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How Process Experts Enable and Constrain Fairness in AI-Driven Hiring

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Organizations risk losing their competitive edge as they struggle to find and hire qualified talent. Hiring personnel turn to artificial intelligence (AI) tools to help acquire talent, increase efficiency, and reduce costs. Yet despite the best intentions for integrating fair and evidence-based systems, exacerbated levels of bias may occur from using these tools. Drawing from scholarship on process expertise and emerging practices of AI use at work, I provide a case study of 42 high-volume recruiters and uncover how hiring personnel enact and justify unsystematic sourcing practices within the confines of their held expertise, organizational demands, and technology choices. I explain how AI-based hiring decisions in organizations are context dependent and blend the capabilities of algorithmic-powered tools with choices and judgments made by process experts. I conclude by offering theoretical and practical considerations for expertise, hiring, and the integration of algorithms at work.

Keywords: hiring algorithms, process expertise, fairness, organizational communication

Finding and attracting top talent from a limited applicant pool is one of the most pressing challenges facing businesses today. To maintain their competitiveness, hiring professionals leverage a constellation of artificial intelligent (AI) hiring tools to acquire qualified job applicants while simultaneously reducing the cost and time-to-fill successful hires. In fact, over the past decade, there has been a consistent upward trend in the use and investment of predictive analytics within talent acquisition processes.[2] In addition to improving human resource (HR) performance, advances in predictive analytics and machine learning technologies are often lauded by developers and employers for their capacity to refine the internal hiring process, mitigating the potential for biased decision making in recruitment. Yet despite the best intentions

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[2] According to a 2022 report by Aptitude Research, a human capital management firm, over 63% of companies has or have plans to invest in predictive analytics for improving their talent acquisition processes, compared with 42% of companies in 2021.

for integrating fair and evidence-based systems, research evidence points to exacerbated levels of bias within these proprietary systems because of little understanding of the development, validation, and use of these technologies (Köchling & Wehner, 2020; Raghavan, Barocas, Kleinberg, & Levy, 2020).

Organizations and technology developers have made notable strides to combat these criticisms stemming from algorithmic bias. Techniques such as developing more explainable and accessible algorithms, ensuring human-in-the-loop processes in AI-driven decision making, and auditing automated procedures are examples of efforts to debias technology (e.g., Black & van Esch, 2020; van den Broek, Sergeeva, & Huysman, 2019). Yet the promise of equity-driven, nondiscriminatory hiring algorithms is still a promise rather than a reality because bias can creep in consciously and unconsciously from employer practices rather than the technology itself (e.g., Cruz, 2021; Kellogg, Valentine, & Christin, 2020). Most research on algorithmic bias in hiring focuses on the root causes and consequences of the technical methodology and back-end development of algorithmic systems, but little empirical scholarship investigates the role that on-the-ground practices of employees and organizational norms shape how bias is produced or mitigated when using AI-driven hiring tools (Li, Lassiter, Oh, & Lee, 2021; Raghavan et al., 2020).

At large, communication and management scholarship lead us to consider how technology use is shaped by the interplay of expertise, norms, ideologies, and structures across individual, organizational, and institutional levels (Bailey & Leonardi, 2015; Barley, 1986; Barley, Treem, & Leonardi, 2020; Fulk, 1993). Effective coordination between work and technology hinges on an employee matching a technology's capability with specific, situated knowledge and expertise relevant to the task requirements at hand (Barley et al., 2020). In relation to sourcing talent—the act of finding and attracting qualified applicants for a job—hiring professionals, specifically recruiters, enact tremendous influence in the hiring process by curating their organization's talent pool. Recruiters use an array of hiring algorithms to systematically search for and attract applicants that match the experience, skills, and qualifications listed on a job ad. A common assumption of candidate sourcing is that recruiters capitalize on using AI tools to narrow down a wide net of qualified and diverse applicants. However, with the applied pressure for efficient, fast, and quality candidate sourcing, recruiters often trade off systematic and fair sourcing practices for inconsistent (van den Broek et al., 2019) and implicit personal judgments or stereotypes about candidates (Rivera, 2016, 2020).

I provide a case study of hiring professionals in high-volume recruitment settings across various work industries, and I uncover how recruiters enact and justify unsystematic and unfair sourcing practices within the confines of their held expertise, organizational demands, and technology choices. I find that recruiters coordinate AI-driven sourcing through a distinct performance of expertise—process expertise (Barley et al., 2020), which is defined here as a communicative form of expertise that relies on a recruiter's situated knowledge and awareness of social processes within a specific, nuanced social context. Using their process expertise when sourcing candidates, recruiters balance pressures for efficiency and quality from hiring managers even as they selectively diverge from AI-driven recommendations to align with their perceived expertise. I find that AI-driven candidate sourcing is a practice by which recruiters use algorithmic technologies to search and evaluate candidates based on explicit criteria relevant to a job posting (such as technical skills, education, or previous work experience). In addition, recruiters justify the use of contextual and situated knowledge of their work to assess candidates on implicit criteria that are often beyond the scope of their algorithmic sourcing capabilities (such as visual and written cues from applicant materials and perception of cultural fit). My findings highlight that to find the right candidate for a job, recruitment experts often inadvertently produce and uphold bias-laden practices over systematic and validated processes.

Background and Theory

The following sections combine theory of expertise, specifically process expertise, and research about emerging practices of AI use at work to explain how the talent acquisition setting offers a unique perspective into how recruiters manage their expertise and organizational demands. I explain how effective decision making in organizations is context dependent and blends the capabilities of algorithmic-powered tools with choices and judgments made by process experts.

Algorithmic Tools Alleviate Candidate Sourcing Demands

Over the last 20 years, there has been an expansion of artificial intelligence technologies aimed at addressing the increasing need to attract and manage human capital within organizations (Black & van Esch, 2020). In the context of this study, AI-driven technology is defined as the application of advanced predictive models in hiring processes, typically involving statistical or machine learning models used for making predictions and analyses about specific individuals or cases (e.g., Landers & Behrend, 2023). Broadly speaking, there are four stages in the hiring process: sourcing (i.e., finding, assessing, and attracting prospective candidates to apply for a job), screening (i.e., evaluating submitted application materials for job fit), interviewing, and selection. This study focuses on the first stage of hiring, sourcing, which is a process that is understudied about a recruiter's direct practice and engagement with algorithmic hiring tools. Sourcing candidates, alternatively referred to as lead generation, cultivation, or applicant tracking, use algorithms to search, expand, or limit applicant pools for current or planned job openings. Sourcing can occur through a third party (e.g., talent agencies) or in-house through HR departments where recruiters use embedded algorithmic software within online job boards (like LinkedIn Recruiter, ZipRecruiter, Indeed, Monster) that host prospective candidate data and materials.

For example, LinkedIn Recruiter tools afford recruiters the ability to efficiently identify potential candidates in a combination of ways, including enabling them to perform natural language searches for specific skills and experiences, apply filters to candidate profiles based on selected attributes, and generate candidate match recommendations using a ranking system derived from a set of predetermined criteria. A significant advantage of using AI techniques in sourcing is to parse, structure, and analyze applicant data quickly; algorithms can search, process, and produce a shortlist of top matching candidates within a fraction of the time it can take a human recruiter (e.g., Cruz, 2021; Li et al., 2021). Often, recruiters who source for competitive talent who possess high degrees of technical expertise (e.g., data science, engineering, or other technical fields) benefit from AI simplifying complex queries in keywords or offering accessible filtering options. Ideally, the recommended outputs from algorithms allow recruiters to apply their expertise to decipher the value and relevance of results directly to their organization's hiring needs. For instance, prospective applicants who are qualified for the same position may have held different job titles and describe their skills in diverse ways on their LinkedIn profiles. These moments of placing data into context are largely left at the discretion of a recruiter and their expertise. Recruiters make use of the results of their AI sourcing activities to aid their work processes but are not privy nor have access to the propriety technical operations that these algorithms run on (Raghavan et al., 2020).

To date, there is no industry standard or mandated guidance on the design and deployment of algorithmic hiring tools in recruiting (Raghavan et al., 2020). This lack of established guidelines may increase the risk of unfair decision making (Landers & Behrend, 2023). To conceptualize fairness in the context of AI used for hiring, I rely on van den Broek, Sergeeva, and Huysman's (2019) perspective, which views fairness as the attempt to make decisions that are "made consistently, represent the interests of affected individuals, suppress personal bias, use as much accurate information as possible, [are] correctable, and [are] compatible with ethical values" (p. 2). Furthermore, the concept of bias, which refers to the prioritization of personal preferences during decision making, poses a substantial challenge to ensuring fairness (van den Broek et al., 2019). Although terms like fairness and bias are multidisciplinary terms that can refer to a wide range of actions, processes, and concepts, this study conceptualizes these related concepts at the individual level through perceptions of one's work practices (e.g., Landers & Behrend, 2023; van den Broek et al., 2019).

Shifting the focus to the practical implementation of these concepts, the majority of popular AI-driven systems are designed, sold, and maintained by third-party developers. The code that instructs algorithmic procedures is private, proprietary property held with developers; therefore, when algorithms are deployed into an employer's applicant tracking system, this lack of transparency often leaves recruiters to work with unexplainable technology or develop working theories about a technology's output through a deploy-and-comply approach (Li et al., 2021; Liao & Tyson, 2021). [3] Recent research on how recruiters use algorithmic insights to inform recruiting decisions reveals how mismatches often occur between AI results and a recruiter's evaluation of a candidate (Li et al., 2021; van den Broek et al., 2019). Mismatches highlight discrepancies in the perceived accuracy related to a candidate's overall fit, experiences, or skills (e.g., Li et al., 2021). Theoretically responding to this issue, emerging research examining the use of algorithmic technologies at work has introduced the concept of algoactivism. Algoactivism is defined as the direct actions that employees take to temper the effects of algorithms in their work (Kellogg et al., 2020). This can provide an alternative explanation as to why a recruiter might leverage their knowledge and experience-based judgments to overrule an algorithm in favor of a job seeker. In practical terms, ambiguities and inconsistencies stemming from algorithmic outputs often empower employees to draw on their organizational expertise and exert control when making decisions based on less transparent data-driven recommendations (Christin, 2020a; Cruz, 2021; Kellogg et al., 2020; Li et al., 2021).

Recruiters as Process Experts When Using AI

At a conceptual level, while interacting with AI-powered hiring tools, recruiters leverage their expertise to align their actions with the needs of the organization and hiring managers. They source

[3] Applicant tracking systems (ATS) are software databases used by human resource departments to manage and organize information related to job candidates. This includes data from past, present, and potential candidates. The primary purpose of an ATS is to streamline the recruitment process by providing a centralized platform for storing, accessing, and managing candidate information.

candidates based on criteria that can predict future job performance. Recruiters are uniquely positioned to enact a distinct form of expertise, process expertise (Barley et al., 2020), which enables them to make decisions that consider different layers of socio-organizational contexts. Within an organization, recruiters serve as intermediaries between hiring managers (who possess specific domain expertise about organizational hiring needs) and algorithmic tools (which are relational technologies that are imbued with forms of domain expertise by their designers, e.g., Bailey, Faraj, Hinds, Leonardi, & von Krogh, 2022; Christin, 2020c). In the process of sourcing candidates, recruiters use their context-specific knowledge and skills, a fundamental practice rooted in the effective coordination of managerial demands and technological capabilities.

Communication research has often conceptualized expertise in organizations as an individual-level property that is enacted, performed, and recognized as the mastery of wisdom or competence within a specific knowledge domain (Collins & Evans, 2007; Treem, 2016; Treem & Leonardi, 2017). According to Treem (2012, 2016), expertise is derived from knowledge in practice. In other words, a person's expertise is not fixed to a specific skill or credential but is interpreted through visible performances where their knowledge is used in practice through tasks or interactions. Three different forms of expertise are enacted within organizations: domain, interactional, and process. Domain expertise refers to the application of deep, specific knowledge to a relevant context (e.g., a scientist running a laboratory experiment.) In comparison, interactional expertise describes the ability to communicate within a specialist's domain expertise without having the competence to perform the activity (e.g., a journalist who reports on the findings of a recently published study; Collins & Evans, 2015). Lastly, process expertise is held by individuals who use "skills and abilities to access, orient to, or manipulate information in a manner that aids others, and therefore involves communicative practices beyond mastery of language" (Barley et al., 2020, p. 7). Process experts rely on situated knowledge that is local to a specific context within organizations. Furthermore, this form of expertise is adaptable and shifts with changes in an organization's structure, membership, or practices. In relation to hiring and recruitment, process expertise helps to contextualize the unique work processes carried out by recruiters who manage, coordinate, and carry out tasks that involve other domain experts across different knowledge domains and sociotechnical contexts.

Key features of process expertise include the degree of access and experience that an employee holds within their workplace (e.g., Barley et al., 2020; Molinengo, Stasiak, & Freeth, 2021; Treem & Barley, 2016). Access takes the form of being centrally positioned in an organization to interface directly with relevant information sources and communicate with other domain experts. In turn, process experts gain legitimacy through repeated interactions or experience, allowing them to be recognized by others as authority figures in particular work processes. Inherent in enacting process expertise is an employee's autonomy to make independent, deliberate decisions that are relevant to their work. In their landmark study detailing process expertise, Barley and colleagues (2020) describe how nurses who effectively coordinate emergency patient transfers between four U.S. hospitals rely on situated knowledge about their patients, attending physicians, and unique hospital policies. Physicians with specialized expertise (i.e., domain experts) often lacked interorganizational knowledge about other partner hospitals and deferred to nurses for decisions on where to transfer patients. Nurses were able to capitalize on established communication networks with key stakeholders like the staff at other hospitals, medics who carried out the physical patient transfers, and access to retrieve and share patient information with other hospital staff in the network.

Relatedly, these features of process expertise are intrinsically present when we consider the on-the-ground practices of recruiters who coordinate and inform hiring practices within their organization.

The Case of AI-Driven Sourcing: Interplay Between Technology and Process Expertise

The ability for recruiters to coordinate their expertise in candidate sourcing with different capabilities of algorithmic technologies is important to inform their hiring decisions. Existing studies examining AI-driven hiring have provided useful understanding to explain how algorithms shape the nature of recruitment—including the motivations for integrating AI into hiring pipelines (Li et al., 2021; van den Broek et al., 2019), challenges that occur over the lack of technical transparency (Kellogg et al., 2020; Köchling & Wehner, 2020), and the industry-wide impact of developing algorithmic hiring platforms (Ajunwa, 2019). As described, when studying AI-driven hiring, scholars place analyzes on factors across individual (e.g., developers, employees, or candidates), organizational (e.g., policies, norms, or ideologies), and institutional (e.g., platforms) levels. Although a recruiter's decision-making hinges on sociotechnical interactions aided by hiring algorithms across organizational levels (for a comprehensive review of AI use cases across the stages of HR recruitment; see Köchling & Wehner, 2020), the process by which individual expertise may influence decision making is excluded from these analyses.

Finding and attracting job candidates for an open role is not completely reliant on algorithmic recommendations. Mismatches over the perceived accuracy of algorithms (Li et al., 2021), lack of transparency on the part of technology developers (Raghavan et al., 2020), and inconsistent training and deployment (Kellogg et al., 2020; van den Broek et al., 2019) are exemplars of situations that demonstrate how AI-driven hiring decisions often employ the coordination between recruiter expertise, organizational demands, and algorithmic design. Although the outcome of effective coordination may not reflect completely unbiased and fair hiring decisions (e.g., Kellogg et al., 2020; Li et al., 2021), placing focus on the practices of how situated AI-driven decisions are coordinated may reveal factors that contribute to a more complete understanding of employer hiring decisions involving artificial intelligent technology. This study aims to uncover the sociotechnical dynamics that influence sourcing decisions within a recruiter's purview by investigating the following research question: How do recruiters enact and justify their process expertise when making AI-driven sourcing decisions about potential job applicants?

I pursue this question via a qualitative case study of 42 recruiters in high-volume recruitment settings across 26 work industries that use an AI-driven tool for sourcing. I examine the communicative practices that recruiters employ when making decisions on searching for and attracting potential job candidates for an open position. In doing so, I explore how recruiters perform their process expertise when consulting with AI technology to make context-dependent sourcing decisions. The following section details methodological considerations given to the context, experience, and processes of recruiters included in this case study.

Methods

To analyze the communicative practices by which recruiters enact their process expertise, I conducted online, semistructured interviews with recruitment personnel who were responsible for sourcing activities within their organization. Data collection for this study lasted 10 months, starting in October 2020 and concluding in August 2021. I responded to shifting virtual methodological approaches due to the COVID-19 pandemic and employed virtual interview methods (Christin, 2020b) to assuage the lack of physical copresence during interviews or observations. This approach cannot fully discern the differences between what respondents say they do from their actions at work, but in-depth, semistructured interviews are particularly suited to studying the subjective interpretations and meaning-making processes perceived by respondents (Yin, 2003). The adherence to two characteristics—high-volume recruiters and those that use AI technologies—formed the essential eligibility criteria for sampling participants for this study.[4]

Interviews: Context, Sampling, and Procedures

Context

A primary focus of data collection was placed on identifying which employee in recruitment possessed hands-on experience with algorithmic hiring tools within their daily repertoire of work tasks. In recruitment and talent acquisition, recruiters are often the first point of contact with potential job applicants during the initial phases of sourcing and screening. The selection of top applicants for interviews and subsequent decisions are left to department-specific or central HR hiring management (Köchling & Wehner, 2020). AI sourcing tools typically allow recruiters to engage in more active forms of candidate engagement, including e-mail outreach, scheduling meetings with prospective applicants, or follow-ups about the application process. For the scope of this study, I focused on data collection and analyses based on a recruiter's interaction with candidate data from candidate profiles or previously available information housed in company applicant tracking systems. To identify and contact recruiters who focused on sourcing candidates, I recruited participants through stratified sampling from publicly available clientele lists found on AI-hiring software websites, searches for recruitment professionals with specific recruiter job titles on LinkedIn (e.g., sourcing recruiter, technical sourcing recruiter), outreach to recruiters on affinity groups within social networking sites like Facebook and LinkedIn, and participant referral chains.

Sampling

To form a standard level of comparison between recruiters working in high-volume recruiting industries, all participants included in the study were U.S. based recruitment professionals who had worked in their current company for at least six months and self-reported using at least one form of an algorithmic hiring tool for recruitment processes. Although participants used various proprietary algorithms to aid candidate sourcing, the tools used for sourcing afforded recruiters the ability to search for, expand, or limit the visibility of specific parameters found in candidate data. Recruiters generally had access to personal and professional information, demographic, and contact information about

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[4] The requirement for high-volume recruiting is a common requisite for efficient and efficacious use of an algorithmic hiring tool. On average, most high-volume recruitment describes job listings that receive a minimum of 250 or more applications per role (HR Research, 2021).

candidates. AI sourcing tools typically allow recruiters to engage in more active forms of candidate engagement, including e-mail outreach, scheduling meetings with prospective applicants, or follow-ups about the application process.

A total of 42 interviews were conducted, with 36 interviews conducted using video conferencing and the remaining six interviews conducted by phone. Follow-up interviews were conducted with three participants to provide more information about the organization-specific use of technology. Table 1 includes information about participant demographic information.

Table 1. Participant Demographics Inventory.

Demographic Category	Subcategory	Count (%)
Industry Type	Technology, Private	9 (21%)
	Education, Nonprofit	5 (12%)
	Legal, Private	4 (10%)
	Media, Private	4 (10%)
	E-Marketing, Private	3 (7%)
	Sales, Private	3 (7%)
	Staffing, Private	2 (5%)
	Consumer Goods, Private	2 (5%)
	Food & Beverage, Private	2 (5%)
	Financial, Private	2 (5%)
	Airlines, Private	1 (2%)
	Health Care, Private	1 (2%)
	Creative, Private	1 (2%)
	Philanthropy/Charity, Nonprofit	1 (2%)
	Chemicals, Private	1 (2%)
	Real Estate, Private	1 (2%)
Gender	Man	18 (43%)
	Woman	24 (57%)
Race	Black	5 (12%)
	Asian	6 (14%)
	Latinx	9 (21%)
	White	22 (52%)

Protocol and Data Preprocessing

Interviews lasted between 25 and 90 minutes, took place through the virtual medium of their choosing, were recorded (unless otherwise indicated), and were transcribed verbatim using Rev.com, an online paid transcription service. The average amount of time for an interview lasted approximately 45 minutes. The interview guide composed of four sections: (1) Background questions related to each recruiter's organization and their role (including tasks, hierarchy, and affiliation to teams), (2) questions related to the types of technologies used during recruitment processes, (3) questions related to the process of engaging with algorithmic tools during recruitment decisions (e.g., "Can you describe a time when you did not agree with the ranking or score produced by the AI tool?"), and (4) demographic-based questions. Following Charmaz's (2014) protocol for evaluating experiential meaning-making, I probed participants for specific examples of memorable interactions about the use of technologies or critical incidents that exemplified the sensemaking of technology use.

Data Analysis

A total of 40 interviews were audio recorded, with two accompanied by handwritten notes per participants' request. Each transcript was verified for accuracy and loaded into the data analysis software NVivo. The average transcript length was about 12 pages, with a total of 435 pages of transcription. I analyzed data using a qualitative data analysis approach (Miles, Huberman, & Saldaña, 2019) while placing emphasis on developing coding categories in tandem with data analyses (Charmaz, 2014). Data were analyzed in three stages: open and focused coding, axial coding, and theoretical coding. Frequent annotation and analytic memos were used to iterate between data and the analysis. During the initial stage of coding, I often referred to my interview notes as I engaged in segment-by-segment coding, where codes were designated to each completed response spoken by a participant. This form of coding captured the wide range of possible interactions that recruiters had with AI technologies at work.

Initial codes informed categories of codes to demonstrate their relation to processes within the data. During axial coding, these fragmented categories of codes were purposefully interpreted to relate to larger categories, giving coherence to the analysis. I adhered to Charmaz's (2014) guidelines for linking categories of codes together by identifying conditions (i.e., circumstances that form structure between phenomena), actions or interactions (i.e., a participant's reaction to specific events, processes, or issues), and consequences (i.e., the outcomes of interactions or actions that were performed).

Finally, axial codes were subjected to theoretical coding, which enabled me to move between data and emerging theoretical reconstruction. The data set was analyzed for thematic relationships, capturing the causes and effects of specific technology practices, the factors and perceptions influencing recruiters' decision to either incorporate or dismiss algorithmic recommendations, and the dynamics between the organization, its recruiters, and technology. I selectively employed in vivo coding, the reference to specific terms spoken by participants, to contextualize technical terms and processes that were fundamental to recruiting.

Findings

Even before applying for a job, algorithmic-driven sourcing plays a powerful role in deciding which candidates are invited to apply for a position and ultimately get hired. Recruiters are experts at coordinating the process by which hiring algorithms are leveraged to find candidates that meet the qualifications and fit the needs of a job. Using their unique positions as intermediaries between technology and organizational social contexts, recruiters source candidates based on explicit and implicit forms of knowledge that are enacted through situated sociotechnical communicative practices—a novel form of labor in itself. A recruiter's sourcing decisions are often justified in practice through evidence from AI-driven outputs, as well as legitimized work activities and routines. In turn, these practices engage recruiters to make consequential sourcing decisions that enable them to paradoxically enable yet constrain perceptions of fairness within candidate evaluations. The decisions are perceived as evidence based and data driven due to their reliance on AI outputs. Simultaneously, they reflect the personal and unsystematic aspects of the recruiter's judgment and work routines.

Expertise of the Process Legitimizes AI-Driven Sourcing Decisions

Recruiters source candidates through a myriad of ways using algorithmic tools and techniques that are integrated into their applicant tracking systems. The majority of participants (n = 36) indicated using LinkedIn Recruiter, a proprietary AI-driven search and recommendation platform that affords recruiters the ability to find, connect, and engage with prospective candidates and manage their talent pools across human resources departments.[5] In action, sourcing typically involves working independently to fill requisitions (i.e., open job positions) that are assigned by internal or external (e.g., companies that contract with talent agencies) hiring managers. The initial stage of fulfilling a requisition involves creating a pipeline of "targeted candidates" that becomes an active candidate pool; Mel, a legal recruiter, explains how "pipeline building is the key to finding competitive talent" and includes scouring through lists of candidates for relevant skills, work experience, and basic qualifications that hiring managers would expect to find in candidates when screened and invited for an interview. Pipeline building is reflective of a filtering process, or the evaluation of candidates based on specific and relevant criteria. Recruiters in this study often described this process as pivotal because it allowed them to "decide who gets in the door" (referring to their applicant pool). Jen, an E-Marketing recruiter, explains: "Every time I send a list of candidates to my manager, I know that I've done my due diligence and quality control to send the best batch of people into the pipeline." Sourcing involves forming a set of standards that adhere to managerial demands through identifying and screening prospective candidates for specific qualities.

Given the importance of finding and matching candidates that meet an organization's hiring needs, recruiters often consider both explicit and implicit knowledge derived from candidate data within the search and recommendation platform. In essence, these algorithmically driven platforms provide a range of search, rank, and filtering options based on available data in candidate profiles. Figures 1 and 2 are demos of the LinkedIn Recruiter product and display the user interface seen by a recruiter when sourcing. These mockups of LinkedIn Recruiter are made available as part of their online demo. Anne, a recruiter in legal, directed me to this image during an interview.

[5] The primary focus of this case study was to examine AI-driven technology practices that recruiters use to source candidates. It should be noted that candidates are also sourced through job fairs and trade association meetings, internal and external referrals, and from past applicant pools where candidate data was stored.

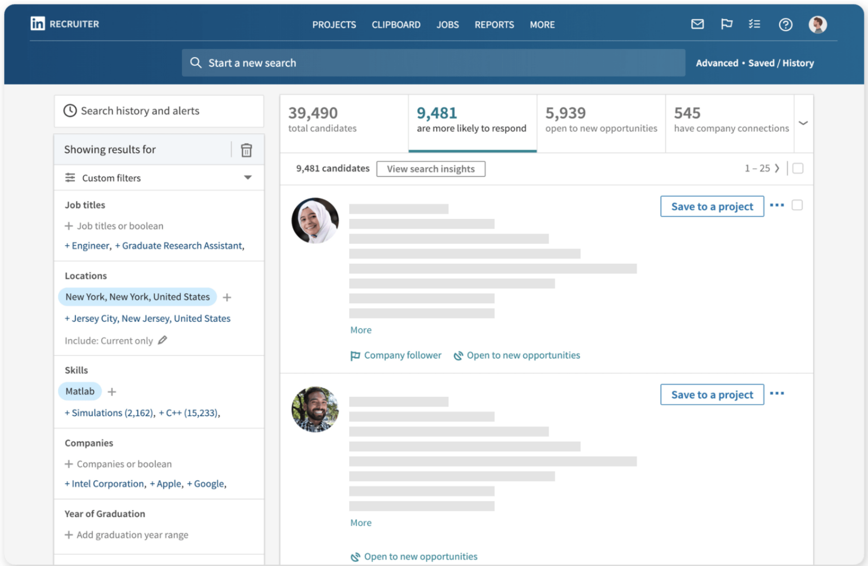

Figure 1. A demo of the LinkedIn Recruiter tool that is used to source candidates (LinkedIn Recruiter, 2023).

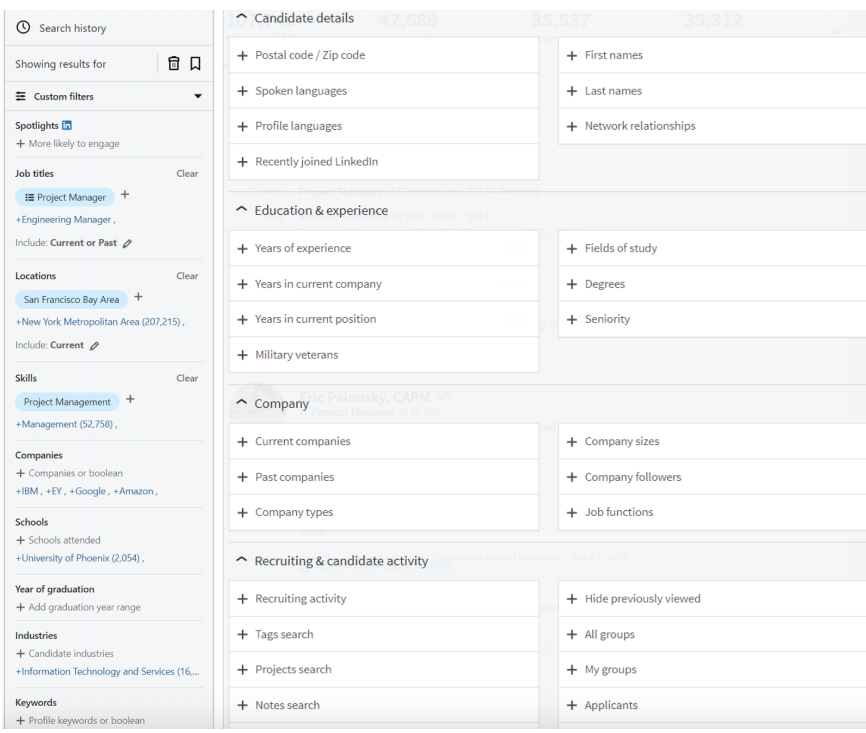

Figure 2. Example of filtering options used to source candidates (LinkedIn Recruiter, 2023).

Experts Use Explicit Criteria

Recruiters use explicit information derived from job advertisements and suggestions from management to guide how they search for and filter applicants. Searches are conducted to match applicant's qualities based on their current and previous job titles, listed skills on their profile, professional affiliations, education level, and location. Recruiters often reference how they use internal rubrics or scorecards to determine the expectations required of a candidate to be eligible for the position. Derek, a technical recruiter for a technology company, describes how hiring rubrics eases the time and work demands of recruiting many candidates:

> I usually start [sourcing] by asking myself, "What are the most important qualities would a person need to do well in an interview?" Say the job ad calls for someone with a master's in data or statistics, and our managers like to see that they [candidates] have, at minimum, two to three years of experience in tech. So then if you work backward and limit the search for those requirements, it saves so much time.

Filtering for specific qualities, as described earlier, are efficient strategies to include or exclude candidates from the hiring pipeline. The logic underlying this method is to adhere to guidelines so managers who screen and interview candidates are "not wasting time verifying credentials" or ensuring candidates are not over or underqualified for a position. However, not all candidate qualities fit neatly into sourcing rubrics. Often, when a required competency is unclear or difficult to ascertain from results in the AI-hiring platform, recruiters use relevant domain expertise about the type of job to make a judgment about the applicant. Will, an educational nonprofit recruiter, explained:

> We look for measurable degrees of leadership in our candidates [measured from 1 = low leadership to 5 = high leadership]. We define leadership as having held a role that is selective and how many people they influence in a position. So if someone is an after-school tutor, sure, those roles are very selective . . . but you're typically influencing one person at a time. I'll rate that person a two on leadership. Now, compare this to a president of a fraternity or president of some ethnicity organization—that's high leadership. Extraordinary levels of leadership are like student body presidents or newspaper editors in chief. Those are highly selective and very influential people. That's how we quantify.

When probed about how exactly leadership levels are computed, he said, "We look at what LinkedIn says, and then we look at the role [open job at his organization], and we make our best guess as to what their classification of leadership is. Then, we upload that [score] to their file." Will echoes similar processes by recruiters who interpret AI-generated data with their expertise in hiring to make determinations about required candidate competencies.

Fulfilling Candidate Quotas

Although most recruiters use explicit criteria from job postings to source candidates, over a third (n = 18) of participants disclosed receiving direct requests from management to source based on personal, surface-level diversity quotas for race and gender.[6] Recruitment professionals often described how requests to source for diversity were mandates rather than expectations. Consequently, recruiters described using keywords to search and select candidates that met their perception of specific demographic characteristics. Marc, a recruiter for a healthcare staffing agency, described his use of searches to identify racially diverse candidates.

> We're trained to take an aggressive approach to recruit URM [underrepresented minorities] to our pipeline. In fact, one of our KPIs [key performance indicators] is diversity.[7] [*pause*] If I'm not meeting my benchmarks, I will go out and find diversity. Most POC [people of color] advertise it on LinkedIn. I just follow the breadcrumbs.

In this quote, Marc describes a practice of overtly including surface-level diversity characteristics in a LinkedIn keyword or filter search. For example, "Black Management Association" or "Black Business Student Association" (to identify Black business graduates) or "First Generation Law Students" or "First Generation Program" (to identify first-generation students) use candidate data as proxies for diverse identity characteristics. These strategies illustrate how recruiters repeatedly coordinate information about prospective candidates and their technological proficiencies to perform sourcing activities that support their organizational demands.

Experts Use Implicit Criteria

A majority of recruiters described how their requisition assignments require them to source candidates that meet certain opaque criteria from hiring managers. Recruiters often decipher implicit screening requests by applying their tacit understanding of an organization. Code words or descriptive phrases that signal specific applicant attributes are employed by managers when requesting candidates with particular types of characteristics. For instance, some recruiters who fill requisitions for non U.S. positions are told to "find people that would feel comfortable there [referring to a geographic region]" (Roger, Executive Recruiter in Finance). In this example, Roger, who recruits for a wealth management firm, describes a moment when, filling requisitions based in the Asia Pacific region (specifically China, Japan, and Singapore), a hiring manager indirectly requested that he source only applicants who identified as Asian.

Technological affordances such as visual elements or descriptive text found in a candidate's profile are cues that enable recruiters to evaluate potential fit for an organization. For example, data like city or suburb names or listed zip codes on a candidate's profile can be mapped to determine whether they live too

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[6] In the United States, adherence to Title VII of the Civil Rights Act of 1964 is legally mandatory for organizations. This act protects job seekers from discrimination based on protected classes such as race, gender, religion, national origin, and disability, and it is supplemented by state-level laws where organizations recruit. Organizations frequently emphasize diversity in recruitment, ensuring adherence to policies prohibiting adverse impacts on protected classes. For a more detailed understanding of algorithms in employment, consult reports by Raghavan et al. (2020) and Raghavan and Barocas (2019). This study does not make any legal claims about the legality of recruitment practices related to diverse hiring or disparate impact; instead, it provides this information as context for a general international audience.
[7] KPIs are measurements that track an organization's progress toward a goal.

far away from a job that requires commuting. Cues generated from searching a candidate's college graduation year are often used as proxies to determine a person's relative age when searching for candidates with "real-world experience." In addition, recruiters described how visual cues from profile pictures (e.g., wearing a suit or having a professional headshot) indicated whether a candidate possessed enough "polish" or "maturity" to fit in within a company. In essence, unique self-presentation styles depicted in candidate profiles were treated as important sources of information that were often used to shape decisions about an organization's applicant pool.

In contrast, recruiters also use their expertise to match tacit understandings of a position on behalf of applicants. Matching an applicant with the "fit" of an organization is one primary strategy that recruiters employ during sourcing. Victoria, a recruiter in Law, shares how sourcing often requires her to use her judgment to attract prospective applicants that can fit the culture of an organization for which she is staffing.

> I have to match the hard skills, right, but I also have to match the culture fit. If I'm placing someone at TikTok (a video-sharing social media company) versus I'm placing someone at a law firm—one of whom, the name partners, used to work for Donald Trump—the people I'm going to send on interviews to those places will not be the same. I have to be cautious about that, and LinkedIn can help screen for the best candidate, but when my best candidate has an "I support Black Lives Matter" banner on their LinkedIn profile, I'm not sending them on an interview with a conservative law firm.

In this situation, Victoria highlights that although sourcing technologies can often be beneficial for screening candidates on explicit criteria (e.g., "hard skills"), her embedded understanding of an organization often supersedes the recommendations provided by the AI software. These forms of implicit knowledge are signaled through cues by applicants from the content they post to their LinkedIn profiles, which are then readily used in searches and filtering within sourcing practices.

Alternate Accounts of Sourcing

This analysis has presented findings that demonstrate how most recruiters use their expertise to evaluate candidates based on a dichotomy of explicit and implicit forms of knowledge. However, it should be noted that not all participants in this case study base sourcing decisions on ambiguous criteria like implied quotas or a candidate's self-presentation style. Six participants expressed strictly adhering to the specific requirements and qualifications in a job requisition's advertisement or description. Interview probes about the relationship that recruiters maintained with their hiring organizations offered insight into their unwavering approach to sourcing for clear, listed criteria. Tao, who sourced for a staffing agency, describes how he "didn't know much about the firm he was sourcing for" or "was unsure of the needs" for a position he was assigned to source for. In such situations, the absence of understanding and familiarity with hiring managers, or their organization's needs, led these recruiters to depend on sourcing software for limited, methodical keyword searches. They focused on specific skills or qualifications present in candidate data.

Moreover, this set of recruiters described working under strict sourcing guidelines mandated by their hiring managers. These managers sought more involvement in the sourcing process, often requesting recruiters to produce a list of prospective candidates for further screening. Consequently, recruiters frequently used "plug and chug" techniques, focusing on keywords listed in a job description to compile an extensive list of prospective candidates. These alternate accounts shed light on how organizational contexts can influence recruiters' decisions when interacting with sourcing technologies. In certain circumstances, recruiters may lean toward more objective and systematic sourcing methods, eschewing the implicit forms of knowledge often associated with the recruitment process.

Recognizing the Value of Sourcing in the Hiring Processes

> It's challenging navigating this job. It's not always a little thumbs-up or little thumbs-down [referring to a tool that includes or excludes a candidate from a sourcing list]. So, there are definitely times where I'm like, "Why did this person come up in the proposed candidates list when they don't have what I need?" I can't always find someone who checks all the boxes [referring to qualifications], but it's my job to find someone who I think is going to do well. If the client doesn't like who I send on a screener [initial interview], that reflects back on me.

In the previous quote, Jessie, a technical recruiter, describes her experience recruiting for a client in the food and beverage industry. This quote underscores the intricate and layered nature of sourcing in recruitment processes. Instead of merely being a binary task of approval or rejection, sourcing emerges as a nuanced endeavor requiring strategic decision making and judgment. The process confronts recruiters with the challenge of aligning algorithmic recommendations with the specific requirements of a role, which can lead to discrepancies in the proposed candidate list. Sourcing, as portrayed here, involves an intricate interplay between the structural features of an organization—including recruitment demands, technological parameters, and extant expertise—and communicative interactions. These interactions are mediated through and influenced by the efficacy of successful candidate searches, demonstrating the reflective nature of this practice. Sourcing provides recruiters an opportunity to exert autonomy and control over the hiring process from an initial stage by identifying, and cultivating candidates based on their expertise. Recruiters often describe providing value to their organizations by marking their ownership over a unique process that influences the remainder of the hiring process. At large, their work refines an organization's applicant pool by reducing the time to select and hire candidates who possess relevant skills, experiences, and qualifications for a job.

Discussion

The findings of this study demonstrate that through the course of candidate sourcing, recruiters engage in a recurrent set of practices that leverage their situated knowledge to coordinate decisions across algorithmic technology and organizational demands, ideologies, and policies. Recruiters in this study occupy an advantageous position as brokers in the search and attraction processes that occur between prospective candidates, hiring managers, and the technologies that present their data in actionable ways. Expert-AI interactions based on an organization's hiring needs enable recruiters to engage in negotiations that straddle the social and technical, using codified and implicit knowledge about applicants that only they possess during the initial stages of hiring. As the empirics of this study demonstrate, sourcing candidates is rarely dependent on a single factor. The process expertise that is used in sourcing accentuates the complexity of different factors that recruitment personnel manage when evaluating a prospective candidate's job fit. In turn, recruiters leverage different forms of algorithmic hiring techniques, creating a paradox of fairness where decisions may appear unsystematic yet are validated within their professional contexts.

Process Expertise Shapes the Algorithmic Playing Field

Sourcing supports larger organizational needs using affordances provided by AI-driven hiring platforms. This work informs the theory of process expertise (Barley et al., 2020; Treem & Barley, 2016) and enriches its understanding through an empirical examination of how experts in talent acquisition coordinate their work to "manage the tension between specialization and integration" of expert knowledge (Barley et al., 2020, p. 33). Moreover, the effective coordination between multiple forms of domain knowledge—including technical knowledge about algorithmic systems, institutional knowledge, and situated knowledge about the hiring process—responds to growing research that assesses the boundaries of communicative frameworks within the study and use of algorithmic technologies (Guzman & Lewis, 2020).

As with the use of any type of technology at work, algorithms are subjected to institutional conventions that are embedded within an organization's social structure. Recruiters complete their jobs by framing technology practices to reaffirm structural norms and ideologies. While explicit and implicit forms of data are available for access by other domain experts in their organizations, recruiters capitalize on their process expertise by gatekeeping sourcing techniques not known to other domain counterparts. Sourcing is a critical component within the hiring process (e.g., from sourcing to screening and selection), and recruiters occupy a legitimized, central role among other domain experts.

Sourcing Enables Paradoxical Decisions

The intent of this study was not to develop a generalized theory of sourcing that is mediated through algorithmic technologies but rather to understand the meaning-making processes that influence different dimensions of searching and selecting prospective job candidates. In doing so, the findings reveal how a recruiter's process expertise is used to justify biased decision-making strategies employed during candidate evaluation. Implicit candidate expectations from management were recognized as mechanisms that allowed recruiters enough latitude to form judgments about a job seeker's merits, qualifications, and personality fit with their organization. To theoretically aid in explaining the process by which experts justify their evaluative decisions about candidates, I turn to research in organizational sociology on cultural matching within employer decision making (Rivera, 2012, 2016, 2020). In essence, cultural matching is an embedded process in hiring where similarities of a candidate's background, leisurely interests, and self-presentation styles are signals for likability and fit to a company (Rivera, 2012). Candidates who appear similar to their prospective employers are often more favored by recruitment and hiring personnel (Ajunwa, 2019; Rivera, 2016). Even more, the effect of culture matching within organizations is substantial because employers are known to hire and promote workers who are similar to their peers (Rivera, 2020). Concerning algorithmic sourcing, the architecture of evaluation, referring to the design of technical tools and metrics, are "not neutral instruments; they are sources of power and engines of inequality that strongly shape how people distribute attention, resources, and rewards" (Rivera & Tilcsik, 2019, p. 3).

In the practice of sourcing, this study reveals a "paradox of fairness" in the use of AI tools for hiring. Although these tools are employed to standardize the search for qualified and competent job seekers, their implementation by recruiters within organizations can introduce a layer of expert judgment, potentially affecting the systematic integrity of the tools' recommendations and insights. In recruiting, organizational pressures to reduce the time for filling a requisition, as well as sourcing for fit, may lead recruiters to use AI-driven outputs to form judgments or perceptions about job seekers.

This paradox sets the stage for the emergence of algoactivism (Kellogg et al., 2020) in the intricate interplay between recruiters, prospective candidates, and algorithmic tools. This form of individual engagement, where recruiters exert experience-based judgments to moderate or counter the outputs of algorithms brings forth a unique dynamic in the sourcing process. Algoactivism is embodied when recruiters, using their nuanced understanding of organizational needs, exert their expertise to shape the outcome of candidate sourcing. For instance, they might preemptively exclude individuals who, despite being algorithmically shortlisted, are deemed unsuitable or include others who might have been overlooked by algorithmic sourcing. In doing so, these experts are engaging in a form of "individual resistance" (Kellogg et al. 2020, p. 383) by strategically using their expertise and leveraging the capabilities and limitations of the AI tools. This normalization of technology practices as part of their expertise not only forms an integral aspect of their workflows but also can influence broader institutional factors such as training regimes, norms, and policies related to future technology use.

Implications Based on the Present Case Study

The aim of this case study does not intend to promote nor dissuade employers from integrating AI-driven technologies into their hiring practices. The findings reflect self-reported behaviors by recruiters who sourced job seekers across various industries, each with unique institutional histories that have shaped employee policies, norms, and ideologies. In addition, these perspectives reflect the sociotechnical experiences and meanings of recruiters who evaluate candidates based on limited information and do not include the perspectives of job seekers, those that are directly impacted by employer decisions.

Another limitation of this study is that it does not delve into the specific features or affordances of the sourcing software or investigate how recruiters adapt their use of the technology according to varying degrees of machine and data bias, which refers to the predispositions embedded within AI systems due to biased training data or data structures. Testing the effects of different software characteristics on recruiters' behaviors and expert decision-making processes could provide valuable insights. This, along with a more comprehensive understanding of how machine bias impacts the recruiting process, provides a fruitful avenue for future research.

As organizations incorporate AI-driven tools into their recruitment practices, those involved in the design and deployment of predictive tools should reconsider the validation and auditing processes of their technologies to better integrate the practical experiences of end users such as recruiters and hiring managers. Furthermore, technology design needs to acknowledge and accommodate different forms of expertise, like process expertise, which are often integral to the ways that outputs are used, interpreted, and incorporated into broader organizational workflows.

Conclusion

Outside of academic spaces, to the average user, an algorithm is commonly viewed as a type of "trick," or tricks of the trade, that are used as a shortcut to help simplify a process that would otherwise be laborious. However, as technology and communication research consistently demonstrate, the applications and implications of these technological shortcuts extend far beyond their intended use (e.g., Bailey & Leonardi, 2015). The integration of technology into the workplace, despite being data driven and systematized, inevitably becomes entwined with value-laden, social, and individual processes. By placing a responsibility to empirically investigate emerging technologies as part of dynamic interactions between experts, tools, and contexts, we can begin to expand our existing frameworks of study toward more aware and fair practices.

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