Algorithmic Hiring in Practice: Recruiter and HR Professional's Perspectives on AI Use in Hiring

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ABSTRACT

The increasing adoption of AI-enabled hiring software raises questions about the practice of Human Resource (HR) professionals' use of the software and its consequences. We interviewed 15 recruiters and HR professionals who used AI-enabled hiring software for two decision-making processes in hiring: sourcing and assessment. For both, AI-enabled software allowed the efficient processing of candidate data, thus providing the ability to introduce or advance candidates from broader and more diverse pools. For sourcing, it can serve as a useful learning resource to find candidates. Though, a lack of trust in data accuracy and an inadequate level of control over algorithmic candidate matches can create reluctance to embrace it. For assessment, its implementation varied across companies depending on the industry and the hiring scenario. Its inclusion may redefine HR professionals' job content as it automates or augments pieces of the existing hiring process. Our research highlights the importance of understanding the contextual factors that shape how algorithmic hiring is practiced in organizations.

CCS CONCEPTS

• **Social and professional topics → Employment issues**; **Socio-technical systems**.

KEYWORDS

Algorithmic hiring, AI-enabled sourcing, AI-enabled assessment, HR professionals, future of work

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1 INTRODUCTION

As Artificial Intelligence (AI)-enabled applications are deployed and actively used within a growing number of industries, a robust debate has been building around the potential impacts of AI within these divergent societal contexts. There has been great interest in examining the underlying dynamics that AI systems may introduce within the social environments where they are being used or will be used in the near future. These emergent dynamics hold important clues to key questions regarding the future of work. Arguments have both been made about the potential for AI to create new forms of work or displace existing workers [10, 14]. This paper continues this line of inquiry by asking: what sociotechnical dynamics arise at the individual and the organizational level when recruiters and HR professionals use AI in their daily workflow?

Due to the critical role employment plays in our lives, important concerns have been raised about AI-induced externalities within this high stakes domain. Recently, many scholars have brought to our attention the potential impact of AI's use in hiring. Some have envisioned AI's use within hiring to potentially reduce human bias and expand access [7]. Others have cautioned about AI's potential to exacerbate, exploit, and further reinforce existing biases [3, 29, 30, 32, 32, 35]. Scholars have investigated topics related to the detection and mitigation of algorithmic bias in the employment assessment process [29]. Work in this area has also focused on the candidates' reactions to the use of AI features before and during recruitment [20, 22, 26, 34]. A growing body of literature examines HR Professional's perspective about the inclusion of AI [7, 21]. Relatively understudied is the individual and organizational dynamics that drive and shape how and why these AI-enabled tools are being sought out, used, and even relegated. Through a case study of HR professionals who engage with AI systems to make decisions during the hiring process, our study introduces a small window into what those complex dynamics consist of.

Decision-making, in the hiring context, does not occur at a single point, but rather with a series of decision points [8, 32]. We look at two such decision points: during recruitment where recruiters source potential candidates and during screening where recruiters and HR professionals assess candidates for job-fit. In hiring, many companies seek to reduce cost while maximizing the quality of their candidate pool [29], which has led to the inclusion of new technologies such as AI into the hiring process. We define AI in this context, as tools that enhance or exceed the human capabilities to process and evaluate data in hiring [7]. As sourcing and assessment software integrate AI into their development stack, companies can process an increasingly large volume of data about candidates. This data then supports the decision-making process for the various stakeholders involved. HR professional's engagement with these tools will shape the set of candidates interviewed and the eventual makeup of the company. Therefore, it is also important to understand, from the recruiters' and HR professionals' perspectives, how the inclusion of AI-enabled tools influences how candidates are recruited and screened.

In our study, we interviewed 15 recruiters and HR professionals. Recruiters are individual contributors responsible for sourcing candidates. HR professionals encompass HR managers, HR consultants, and HR data analysts involved in the hiring process but may not be responsible for sourcing candidates. Participants discussed how they used AI-enabled software during sourcing and assessment. Findings detail the reasons for adoption, the use of the AI recommendations to aid decision-making, and how they develop an understanding of the AI-assisted results through their usage over time. Our study advances existing research on AI in hiring by illuminating the nuanced social factors that come into play when AI-enabled hiring tools enter recruiters' and HR professionals' daily work.

2 BACKGROUND

2.1 Overview of the Hiring Process

Due to differences in organizational size, locality and industry, companies face a unique set of hiring challenges. The use of hiring software broadly tackles two key problems: talent scarcity and applicant glut. The two predominant activities that directly address those two issues are candidate sourcing during recruitment and candidate assessment during screening.

Within the human resource management literature, Barber characterized the sourcing part of the recruitment process as "practices and activities carried on by the organization with the primary purpose of identifying and attracting potential employees" [5]. We adopt this definition of recruitment. Connerley described selection as the stage where the hiring team decides whether to advance or reject an applicant based on a specific set of established criteria [12]. Here, we define screening as a stage after the recruitment process, before the selection process, where candidates are initially assessed for job-fit.

2.2 Recruiter's and HR Professional's Role

Many groups of people are involved during the hiring process. During recruitment, candidate sourcing can either be done internally within the company or outsourced externally to agencies. Although organizational structures differ, internal recruiters are typically situated within the HR department. In smaller companies, recruiting can also be delegated to the hiring managers [12]. During screening, recruiters, HR managers, hiring managers, and the rest of the hiring team may be involved. While there are many job titles used to describe individuals who play a role in the hiring process, in this paper, we define recruiters and HR managers as individuals whose main responsibilities is supporting the hiring and talent sourcing process within a company or a recruitment agency. Recruiters are individual contributors, while HR managers support a team of HR professionals including HR generalists, HR specialists, and HR analysts.

Recruitment activities include writing job descriptions, posting job advertisements, or scouting potential candidates by evaluating resumes [8]. When sourcing candidates, recruiters want to know who would be open to a new job opportunity and might be a good fit. The resume is one of the main pieces of information recruiters engage with to qualify candidates for the next round. Whether a recruiter works externally at a staffing agency or internally within a company, the overarching goal is to help their customers or employers build a robust talent pipeline. For HR managers, the hiring tasks have significantly evolved; these changes have altered the ways interviews are conducted. More and more, algorithms are used to provide rankings of candidate features [13].

2.3 Algorithmic Hiring

We define hiring software as technology that assists employers during hiring. It encloses a broad category of tools used throughout the recruitment, screening, interview, and selection stages of hiring. Kaplan and Haenlein define AI "as a system's ability to correctly interpret external data, to learn from such data, and to use those findings to achieve specific goals and tasks through flexible adaptation" [19]. Black and van Esch take the idea of AI exceeding human capacities to the hiring process and see the use of AI in hiring as its ability to "more effectively identify, attract, screen, assess, interview, and coordinate with job candidates" by processing information and making decisions at volumes and speeds far exceeding human capabilities [7]. While some hiring software vendors have begun to release whitepapers about how these systems function at a high level, much of the technical details about how these systems operate remains opaque for outside researchers.

2.3.1 *AI-enabled sourcing software.*

Within the candidate sourcing domain, some software supplies the best matches between job openings and candidates. ZipRecruiter describes their technology as a "smart matching" system that connects recruiters and candidates [18]. Others behave like search engines where recruiters can define a set of job criteria that would result in a ranked list of candidates most closely meeting the requirements. LinkedIn details the use of a ranking algorithm in LinkedIn Recruiter. The LinkedIn Recruiter search engine uses the supplied query, job posting, or an ideal candidate profile [16] to build the qualification criteria set. It then uses its machine learning models to generate a ranked list of candidates by applying the qualification criteria. Still others described their system as a candidate recommender engine.

2.3.2 *AI-enabled assessment software.*

There are three common categories of assessment during screening: task-based, video-based, and game-based assessments. Task-based assessment refers to written or multiple-choice questionnaires. Video-based assessment refers to questions that require candidates to record a one-way video response. Game-based assessment refers to a type of assessment with a single-player game as part of the evaluation process. Often, an assessment involves a combination of two of the three categories [27].

	Age	Gender	Race	Job Title	HR Exp.	Software Discussed [1]
AI-Enabled Sourcing Software						
P1	N/A	Male	White	Founder and President	17 years	HireVue, Hiretual, LinkedIn*
P2	<30	Male	White	Talent Acquisition Partner	3 years	Textio*, HiredScore
P3	<30	Female	White	HR Generalist	0.5 years	Loxo*
P4	30-39	Male	White	Director	6 years	Skill Soft, SourceBreaker*, LinkedIn Helper, Hiretual
P5	30-39	Female	White	Senior Recruiter	8 years	SkillSoft*, SeekOut*, Modern Hire*, Avature*, Hiring-Solved*, iCMS*, Textio
P6	N/A	Male	White	Senior Sourcer	22 years	SeekOut*, HireVue, Hiertual*, Connectifier
P7	N/A	Female	White	Technical Recruiter	5 years	ZipRecruiter*, LinkedIn*, SmartMatchApp
P8	50-59	Male	White	HR Director	17 years	Paradox.ai*, SparkHire*
AI-Enabled Assessment Software						
P9	N/A	Male	White	Talent Acquisition Manager	5.5 years	Vervoe*
P10	30-39	Female	White	President	15 years	Vervoe*, ZipRecruiter, SparkHire
P11	<30	Male	Hispanic	HR Analyst	2 years	Pymetrics*
P12	30-39	Male	Asian	HR Consultant	9 years	InterviewStream*, HireVue*, Pymetrics*, Wonderlic*
P13	50-59	Male	White	Senior Recruiter	25 years	HireVue*
P14	30-39	Male	White	HR Business Partner	14 years	Wonderlic, Hogan*
P15	N/A	Female	White	Vice President-HR Recruitment	20 years	HireVue*, Traitify, HiredScore, Allyo, Pymetrics, SeekOut

(*) indicates that the software was the interview focus

Table 1: Interview participant demographic and background information

Task-based assessment evaluates some aspect of the job-fit. Automated scoring of written responses may use AI, but other formats (e.g., multiple choice) have predetermined correct/incorrect responses. The clearest use of AI-based predictive scoring is within the game-based context (e.g., Pymetrics) which has gained interest among HR professionals [15]. Game-based assessment is often aimed at providing an improved candidate experience [6] due to its gamified nature. The games played have indirect correspondence with skills associated with a given position. The assessments can be seen as indirect cognitive tests aimed to derive General Mental Ability (GMA) [31] and/or trait information through analyzing behavioral data collected during game play. For example, game-based assessment is reported to profile how an individual problem-solves, handles challenges, and manages uncertainty [23]. Video assessment is often referred to as Asynchronous Video Interviews (AVI) [33], one-way interviews, or structured interviews [9]. The video assessment (e.g., HireVue) allows candidates to record video responses to predefined questions. Similar to game-based assessment, AI functionality within video assessment seeks to detect various signals captured through video [23]. Besides the three primary types of assessments, conversational AI, or chatbots (e.g., Paradox.ai), have also emerged in the assessment space. AI chatbots often act as the first point of contact between a potential candidate and the employer. It pre-screens the candidate for minimum job requirements.

3 RESEARCH QUESTIONS

Due to AI's increasing role in hiring, our research focuses on when and how AI software are used by recruiters and HR professionals in hiring. Research questions include:

- Why and how do recruiters and HR professionals adopt AI-enabled hiring software into their hiring process?
- How do they interact with the software?
- How do they make sense of how the software works?
- How much trust do they place on the results generated by AI?
- In what way is the use of AI in the hiring process beneficial, and what risks does it pose?

4 METHODS

4.1 Recruitment Process

We applied two primary recruitment methods: direct email and group posts/direct message via social media. We aggregated a starter list of companies based upon the five major AVI platforms. From there, we utilized LinkedIn to directly contact company representatives. Besides using LinkedIn, we distributed recruitment callouts through several social media platforms, like Facebook and Reddit. We asked recruitment affiliates to post callouts which were later distributed through recruiter-only Facebook groups. On Reddit, we posted the callouts through several recruiter-centric subreddits and messaged more than 300 redditors from these forums. Overall, we reached out to over 200 potential participants in addition to the

Industry Sector	Company Size
Hospital and Healthcare	<500,000
Hospitality	<100,000
Financial Services	<100,000
Insurance	<50,000
Retail	<50,000
Marketing and Advertising	<10,000
Marketing and Advertising	<500
Internet	<500
Education Management	<500
Management Consulting	<500
Biotechnology	<100
Staffing and Recruiting	<100
Real Estate	<10
Staffing and Recruiting	<10
Information Technology Services	<10

Table 2: Industry sector and company size of participants

callouts on social media. Through these efforts we interviewed 26 participants.

4.2 Participants

Of the 26 interviews we conducted, we selected 15 most relevant for this study as they had most experience with AI-enabled software. Table 1 shows the list of participants included in this study and the AI-enabled software discussed. We interviewed three agency recruiters, six in-house recruiters, four HR managers, one HR consultant, and one HR data analyst. On average, the participants had 11.27 (SD=7.80) years of experience within the recruitment/HR industry. All participants worked in North America except for two in Europe and one in Australia. They have graduate degrees in Industrial and Organizational (I/O) psychology, or business administration. They received undergraduate degrees in communications, business administration, human resources, and economics. Each participant's status as recruiter/HR professional was verified via their LinkedIn profiles.

Table 2 shows the breakdown of industries the participants currently work in as well as the size of these companies. Altogether, they represent eleven industries: information technology, staffing and recruiting, real estate, management consulting, education management, marketing/advertisement, retail, insurance, financial services, hospitality, and healthcare.

4.3 Interviews

The semi-structured interviews were conducted between June and September 2020. All were conducted remotely via Zoom. They averaged 45-60 minutes. Participants were compensated with a $25 or $30 Amazon gift card. The questions were divided into six parts. In Part 1, participants introduced themselves and provided their educational background and work experience in recruitment/HR. In Part 2, we asked them to select one or more AI-enabled HR software they were most familiar with and to describe the features and usage pattern associated with it. In Part 3, they were asked to describe in detail the AI features they encountered within the tool. In Part 4, we discussed how the participants utilized the results generated by the AI to assist in the sourcing or assessment tasks involved in the hiring process. In Part 5, we asked them about their experience of on-boarding the software. In Part 6, we let them describe their understanding of current trends within recruitment/HR with regard to the use of AI.

4.4 Analysis

We used thematic analysis [11] to code the responses from the interviews. The initial coding occurred at the sentence level. This resulted in 114 concepts. These concepts were summarized into 22 categories with two major groups emerging between sourcing and assessment software. Categories related to sourcing were further grouped into 5 top level themes; likewise for assessment.

The remainder of the paper will discuss the findings of our study, focusing on these 10 themes. The findings are divided into two sections. The first section discusses the use of AI-enabled sourcing software during recruitment. The second section discusses the use of AI-enabled assessment software during screening. In each section, we examine how the software is being used and why, and what recruiters and HR professionals believe are the benefits and drawbacks to using AI.

5 FINDINGS

5.1 AI-Enabled Talent Sourcing Software

5.1.1 Reasons for use. Many of the recruiters working in sourcing were looking to fill roles requiring skills with a high degree of expertise (e.g., data science, data engineer, and other technical roles) (P1, P2, P5, P6, P7). The competition for talent is fierce for these roles. The competitive nature of sourcing has spurred recruiters to adopt AI-enabled sourcing software to help search for potential candidates across a broader spectrum of data sources more efficiently (e.g. LinkedIn, Github, or Medium). AI can help simplify the search process by assisting recruiters to build complex search queries with keyword suggestions. This was an especially welcoming feature for a junior recruiter who might not be familiar with the terminologies used to describe certain candidate roles (P3).

5.1.2 Competitive advantages and sourcing software as sources of learning. Some recruiters viewed AI-enabled sourcing software as highly valuable tools. P3 and P6 considered access to them as possessing an added advantage because it allowed them to be time efficient in a highly competitive hiring space. P3, who was in the early stage of their career, was initially deterred from becoming a recruiter when a colleague, who did not use AI, described the difficulties in constructing queries to source candidates. However, P3 was surprised by how easy it was to use the software. *"Whenever I first started [recruiting], it was a lot easier than I thought it was going to be. I was almost like, is this too good to be true? Like I just have to type in these keywords and I can find people and email them. (P3)."* Instead of manually constructing queries, by typing in the name of a position, the software automatically generated related terminologies used to describe that position. To further highlight the value some recruiters found in the tool, P6 even paid for it out of pocket when their company refused to provide access. *"It can hurt recruiters that don't have access to the AI software because we're finding candidates so much faster. (P3)."* While P4 and P5 did not express the same optimism toward AI-enabled sourcing software as P3 and P6 did, they did uncover other strategic uses of the software. The tool helped by serving as a learning resource. Here, the use of the tool was less focused on the matches and recommendations. The software could also be used for identifying contact information of potential candidates, uncovering new data sources to identify them, and broadening the search vocabulary when sourcing for a new type of candidate role. Here, the candidate role is defined as the role that candidates apply for. Regardless of one's tenure in the field, as candidate roles change and new ones emerge, recruiters must learn to keep up with hiring demands. Without keeping up with trends in the field, P4 noted that AI-enabled sourcing software would fill in the gap where recruiters lacked the necessary skills to meet the recruitment needs. *"We learned, we taught ourselves, and if you didn't teach yourself then you ended up quitting and not coming back [to recruiting]. So, I think the likes of SourceBreaker, that kind of thing is more to help with the skill shortage on our end, in terms of having folks that have an interest and are willing to work hard enough to then be able to qualify folks. (P4)."*

5.1.3 Lack of precise control over sourcing result. Recruiters learned how to use and control the sourcing software through working with the tools. By using them, they developed ideas and beliefs about how the underlying algorithms produced results. Among the many sourcing software out on the market, the software described by the recruiters was mostly of the plug and play variety. Namely, they did not require substantive training. Recruiters relied on webinars and information found online to learn and train by themselves (P4, P5, P6, P7). Some recruiters also trained others on their team (P5). Recruiters developed an understanding of sourcing software through their experiences using consumer-facing search applications (P6, P10, P15). For instance, P6 and P10 used metaphors from consumer-facing matching systems (e.g., eHarmony) or recommender systems (e.g., Pandora) to construct their own understanding of how the software worked.

P6, comparing sourcing software to music recommendation systems, actively "liked" candidate recommendations provided by the tool to train the system on their set of preferences. These interactions sometimes resulted in significantly skewed recommendations: *"the problem was if you keep liking certain [profiles]. I liked a bunch of people, at one point, from Google, and it stopped giving me anyone else but Googlers. (P6)."* When this occurred, P6 said that they did not have precise control over the sourcing tool to mitigate the skewed result. Even though P6 acknowledged that sometimes the tool returned bad results, they believed that the AI search system would continue to improve.

Based upon their experience using other "websites", P7 similarly constructed an understanding about how their interaction with the tool would train the underlying AI model. Yet, P7 took a very different approach from P6 in how they interacted with the tool. Instead of treating it as another consumer-facing product, they took a more cautious approach. This approach stemmed from uncertainties around how their interaction would drive the search outcome. For instance, because P7 was using their employer's account to access the matching service, they spoke about refraining from providing up/down votes to the suggested matches due to concerns about how these evaluations would impact matches their colleagues see, or future matches they would see. To maintain control over the search, P7 tried to use the sourcing software as manually as possible to mitigate the influence of AI suggestions. *"I actually do use ZipRecruiter and I use LinkedIn Recruiter all the time, every day, but I use it more in a manual capacity, and comb through, and look for candidates using refined Boolean searches. I might change the order of the search results pretty frequently like I was talking about. So I use the same tools just in a different way that sort of skirt the AI functionality. (P7)."* Despite these efforts to "skirt the AI functionality", P7 noticed that increasingly, sourcing software had been removing manual search capabilities while defaulting more to AI assisted results. *"Something that I've noticed too is websites are taking away or limiting the options that you have to refine your search in a manual way. They're simply just relying on AI. So I'd rather they not do that. But if they do decide to do that, I'd rather they bring additional manual features back, or search widgets back, so that you can continue to use them in conjunction with the AI features. So you can refine your search more manually than it is currently meant. (P7)."*

5.1.4 Mismatch between algorithmic results and recruiter's expectations. For P7, the desire to manually search rather than relying too much on AI-assisted results partly arose from concerns of sourcing algorithms possibly overlooking promising candidates. Being a technical recruiter not situated within a technology hub, P7 described occasions where they had to look beyond the predefined set of job criteria to find candidates with transferable skills. This flexible search strategy had been advantageous for them in finding good matches despite regional limitations. Keeping the search process as manual as possible was one way to guard against shrinking the pool of potential candidates. *"I don't want to ask any questions that might rule those folks out because I've had a lot of success in my career hiring people who aren't 100% slam dunk fits; a bit, more of that 75%, 80% fit who might not be super close to what they're looking for on paper but thrive in the actual position. (P7)."* P4, an independent technical recruiter, similarly witnessed cases where outlier candidates turned out to be better than what was presented on a search profile. P4 also voiced concerns about missing potentially good fits using sourcing software. *"So, if I was to ask SourceBreaker to find me only senior software developers, and it showed me only people with five years plus experience, I know that there's probably quite a few out there that I'm missing that probably are really qualified for my job. (P4)."* These recruiters factored in insights collected over time when they approached the use of AI-enabled sourcing software.

Applying these approaches to the use of a sourcing tool did not always result in optimal search outcomes. Unlike P6 who provided feedback to the tool, P7's more flexible search approach (e.g., using limited search terms) meant a less parameterized search process. The top results became too generalized and imprecise to offer relevant matches. This in turn left P7 manually evaluating more profiles further down the search result pages. P7 described an instance where they queried for candidates with experience in Python. While the top matches did include the desired skill, it was not the right fit. Although Python did appear on the top profile, the context of how the programming language was used did not align with what the recruiter was seeking. Without including more detailed context of Python's use, the search returned a suboptimal match. *"[Python] is one of the scripting languages that they've used. But it isn't their focus and scrolling through their resume, it doesn't look like Python web development was ever really their focus. And these are the kind of results that I might get with a lot of the AI tools that deemed somebody a great match. (P7)."* This mismatch created a frustration in the software, and the low quality "top matches" became the software's perceived inadequacies. It also augmented the recruiter's belief about their own ability to source candidates successfully. *"Because I am very confident in my manual search efforts, and I feel like by doing it that way, also, I'm able to have a more personal touch with candidates and review their resumes while using minimal keyword searching or algorithmic suggestions. (P7)."* Similarly perceiving sourcing tool's shortcomings, P4 stopped its use. P4 believed that while such a tool could be useful for onboarding junior members to the team, echoing P3's positive reactions, it was not worth the cost. For them, the capabilities provided by AI-enabled sourcing software were features they could achieve with manual effort. *"[sourcing software] is not worth it. I can do everything that it can do for me, just with a little bit of time. (P4)."* This view provides a stark contrast to P6 who was willing to pay for these tools themselves.

Recruiter's use of conservative search strategy, coupled with expressed confidence in their own sourcing ability, highlighted a tension around who is more capable at finding quality candidates: an increasingly sophisticated AI software or a recruiter? When sourcing software began to recommend good matches, some recruiters perceived this as decreasing their sense of control because it was no longer just showing the set of candidates the recruiter wanted to see, but rather telling recruiters who they might want to focus on. Despite this decrease in control, not all recruiters shared this frustration, especially when the focus of the tool was not solely related to the quality of the search results but its ability to help recruiters increase the efficiency of sourcing, as P3 and P6 described.

5.1.5 Short life span and data accuracy. Despite the increased efficiency AI-enabled sourcing software may bring, the software's longevity could be short. Often, new fashionable tools appear on the market which recruiters would have to get used to, and the cycle would repeat over and over. This continual churn could lead to a decline in the trust recruiters had towards the underlying data and the search results generated (P1, P5). P1 was very cognizant of this constant churn noting that job terms were non-standardized even within an industry, and that data can become stale very quickly as people move to and from different jobs. The lack of clean and reliable data, controlled vocabulary, and standardized resumes across industries were some of the hurdles toward increasing the trust in sourcing results. *"I'm making sure that there's not duplicate accounts, making sure that the number and email and all that is accurate and still accessible for the candidate. So, there's just a lot of junk data out there. (P1)."*

In terms of the validity of the underlying data, P1 noted that the long-term viability of sourcing software would be highly coupled with the data sources. The software depended on how much the data sources themselves enabled data collection on their platforms. Because major data sources such as LinkedIn often change what and how much data would be shared with third-party sourcing software, sourcing software must also constantly adapt. More than once, recruiters noted that the tool ceased to be useful after a short stint. Due to the changing policies from data sources themselves, P5 described the continual churn within the sourcing software market as this: *"I feel like these [sourcing] algorithms are new, and they kind of can beat the system of whatever you're trying to find. And then after a while, those systems get smarter, and then the [data sources] block whatever [sourcing algorithm] it is. (P5)."*

5.2 AI-Enabled Applicant Assessment Software

5.2.1 Reasons for use. Assessments generally allowed companies to tackle the problem of applicant glut. The size of the company, the cost of implementation (P13, P14), the kind of candidate roles (P15), all played a part in the decision to adopt an AI-enabled assessment. Recruiters and HR professionals aimed to increase efficiency of screening (P9, P13, P15). The efficiency gained, they believed, would yield a decrease in hiring cost (P9, P15) and an increase in diversity (P9, P10, P11, P13). Inclusion of a systematic assessment would improve talent identification (P9), enhance talent retention (P9, P15), eliminate recruiter bias (P9, P11, P15), and free up recruiters for more specialized hires (P9). For AI-enabled video assessments, HR professionals further identified improvements in the quality of candidates (P15), the ability to screen for candidate's motivation (P2), evaluation of personality and communication style (P9), and the ability to elicit authenticity from candidates (P13) as reasons for adoption.

5.2.2 Onboarding and configuration process. During onboarding, HR professionals and managers orchestrated the system implementation of the assessment tool with multiple stakeholders including the HR team, I/O and legal consultants, and assessment software vendors. P9 and P15 both oversaw the implementation of the assessment at their companies and described the preparatory work before onboarding the assessment platform. Consultation was conducted with I/O psychologists to develop a valid job-fit assessment (P9, P15). Negotiation with the internal HR team was carried out to approve the set of features to deploy (P9). Verification, such as running adverse impact studies, was conducted with the legal team to ensure the assessment followed legal, policy, and ethical standards (P15). P15 noted that only after the validity and legal questions were assessed could the team move forward with onboarding the software. *"We have a front end (e.g., I/O, legal), they say, yes, we sign off, [name] signs off, my legal team signs off work. We are a relatively risk averse company and those checks are what would allow us to be able to spend money on an assessment. I wouldn't be able to get the budget for it otherwise. (P15)."*

The HR team collaborated closely with software vendors to complete any necessary configuration, customization, integration work to run pilot tests (P9, P13, P15). The complexity of assessment configuration varied depending on how easily the vendor could plug into the company's existing Applicant Tracking System. It also depended on the type of assessment. P15 described the relative ease of onboarding a video assessment platform in comparison to an AI chatbot screening platform where questions had to be developed upfront. *"We co-developed essentially the series of questions, the responses, the integration mapping into our system with [assessment vendor]. And that co-development took a long time. (P15)."* In contrast, P9's onboarding process did not involve co-developing content; rather, the process involved translating an existing paper-based assessment into one that ran on the assessment software. *"I'd kind of had two years of running it as a manual process where we'd have people come in and I'd hand them a paper test and they'd fill it out and I'd mark it manually. So because we already had a really well established process that we just wanted to duplicate online with AI, it was more around the functionality in the user experience than necessarily about the content. (P9)."*

5.2.3 Increased candidate participation in the screening process. Due to variances in the type of candidate roles, some HR professionals saw increased rates of participation after the software adoption, while others struggled to get applicants on board with the new process. After porting the paper-based assessment, for P9, the new process increased the number of individuals who were able to engage in the screening process. *"I wanted to implement [assessment software] to be able to [interview all candidates] so that we could have a much more inclusive recruitment process, where as long as you have working rights in [country], we'd be able to include you in our testing process. (P9)."* While inclusivity was one aspirational outcome of the software adoption, for P15, the high rates of participation was a necessary component when hiring at scale. *"[After implementing AI-enabled assessment] we started seeing, really you can't use it on roles that you're not hiring, you know, more or less than 1,000 people in that exact same role. (P15)."* For P15, the predictive capabilities of the assessment software, and thus the return on investment of AI only paid off when the assessment was targeted at high-volume hiring scenarios. Even though there was a huge difference in the scale of hiring between P9 and P15, both voiced success in the implementation of AI-enabled assessment in their hiring pipeline.

5.2.4 Challenges in assessment completion. While assessment completion rate was not an issue for P9 or P15, P10 experienced such challenges. After onboarding the assessment software, P10 faced difficulties getting candidates to complete the assessments. The software actually created more problems than it solved. P10 had to send followup emails to clarify the process and nudge candidates toward completion. This negated the original goal of using the assessment to replace the initial phone screen. P10 eventually stopped using the software altogether. *"We had technology issues; people had problems getting things recorded. Or, you know, the recording was really poor. So, even when we got people to complete it, the results weren't satisfactory. (P10)."* Compared to P9, P10's applicant pool was smaller, with relatively older applicants. In P9's case, the younger applicant pool and the personality type drawn to their industry were cited as potential reasons for the overall high completion rate: *"I think particularly because we're using it for entry level roles, and Millennials and Gen-Z, you know, they're much more comfortable using technology for applications and doing video interviews and that kind of thing that most of them haven't been disadvantaged. (P9)."* Depending on the skill requirement of the candidate roles, candidate's willingness to engage with AI-enabled assessment software differed. P6, a technical recruiter who sources talent, noted the difficulties in asking highly skilled candidates to engage in the assessment. Eventually, they had to override company directives in fear of loosing a strong candidate: *"It was awful trying to get these really great candidates to agree to [complete the assessment]. Um, I lost a lot of candidates. So, there was an override, where I can override it and ask the questions myself. And it took a lot longer, but I did it. And one candidate that I did that with, because I wasn't even going to ask him to do it, he was the best hire I made. (P6)."* As the skill-level increased, the willingness to engage in video, game, and task-based assessments decreased. The disparities in candidate outcome along age, gender, socioeconomic, personality type, career stage, and ability lines were all mentioned as possible risks in leaving individuals out by adopting assessment technology (P1, P9, P10, P11).

5.2.5 Using assessment scores for candidate evaluation. Because more candidates could participate in the initial stage of the interview process, HR teams that did not face low completion rates saw an increase, sometimes a dramatic one, in the number of assessments to evaluate. The ability for AI-enabled assessment to efficiently score and rank candidates allowed HR teams to focus only on those who met the set threshold. This algorithmically aided initial pass achieved the desired outcome by efficiently whittling down the applicant pool to a manageable number of top candidates. There exist tension between inclusivity and efficiency in that while the new process does enable more candidates to participate, only a small subset of top scoring candidates will move forward. Although P9 advocated for assessment's ability to increase the inclusivity of the screening process, they noted the utmost importance of the predictive score generated to efficiently evaluate top candidates. They also emphasized the importance of doing preparatory work ahead of time to ensure assessment validity. *"So for me, this predicted score actually becomes the most important just because with 41 candidates that have completed the test, it gives me an order in which to prioritize candidates. So yeah, I'd say that the predicted score is probably the most important part that comes out of it. But I do think that you need to put in the preparatory work. Because if there ends up being a huge deviation between the predicted score and my [manual evaluation] after I've checked what the AI is done, that's a problem. (P5)."*

P12, with an I/O psychology background, believed that these assessments should not be used as a form of cutoff: *"So there's nothing wrong with using [game-based assessment] like this to hire. We just have to be really careful. Once again, but you know, we're using this as supplemental information that adds to our understanding of the candidates. We are not supposed to use these as a hard line threshold. (P12)."* P15 similarly mentioned such reactions from I/O consultants on the use of ranked assessment to shortlist candidates. Yet, the scores were used by some HR teams to manage the sheer volume of candidates. P9 came up with the threshold by considering the number of assessments collected and the distribution of the scores: *"I try to pick [a threshold] that's relevant from a productivity point of view, so that we don't lose the benefit of the ranking system by the AI. We still get the productivity gains, but there's also, you know, a human sense to what the AI has done."* While candidates who fell within the top result tiers were advanced to the next stage, P11 noted that rarely did the bottom tiered candidates got reviewed. Even though using assessments this way greatly improved the efficiency of the process, for P15, the potential legal liability and negative publicity, in case the AI use was or seemed biased or flawed, were cited as deterrence for its continual adoption. *"Although we all love to think that AI or technology would immediately be able to replace human beings, that would actually be a cost saving, I think the downside for the company is certainly there is risk in being first in the marketplace or early in the marketplace with new technology and new tools, you end up with some bad press, you can end up with some risks, you could end up with some lawsuits. (P15)."*

5.2.6 Reducing recruiter bias. As the new assessment process became part of the hiring pipeline, some HR professionals noted its potential to mitigate recruiter bias. Amongst a highly competitive group of applicants for internship positions, P11 noted that name recognition of the school attended and previous internships influenced recruiter's selection. Since they implemented the assessment process, the diversity of the candidate pool had increased. *"We saw a lot more diversity when it comes to what schools, work, where these participants or candidates were coming from. (P11)."* While age might have been a barrier for some in completing the assessment, it also had the potential to help in others. P9 described an instance where an older applicant who had previously hit roadblocks passing the initial screening phase became shortlisted after completing the AI-enabled assessment. *"Prior to applying for our role, they hadn't gotten a call back from anyone. They hadn't had an opportunity to interview. And they put it down partly to the fact that, you know, they had 20 years of experience, they are massively overqualified for the role, and then people were discriminating against them because of their age. And because we'd moved to a process that basically eliminated a lot of the opportunity for bias and discrimination, we were basing our short-listing on your potential aptitude doing the core functions of the role. (P9)."* Although the assessment process may be "de-personalized", HR professionals and HR managers (P9, P11) described cases where atypical candidates who previously might not have made it through the screening process received a chance.

5.2.7 Shifts in recruiter's role due to new assessment workflow. An HR manager (P15) and an HR analyst (P11) described the shift in recruiter's role after the implementation of an assessment platform. P11 noted that because these assessments could be remotely administered across a wider array of colleges, this cut down the need for on-campus recruitment where initial screening generally took place. The assessment allowed the hiring team to distribute the screening process more broadly, across college campuses that otherwise would not have been visited. By using video-based assessment to conduct initial screening, P15 described the shift in recruiter's role from conducting screenings to being in charge of extending the offer. P15 noted that the recruitment team pushed back when the functions of a new AI screening chatbot were too similar to what the recruiters did. *"And that's where we got a tremendous resistance from the recruiters themselves. The recruiters did not understand how [AI screening chatbot] worked, did not want another tool in their toolkit, and I think in many ways, probably felt a little threatened that their roles would be less important because [AI screening chatbot] was asking the same questions that they were asking. And as I pointed out, that means you don't need to ask those questions anymore. You can ask different ones. But that's not really welcomed by our hiring teams. (P15)."*

In other settings, while HR professionals' job content also shifted, they became an integral part of ensuring AI-enabled assessment's accuracy. For the candidate roles P9 and P10 were hiring for, the inclusion of the human element remained an important aspect of the validation process as assessment software matured. *"When I go through and mark [the assessment], it will then go back and change [the AI evaluation] to your score. 'Team score' means that a hiring manager has looked at [the assessment] as well rather than just me. And so multiple people can keep scoring and the AI keeps learning based on different people and different inputs of what a good score is and how to score. (P9)."* While video-based assessments can be useful, P9 noted that questions remained about AI's ability to detect traits, speech patterns, and personalities through these recordings. Although video interviews may be a part of the assessment process, for some team's (P9) evaluation procedure, there was lesser weight placed on the AI generated results from them. Similarly for P10, while tasked-based assessments may be automatically evaluated by AI, video assessments still underwent a more manual evaluation process. *"But once they got into like the skills and personality and presentation part of the assessment, I think we looked at almost all of them, unless it was a very, very low score. (P10)."*

6 DISCUSSION

In prior work about the adoption of AI in hiring [7, 26, 34], "job candidates" are often referenced with an implied understanding about who those candidates are without making a distinction between the different types of roles candidates are applying for. By examining algorithmic hiring in practice, our work shows that HR professionals' individual motivation and their organizational practices depend on the candidate roles employers hire for; these socio-organizational contexts shape the adoption and use of AI-enabled hiring software, which highlights the importance of distinguishing different candidate roles. In this section, we describe varying contexts associated with candidate roles in sourcing and assessment. Then, we explain how these contextual factors influence the set of strategies and procedures recruiters and HR professionals might engage in. Finally, we offer suggestions about how AI-enabled software may support recruiters and HR professionals to more equitably source and assess the candidate roles they are hiring for.

6.1 Contexts & AI-Based Sourcing Strategies

6.1.1 Recruiter's social capital and performance evaluation metrics. Sourcing software tackles the problem of talent scarcity. As such, the majority of the sourcing recruiters we interviewed were technical sourcers—they sourced sought-after talents for technical roles such as software engineering, data science, biotechnology, etc. Within a highly competitive environment, individual factors such as a recruiter's social capital [2] play an important part in their recruitment success. Organizational factors such as the internal reward structure guides what that recruitment success would look like. These success metrics, or Key Performance Indicators (KPI), include time-to-hire, number of interviews-to-offer, and satisfaction surveys from hiring managers and candidates (P5). While the overarching theme for these KPIs center around efficiency and quality of hire, the exact weighted distribution for how KPIs are measured may differ based on the candidate role. Societal factors can cause shifts in employer's hiring focus. For example, during 2020, the social atmosphere around diversity was particularly salient. As a result, diversity became an important recruitment metric. Changing social conditions are translated into new KPIs for some roles which revises the reward structures to hire for those roles. New evaluation metrics then update the set of tools and strategies recruiters will use to find those candidates. For instance, a focus towards diversity has popularized certain AI-enabled sourcing software that highlighted diversity as one of their key features.

6.1.2 Different strategies in the use of AI-enabled sourcing software. Depending on the interplay between the social, organizational, and individual factors, recruiters deployed different strategies towards their use of AI-enabled software. Sourcing software generally did not pose a threat to a recruiter's job, but was viewed as another tool in the recruitment toolbox, albeit sometimes viewed as merely a trendy tool. In some cases, AI-enabled sourcing software acted as a learning resource to support recruiters in rapidly finding and growing new relationships with potential candidates. In other cases, building social capital meant relying less on algorithmic matches but instead putting effort into building an online community to grow one's network of candidates, as P7 did. Recruiters can flexibly change their usage strategy depending on who they are trying to recruit; as a result, the use of AI sourcing tool changes accordingly. Next, we discuss some of the implications for these strategies.

When recruiters aimed to expand their pool of candidates, some embraced the ease of use of sourcing software by providing up/down votes on recommended matches. Tools used for finding candidates follow similar design paradigms as those that are built for our everyday enjoyment. A potential risk is that decisions could be made too quickly without enough reflection on the consequences that might follow. These concerns echo longstanding research within the field of human factors where problems of complacency and automation bias have been studied [28].

On the other hand, one recruiter (P7) used an almost opposite strategy. They tried instead to limit such interactions through sourcing software partly to circumvent algorithmic suggestions in order to maintain a looser set of criteria for a candidate role in order to find more potential candidates. This recruiter's approach to AI-enabled sourcing was more methodical, cautious, and deliberate. When they approached the tool in this way, they encountered limits on the level of control the tools could provide which evoked a sense of frustration. In this case, the software's increasing ease of use via algorithmically driven suggestions had a disempowering effect on the recruiter.

6.2 Contexts & AI-Based Assessment Strategies

6.2.1 Candidate roles & their diverse assessment implementations. In the screening context where assessment software tackles applicant glut, we observed a different dynamic in the role of AI. While the goal of improving hiring efficiency was shared by most participants, depending on what the target candidate roles were, there were major differences in participants' description of how the inclusion of AI-enabled assessments were carried out. There was not a one-size-fits-all solution. We saw four scenarios to the assessment's implementation: 1) at a recruitment agency looking to fill several dozen roles at multiple experience levels, 2) at a large company looking to fill fifty or more entry-level office-based roles, 3) at a multinational company looking to fill a few hundred internship roles, 4) and finally at another multinational company looking to fill thousands of identical call-center roles. In each of these cases, as the scale of hiring increases for different candidate roles, the inclusion of recruiters' involvement in the evaluation process decreased, and vice versa.

6.2.2 Assessment implementations and its impact on HR professionals' job content. The inclusion of AI in assessment has shifted aspects of HR professionals' job content [1]. Job changes hold different implications for recruiters and HR professionals depending on the type of candidate roles they hire for. From HR managers' perspective, one of the benefits of implementing an AI-enabled assessment process is the ability to free up HR professionals' time to engage in more specialized hires providing HR professionals opportunities to build social capital. Yet some recruiters might sense these changes as a threat to their jobs; one HR manager discussed the pushback they received when management introduced chatbots that resembled the human exchanges that recruiters were responsible for. In other cases, updated assessment procedures meant more collaboration between HR professionals and AI-enabled software; entry to mid-level office roles at small to mid-sized companies we interviewed used video and/or task-based assessments as substitution or supplements to existing application processes, and often, these assessments were still manually evaluated by HR professionals.

6.2.3 New assessment process and its influence on candidate-employer relationship. One implication for these procedural changes is that while efficiency improvements might be gained through this substitution, not only can the introduction of AI reshape the HR professionals' role within the organization, it may also reshape the relationship between the candidates and the employer. New lines would be drawn between candidate roles that hold the opportunity to be evaluated and interviewed by humans versus those whose interview experience and assessment are highly mediated by software. While the HR managers and HR analyst we interviewed discussed second-hand accounts of the various changes to recruiter's job, we did not directly hear from recruiters and HR professionals who may have been affected by these changes. Future work would benefit from interviews with them, particularly within mid to large firms where AI-enabled assessments are implemented.

6.3 Empowerment of HR Professionals

Our findings emphasize the differences that exist within different candidate roles, and how these differences in turn influence the strategies and the tools used and deployed by individuals and organizations.

6.3.1 Balancing control and ease of use. Recruiters in the sourcing case raise important questions about how best to empower recruiters in building relationships with candidates and hiring managers. How much precise control should increasingly AI-driven sourcing software preserve for its users? Does the inclusion of AI features necessarily mean that manual search features should be taken away? For some recruiters, it might be advantageous to be able to add their experience and intuition with regards to candidates to override perceived shortcomings of AI. While other recruiters with less experience might not want the same control, leaving the option to do so might still be beneficial for them later down the line. In short, ease of use need not be sacrificed by increasing the level of control recruiters have over the tools [4]. By preserving some manual search functionality, it would provide recruiters with more control over the search process for those who wish to have it. The ability to view sorted results alongside manual search results would allow baseline comparisons across these two methods. This may increase recruiters' trust in the tool when they can directly make comparisons about the quality of search results themselves. When reflecting more deeply about why this recruiter tried the approach of minimizing algorithmic suggestions, besides widening the applicant pool, we speculate the approach also emerged from years of offering chances to candidates who may not fit the job description 100% but have turned out to be great hires. If the inclusion of AI-enabled software drives away the genuine desire to help someone find a job, what would be the consequences for the recruiting profession overall, and for job candidates more broadly?

6.3.2 Considerations for recruiters and HR professionals' role within AI-enabled assessment. For assessment, the question regarding the level of human involvement becomes a major issue that companies, especially companies that hire at scale, need to seriously grapple with. Similar to the issue of control raised by sourcing software, the choice between AI-enabled assessment and HR professionals' evaluation need not be mutually exclusive regardless of the candidate role being hired for [17, 25]. Options for random sampling of assessment results can be introduced such that candidates who fall below the set threshold may still be evaluated by someone. From an efficiency standpoint, additional personnel effort spent in manual evaluation of AI-assessment might not be an attractive option. However, maintaining human-in-the-loop contact, as one organization has done, might prove important especially considering the long term impacts of assessments, matches, and recommendations made by AI. As AI continues to make its way into the current and future hiring process, the line between the recruiters/HR professionals and AI-enabled hiring software also continues to blur. As such, vigorous debates about where these lines should be drawn needs to continue. Voices from those who will be most impacted by these changes must be included in these discussions.

7 LIMITATION

Our findings are with a small sample of recruiters and HR professionals. Since the details about the hiring process or software are proprietary, it was challenging to find appropriate participants who have used AI hiring software. We had limited success in reaching individuals at large companies where high-volume assessments take place. Having access to more HR professionals at those companies would be helpful in painting a fuller picture of its usage. Additionally, only a few participants were able to demonstrate the software to us. Given the closed nature of these software, it restricted the level of our analysis to participant responses and publicly available data on software vendors' websites.

8 FUTURE DIRECTION

There are several directions to extend our research. First, our research was conducted in the specific context of sourcing and assessment in the hiring pipeline. It would be beneficial if future studies could examine other phases of the hiring pipeline, such as how automated Applicant Tracking Systems function or how offer packages are generated using AI. Another direction would be to delve deeper into the cultural differences in hiring. We interviewed people working at multinational corporations in and outside the U.S.. Those participants we spoke to have talked about their experience from different cultural backgrounds which we did not elaborate on in our analysis. If cultural differences can be analyzed in the context of hiring, it would be another valuable extension of our research. Third, we conducted 11 additional interviews with recruiters who used HR technology without AI, I/O psychologists, project managers, data scientists, and HR tech startup CEOs. Their perspectives allowed us to better understand the reasons behind the ease and frustrations that HR professionals expressed. We believe that voices from I/O psychologists are crucial to further explore, as well as those of data scientists, engineers, and designers who bring these software to market [24]. These stakeholders are in many ways the "gatekeepers" to the deployment and the use of AI hiring software. Finally, long-term research needs to be done about how well the system has worked with AI-enabled hiring software by looking at the outcomes from the selected candidates. Since using AI features is still in its early stage, there is not enough data from companies that deployed sourcing and assessment systems within the past 2 to 4 years to see their effects.

9 CONCLUSION

Algorithmic hiring, through the lens of recruiters and HR professionals, highlights the dynamics that arise when humans use and work with AI systems. Through interviews with recruiters and HR professionals, we examine how candidate sourcing and assessment decisions are made using AI-enabled software. Our work shows that when considering the potential to adopt AI in hiring, the relative drawbacks and benefits of these AI systems differ greatly by the type of decisions and the type of candidate roles these systems are built to assist.

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REFERENCES

[1] Daron Acemoglu and Pascual Restrepo. 2019. Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives* 33, 2 (2019), 3–30.

[2] Paul S Adler and Seok-Woo Kwon. 2002. Social capital: Prospects for a new concept. *Academy of management review* 27, 1 (2002), 17–40.

[3] Ifeoma Ajunwa. 2019. The paradox of automation as anti-bias intervention. *Cardozo L. Rev.* 41 (2019), 1671.

[4] Saleema Amershi, Maya Cakmak, William Bradley Knox, and Todd Kulesza. 2014. Power to the people: The role of humans in interactive machine learning. *Ai Magazine* 35, 4 (2014), 105–120.

[5] Alison E Barber. 1998. *Recruiting employees: Individual and organizational perspectives.* Vol. 8. Sage Publications.

[6] Josh Bersin and Tomas Chamorro-Premuzic. 2019. New Ways to Gauge Talent and Potential. *MIT Sloan management review* 60, 2 (2019), 1–.

[7] J Stewart Black and Patrick van Esch. 2020. AI-enabled recruiting: What is it and how should a manager use it? *Business Horizons* 63, 2 (2020), 215–226.

[1] https://goodsystems.utexas.edu

[8] Miranda Bogen and Aaron Rieke. 2018. HELP WANTED. *An Examination of Hiring Algorithms, Equity, and Bias* (2018).
[9] Falko Brenner. 2020. *Asynchronous video interviews in selection: A systematic review and five empirical investigations.* Ph.D. Dissertation.
[10] Erik Brynjolfsson and Andrew McAfee. 2014. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies.* WW Norton & Company.
[11] Victoria Clarke, Virginia Braun, and Nikki Hayfield. 2015. Thematic analysis. *Qualitative psychology: A practical guide to research methods* (2015), 222–248.
[12] Mary L Connerley. 2014. Recruiter effects and recruitment outcomes. *The Oxford handbook of recruitment* (2014), 21–34.
[13] C. Fernández and A. Fernández. 2019. Ethical and Legal Implications of AI Recruiting Software. *ERCIM News* 2019 (2019).
[14] Carl Benedikt Frey and Michael A Osborne. 2017. The future of employment: How susceptible are jobs to computerisation? *Technological forecasting and social change* 114 (2017), 254–280.
[15] Konstantina Georgiou, Athanasios Gouras, and Ioannis Nikolaou. 2019. Gamification in employee selection: The development of a gamified assessment. *International journal of selection and assessment* 27, 2 (2019), 91–103.
[16] Sahin Cem Geyik and Krishnaram Kenthapadi. 2018. *Building Representative Talent Search at LinkedIn.* Retrieved December 10, 2020 from https://engineering.linkedin.com/blog/2018/10/building-representative-talent-search-at-linkedin
[17] Tad Hirsch, Kritzia Merced, Shrikanth Narayanan, Zac E Imel, and David C Atkins. 2017. Designing contestability: Interaction design, machine learning, and mental health. In *Proceedings of the 2017 Conference on Designing Interactive Systems.* 95–99.
[18] ZipRecruiter. Inc. 2019. *The AI Advantage: A Guide to a Smarter Recruitment Strategy.* Retrieved December 10, 2020 from https://static.ziprecruiter.com/pdf/whitepapers/ZipRecruiter-ai-smarter-recruitment-wp.pdf
[19] Andreas Kaplan and Michael Haenlein. 2019. Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons* 62, 1 (2019), 15 – 25. https://doi.org/10.1016/j.bushor.2018.08.004
[20] Markus Langer, Cornelius J König, and Kevin Krause. 2017. Examining digital interviews for personnel selection: Applicant reactions and interviewer ratings. *International journal of selection and assessment* 25, 4 (2017), 371–382.
[21] Vanessa Laurim, Selin Arpaci, Barbara Prommegger, and Helmut Krcmar. 2021. Computer, Whom Should I Hire?–Acceptance Criteria for Artificial Intelligence in the Recruitment Process. In *Proceedings of the 54th Hawaii International Conference on System Sciences.* 5495.
[22] 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.
[23] Kiki Leunter, Josh Liff, Lindsey Zuloaga, and Nathan Mondragon-Chief. 2020. *HireVue's Assessment Science.* https://webapi.hirevue.com/wp-content/uploads/2020/08/HireVue-Assessment-Science-whitepaper-2020.pdf
[24] Cynthia CS Liem, Markus Langer, Andrew Demetriou, Annemarie MF Hiemstra, Achmadnoer Sukma Wicaksana, Marise Ph Born, and Cornelius J König. 2018. Psychology meets machine learning: Interdisciplinary perspectives on algorithmic job candidate screening. In *Explainable and interpretable models in computer vision and machine learning*. Springer, 197–253.
[25] Mansoureh Maadi, Hadi Akbarzadeh Khorshidi, and Uwe Aickelin. 2021. A Review on Human–AI Interaction in Machine Learning and Insights for Medical Applications. *International Journal of Environmental Research and Public Health* 18, 4 (2021), 2121.
[26] Agata Mirowska. 2020. AI Evaluation in Selection. *Journal of Personnel Psychology* (2020).
[27] Nathan Mondragon-Chief, Josh Liff, and Lindsey Zuloaga. 2020. *The Next Generation of Assessment.* https://webapi.hirevue.com/wp-content/uploads/2020/07/next-gen-assessment-04-2020.pdf
[28] Raja Parasuraman and Dietrich H Manzey. 2010. Complacency and bias in human use of automation: An attentional integration. *Human factors* 52, 3 (2010), 381–410.
[29] 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.
[30] 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.
[31] Frank L Schmidt and John Hunter. 2004. General mental ability in the world of work: occupational attainment and job performance. *Journal of personality and social psychology* 86, 1 (2004), 162.
[32] Candice Schumann, Jeffrey S Foster, Nicholas Mattei, and John P Dickerson. 2020. We Need Fairness and Explainability in Algorithmic Hiring. In *Proceedings of the 19th International Conference on Autonomous Agents and MultiAgent Systems.* 1716–1720.
[33] Rupert Sellers. 2014. Video interviewing and its impact on recruitment. *Strategic HR Review* (2014).
[34] Patrick van Esch and J. Stewart Black. 2019. Factors that influence new generation candidates to engage with and complete digital, AI-enabled recruiting. *Business horizons* 62, 6 (2019), 729–739.
[35] Lynette Yarger, Fay Cobb Payton, and Bikalpa Neupane. 2019. Algorithmic equity in the hiring of underrepresented IT job candidates. *Online information review* 44, 2 (2019), 383–395.