role for some automation in the process due to the number of applicants, but emphasized the need for some human oversight:

> I think it depends on how the computer is being used. If it's being used to essentially filter out all the candidates and then say once a computer filters them out they're never going to be seen by humans, maybe not... but if you could compare the human [ranking] with the computer [ranking] and use the computer as a secondary opinion then maybe it would be helpful to have it. — Participant #8

Participant #15 expressed how algorithmic decisions can go very badly and should always be reviewed by humans:

> I think algorithms can make really bad decisions because it can never take all the scenarios into consideration. There should always be a person who checks again and sees if there's something that should be fixed and if there are some externalities that should be taken into account. — Participant #15

Other participants deemed that computers should not be part of the hiring process at all, pointing out the inequities that arise when a system is automated. Participant #1 mentioned that computers reflect the bias of their programmers:

> I don't think so because computers work on our biases and are given training data it is influenced by our biases. They kind of train to our biases, so they're harder to correct in the long run. — Participant #1

Many participants expressed the difficulty of this problem. Participant #2 disliked the automated parts of the hiring process, but struggled to come up with a better solution:

> Yeah just to summarize, I think everyone who does these processes thinks the automated part is the worst part of the interview process, but it feels like a necessary evil because of the scale problem. I think we need some really smart people to figure out how to do it right. — Participant #2

In the post-interview survey, which collected demographic information and provided space for additional comments, one participant changed their mind on whether computers should be involved in the hiring process:

> I think I gave a wishy-washy answer on whether I thought the hiring process was fair. Going back I would say no, it's not fair. I had internalized the arbitrariness of things like LeetCode assignments, and anecdotes like the fact that almost everyone I knew at [university] is going to a FAANG or a unicorn.
> — Participant #10

5 DISCUSSION

Our research revealed that the students and recent graduates we interviewed seemed to believe that the lack of transparency surrounding current automated hiring algorithms perpetuated an unfair system where some people were in the know and some people were not. Many participants who secured a job attributed it to knowing how to "play the game" to get through automated rounds. In the current landscape of automation, participants used a variety of strategies, such as modifying resumes, practicing for online assessments, gaining experience with automated interviews, getting referrals, connecting with recruiters, and mass-applying. Participants also had different levels of knowledge of the system, often based on their parents', communities', or peers' understanding of hiring processes. Some guessed at how to get through automated systems, while others attributed success to having information about the process or a contact within the company. Both participants who had and did not have insider knowledge perceived a lack of transparency with what is automated in the process and how applicant data was used.

While there were varying experiences with power dynamics between applicants and the companies they are applying for, many participants expressed that they felt current automated practices did not assess their full potential. There was a perception of unfairness in the two-sided exchange where people were assessed by companies, but unable to assess the companies throughout the process with automated systems. Similar to prior work on perceptions of algorithmic fairness in automated hiring, participants had different perceptions of whether computers should make hiring decisions based on their experiences [29, 33, 50]. Participants varied in their level of critical reflection. Some participants saw the potential for bias in automated systems, while others did not. Aligning with prior work that participants were more comfortable with more mechanical tasks having algorithmic decision makers [33], many participants acknowledged that automation could be a solution to the scale problem, but expressed that inequity concerns need to be mitigated by human reviewers.

Consistent with SCCT [34], participants mentioned identity, experience, and self-efficacy influenced their self-perception of qualification and career choices. However, our results suggest that the role of agency has changed with the added opaqueness of hiring algorithms. Many participants were not aware of processes and resources in the job hiring process. By not explicitly mentioning their assessment metrics, companies created barriers in the application process and left applicants to guess at the automated hiring process. While some participants' self-perception of a lack of qualification led to not applying for certain jobs, others resorted to mass-applying, not sure what companies were looking for. Participants' perceptions and experiences demonstrated a tension between many competing forces: 1) their perception of fairness with automated systems, 2) their need for a job, 3) their ability to game current hiring systems, 4) their desire for feedback, 5) their understanding of the complex problem of scale that companies were trying to solve. Their reactions to these forces sometimes led to cheating, opting out, or feeling ethically trapped due to a need for work. Analysis of interviews suggested that hiring practices remain a "black box" to many applicants and perpetuate inequality in the hiring process. Some participants suggested that information could be distributed more equitably by providing all applicants with resources to see how their materials are being perceived by algorithms.

This study is of course limited to the perspectives of the participants we interviewed. By using convenience sampling through online computer science groups, perspectives from people who are not in online groups and have a weaker online presence are excluded. There might be different results with different participants and different interviewers. Future research is needed to address this gap and include more perspectives, especially from people who are not a part of communities that know how these hiring systems work. There is also a need for further intersectional investigations into how gender, race, class, ability, and other factors interact to shape job seekers' experiences. Additionally, there may be issues with participants having different understandings of region-specific norms and language in the interview. Since interview questions asked specifically about automated hiring algorithms, feedback, and data, they may have directed the conversation towards those factors and left out other salient factors to participants' perceptions and experiences with automated hiring algorithms. The interview questions were designed by the first and third authors, interview conducted by the first author, and analysis done by the first and second author, so the results may be also limited by the perspectives of the researchers.

Future work is needed to address other factors in applicants' perceptions of automated hiring algorithms, including other perspectives to see how it impacts different groups of people. There could be follow-up studies to determine whether perceptions of resume filtering and referrals are reflective of current recruitment practices. Additional work needs to be done to audit hiring systems and assess how strategies and connections to people in the company relate to job recruitment success. Further work could investigate the bias of these algorithms by comparing automated and human reviewers, taking into account human experiences, checking job satisfaction, and determining who is excluded by this process.

Considering our work alongside prior work on bias in automated hiring systems [11, 17, 45, 47], career identity [34], and perceptions of algorithmic fairness [7, 33, 49], there are a number of possible implications for policy and practice. For example, our work suggests that companies may need to provide more transparency on what is automated, how data is collected, and how applicants are assessed. It also suggests that job seekers may need new resources on how to successfully navigate algorithmic hiring systems, placing new demands on career services and counselors, in and outside of schools. There may also be a role for computing educators to discuss automated hiring and algorithmic fairness issues to mitigate discrepancies in the understanding of these systems. Additionally, with subtle perceived inequity arising from details like camera quality and backgrounds affecting evaluations, companies likely need to reflect carefully on what they are trying to achieve with automation. While automation clearly aids in streamlining hiring processes, it seems clear that evidence of bias, plus our work's evidence of how perceptions and experiences warp job seekers' practices, might inadvertently dissuade qualified job seekers from applying, and further amplify the privileges of personal connections. Finally, to mitigate discrimination in the job recruitment process, there may also need to be new policies on automated hiring, such as transparency or audit requirements. These many implications for employers, educators, job seekers, and public policy suggest that equitable and fair response to scale in hiring has never been more complex or necessary.

ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under Grant No. 1539179, 1703304, 1836813, 2031265, 2100296, 2122950, 2137834, 2137312.

REFERENCES

[1] Chaza Abdul, Wenli Wang, and Yating Li. 2020. The Impact of Technology on Recruitment Process. *Issues in information systems* 21, 4 (2020).

[2] Ifeoma Ajunwa. 2019. An Auditing Imperative for Automated Hiring. (2019).

[3] Joseph Appianing and Richard N Van Eck. 2015. Gender differences in college students' perceptions of technology-related jobs in computer science. *International Journal of Gender, Science and Technology* 7, 1 (2015), 28–56.

[4] Andrew Begel and Beth Simon. 2008. Novice software developers, all over again. In *Proceedings of the fourth international workshop on computing education research*. 3–14.

[5] Mahnaz Behroozi, Chris Parnin, and Titus Barik. 2019. Hiring is broken: What do developers say about technical interviews?. In *2019 IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC)*. IEEE, 1–9.

[6] Mahnaz Behroozi, Shivani Shirolkar, Titus Barik, and Chris Parnin. 2020. Debugging hiring: What went right and what went wrong in the technical interview process. In *Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering: Software Engineering in Society*. 71–80.

[7] Reuben Binns, Max Van Kleek, Michael Veale, Ulrik Lyngs, Jun Zhao, and Nigel Shadbolt. 2018. 'It's Reducing a Human Being to a Percentage' Perceptions of Justice in Algorithmic Decisions. In *Proceedings of the 2018 Chi conference on human factors in computing systems*. 1–14.

[8] Skyler J Bock, Lindsay J Taylor, Zachary E Phillips, and Wenying Sun. 2013. Women and minorities in computer science majors: Results on barriers from interviews and a survey. *Issues in Information Systems* 14, 1 (2013), 143–152.

[9] Steven D Brown and Robert W Lent. 2017. Social cognitive career theory in a diverse world: Closing thoughts. *Journal of Career Assessment* 25, 1 (2017), 173–180.

[10] Maarten Buyl, Christina Cociancig, Cristina Frattone, and Nele Roekens. 2022. Tackling Algorithmic Disability Discrimination in the Hiring Process: An Ethical,

Legal and Technical Analysis. In *2022 ACM Conference on Fairness, Accountability, and Transparency*. 1071–1082.

[11] Aylin Caliskan, Joanna J Bryson, and Arvind Narayanan. 2017. Semantics derived automatically from language corpora contain human-like biases. *Science* 356, 6334 (2017), 183–186.

[12] Lei Chen, Gary Feng, Chee Wee Leong, Blair Lehman, Michelle Martin-Raugh, Harrison Kell, Chong Min Lee, and Su-Youn Yoon. 2016. Automated scoring of interview videos using Doc2Vec multimodal feature extraction paradigm. In *Proceedings of the 18th ACM International Conference on Multimodal Interaction*. 161–168.

[13] Lei Chen, Ru Zhao, Chee Wee Leong, Blair Lehman, Gary Feng, and Mohammed Ehsan Hoque. 2017. Automated video interview judgment on a large-sized corpus collected online. In *2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)*. IEEE, 504–509.

[14] Phoebe K Chua, Hillary Abraham, and Melissa Mazmanian. 2021. Playing the Hiring Game: Class-Based Emotional Experiences and Tactics in Elite Hiring. *Proc. ACM Hum. Comput. Interact.* 5, CSCW2 (2021), 1–27.

[15] Phoebe K Chua and Melissa Mazmanian. 2020. Are you one of us? Current hiring practices suggest the potential for class biases in large tech companies. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW2 (2020), 1–20.

[16] John W Creswell and Cheryl N Poth. 2016. *Qualitative inquiry and research design: Choosing among five approaches*. Sage publications.

[17] Jeffrey Dastin. 2018. Amazon scraps secret AI recruiting tool that showed bias against women. In *Ethics of Data and Analytics*. Auerbach Publications, 296–299.

[18] Meenakshi Dhingra and Subhash C Kundu. 2021. Factors affecting placement and hiring decisions: A study of students' perceptions. *Industry and Higher Education* 35, 3 (2021), 223–232.

[19] Allan Fisher and Jane Margolis. 2003. Unlocking the clubhouse: Women in computing. In *Proceedings of the 34th SIGCSE technical symposium on Computer science education*. 23.

[20] Marcelline R Fusilier and Michael A Hitt. 1983. Effects of age, race, sex, and employment experience on students' perceptions of job applications. *Perceptual and Motor Skills* 57, 3_suppl (1983), 1127–1134.

[21] Michail N Giannakos, Ilias O Pappas, Letizia Jaccheri, and Demetrios G Sampson. 2017. Understanding student retention in computer science education: The role of environment, gains, barriers and usefulness. *Education and Information Technologies* 22, 5 (2017), 2365–2382.

[22] 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 (2022), 107179.

[23] Brian Patrick Green, Patricia Graybeal, and Roland L Madison. 2011. An exploratory study of the effect of professional internships on students' perception of the importance of employment traits. *Journal of Education for Business* 86, 2 (2011), 100–110.

[24] David Hammer and Leema K Berland. 2014. Confusing claims for data: A critique of common practices for presenting qualitative research on learning. *Journal of the Learning Sciences* 23, 1 (2014), 37–46.

[25] Louis Hickman, Nigel Bosch, Vincent Ng, Rachel Saef, Louis Tay, and Sang Eun Woo. 2022. Automated video interview personality assessments: Reliability, validity, and generalizability investigations. *Journal of Applied Psychology* 107, 8 (2022), 1323.

[26] Kay A Hodge and Janet L Lear. 2011. Employment skills for 21st century workplace: The gap between faculty and student perceptions. *Journal of Career and Technical Education* 26, 2 (2011), 28–41.

[27] James Hu. 2021. Report: 98 of fortune 500 companies use ATS. https://www.jobscan.co/blog/fortune-500-use-applicant-tracking-systems/

[28] Gareth R Jones. 1986. Socialization tactics, self-efficacy, and newcomers' adjustments to organizations. *Academy of Management journal* 29, 2 (1986), 262–279.

[29] Maria Kasinidou, Styliani Kleanthous, Pınar Barlas, and Jahna Otterbacher. 2021. I agree with the decision, but they didn't deserve this: Future Developers' Perception of Fairness in Algorithmic Decisions. In *Proceedings of the 2021 acm conference on fairness, accountability, and transparency*. 690–700.

[30] Pauline T Kim and Sharion Scott. 2018. Discrimination in online employment recruiting. *Louis ULJ* 63 (2018), 93.

[31] Styliani Kleanthous, Maria Kasinidou, Pınar Barlas, and Jahna Otterbacher. 2022. Perception of fairness in algorithmic decisions: future developers' perspective. *Patterns* 3, 1 (2022), 100380.

[32] Sven Laumer, Christian Maier, and Andreas Eckhardt. 2015. The impact of business process management and applicant tracking systems on recruiting process performance: an empirical study. *Journal of Business Economics* 85 (2015), 421–453.

[33] Min Kyung Lee. 2018. Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society* 5, 1 (2018), 2053951718756684.

[34] Robert W Lent, Steven D Brown, and Gail Hackett. 2002. Social cognitive career theory. *Career choice and development* 4, 1 (2002), 255–311.

[35] Lan Li, Tina Lassiter, Joohee Oh, and Min Kyung Lee. 2021. Algorithmic hiring in practice: Recruiter and HR Professional's perspectives on AI use in hiring. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*. 166–176.

[36] Iftekhar Naim, Md Iftekhar Tanveer, Daniel Gildea, and Mohammed Ehsan Hoque. 2016. Automated analysis and prediction of job interview performance. *IEEE Transactions on Affective Computing* 9, 2 (2016), 191–204.

[37] Selin E Nugent and Susan Scott-Parker. 2022. Recruitment AI has a Disability Problem: anticipating and mitigating unfair automated hiring decisions. In *Towards Trustworthy Artificial Intelligent Systems*. Springer, 85–96.

[38] Joann S Olson. 2014. Opportunities, obstacles, and options: First-generation college graduates and social cognitive career theory. *Journal of Career Development* 41, 3 (2014), 199–217.

[39] Cathy O'Neil. 2016. *Weapons of math destruction: How big data increases inequality and threatens democracy*. Broadway books.

[40] Prasanna Parasurama and João Sedoc. 2022. Gendered information in resumes and its role in algorithmic and human hiring bias. In *Academy of Management Proceedings*, Vol. 2022. Academy of Management Briarcliff Manor, NY 10510, 17133.

[41] Manish Raghavan, Solon Barocas, Jon Kleinberg, and Karen Levy. 2020. Mitigating bias in algorithmic hiring: Evaluating claims and practices. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 469–481.

[42] Alene Rhea, Kelsey Markey, Lauren D'Arinzo, Hilke Schellmann, Mona Sloane, Paul Squires, and Julia Stoyanovich. 2022. Resume Format, LinkedIn URLs and Other Unexpected Influences on AI Personality Prediction in Hiring: Results of an Audit. In *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society*. 572–587.

[43] Alene K Rhea, Kelsey Markey, Lauren D'Arinzo, Hilke Schellmann, Mona Sloane, Paul Squires, Falaah Arif Khan, and Julia Stoyanovich. 2022. An external stability audit framework to test the validity of personality prediction in AI hiring. *Data Mining and Knowledge Discovery* 36, 6 (2022), 2153–2193.

[44] Harriet Rodney, Katarina Valaskova, and Pavol Durana. 2019. The artificial intelligence recruitment process: How technological advancements have reshaped job application and selection practices. *Psychosociological Issues in Human Resource Management* 7, 1 (2019), 42–47.

[45] 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*. 458–468.

[46] Curtis J Simon and John T Warner. 1992. Matchmaker, matchmaker: The effect of old boy networks on job match quality, earnings, and tenure. *Journal of labor economics* 10, 3 (1992), 306–330.

[47] Mona Sloane, Emanuel Moss, and Rumman Chowdhury. 2022. A Silicon Valley love triangle: Hiring algorithms, pseudo-science, and the quest for auditability. *Patterns* 3, 2 (2022), 100425.

[48] Mindi N Thompson, Jason J Dahling, Mun Yuk Chin, and Robert C Melloy. 2017. Integrating job loss, unemployment, and reemployment with social cognitive career theory. *Journal of Career Assessment* 25, 1 (2017), 40–57.

[49] Ruotong Wang, F Maxwell Harper, and Haiyi Zhu. 2020. Factors influencing perceived fairness in algorithmic decision-making: Algorithm outcomes, development procedures, and individual differences. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–14.

[50] Allison Woodruff, Sarah E Fox, Steven Rousso-Schindler, and Jeffrey Warshaw. 2018. A qualitative exploration of perceptions of algorithmic fairness. In *Proceedings of the 2018 chi conference on human factors in computing systems*. 1–14.

[51] Lixuan Zhang and Christopher Yencha. 2022. Examining perceptions towards hiring algorithms. *Technology in Society* 68 (2022), 101848.