AI and Inequality in Hiring and Recruiting: A Field Scan

Dinika, Adio-Adet; Sloane, Mona

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AI AND INEQUALITY IN HIRING AND RECRUITING

A FIELD SCAN

Dinika, Adio-Adet
Bremen International Graduate School of Social Sciences (BIGSSS)/
Distributed AI (DAIR) Institute
Bremen, Germany
adinika@uni-bremen.de

Sloane, Mona
University of Virginia
Charlottesville, USA
mona.sloane@virginia.edu

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ABSTRACT

This paper provides a field scan of scholarly work on AI and hiring. It addresses the issue that there still is no comprehensive understanding of how technical, social science, and managerial scholarships around AI bias, recruiting, and inequality in the labor market intersect, particularly vis-à-vis the STEM field. It reports on a semi-systematic literature review and identifies three overlapping meta themes: productivity, gender, and AI bias. It critically discusses these themes and makes recommendations for future work.

1 INTRODUCTION

Artificial intelligence (AI) has taken a strong foothold in the human resources (HR) management domain, and recruiting specifically: the global market of AI-driven tools used in recruiting is expected to grow to $695 million (A2Z Market Research 2022), seemingly addressing automation needs of recruiting professionals across the hiring funnel. These developments run parallel to two other major phenomena: an ever raging "war on talent" in the science, technology, engineering, and mathematics (STEM) fields that maps onto the most promising fields of technology innovation and global competition, most recently the semiconductor industry (Shein 2023); and the escalation of global inequality (Savage 2021; Piketty 2014).

While regulatory concerns around enhancing the technical workforce rub shoulders with efforts to curb AI bias in recruiting, there still is no comprehensive understanding of how technical, social science, and managerial scholarships around AI bias, recruiting, and inequality in the labor market intersect, and importantly what similar or distinct narratives emerge. Therefore, the objective of this paper is to provide a comprehensive overview of the research conducted on these intersecting topics, to synthesize the knowledge, and to identify key themes that can provide new avenues for interdisciplinary research on AI, inequality, and recruiting.

2 METHODS

Since the goal of this paper is to accurately map existing scholarly works on AI bias, recruiting, and inequality in STEM across more than one discipline, a literature review is the most appropriate method. As the intersection of AI bias, recruiting, and inequality in STEM is a novel topic, a semi-systematic approach to literature review was chosen as this method provides an *overview* of a research area. Furthermore, the semi-systematic approach focuses primarily on research articles as source material rather than, for example, quantitative datasets from past studies (Snyder 2019). Also labeled a narrative review approach, it allows the examination of *topics* that have been conceptualized differently by different research communities across diverse disciplines (Wong et al. 2013). To provide a field scan, rather than an exhaustive literature review, the semi-systematic approach mandates a meta view that does not aim to review every single paper on any given topic, but that aims at reviewing a topic by way of examining how a topic has developed across a selection of disciplinary domains (Snyder 2019).

For this paper, we used a three-step strategy for our semi-systematic literature review. First, we conducted a high-level topical search across social science and technical fields to identify the most relevant domains for our more focused literature review. We made this decision based on papers available per topic (AI bias, recruiting, and inequality in STEM) per domain. Technical scholarship, mostly in computer science, social science, and management emerged as the dominant domains. We analyzed the collected papers by way of qualitative coding to identify key themes. In a second step, we expanded our literature search by way of keyword search along the themes and across these three domains and collected further relevant scholarly papers that were available. Our final dataset included 56 papers. In the third and last step, we read and analyzed the papers, summarizing and further coding the data to condense themes which we then clustered into the three meta themes we discuss below: productivity, gender, and AI bias. It is important to note that these themes are not neatly distinct but overlap and converge at times, and that cited papers are representative of wider discourses. It is also important to note that due to language restrictions (all papers had to be available in English to be accessible by the research team), selection bias occurred.

3 FINDINGS

3.1 Productivity

The first meta theme of *productivity* describes the major concern of making all things recruiting more "efficient" by way of introducing AI. It echoes well-known narratives of techno-solutionism deployed in the general discourse around work and automation. Generally, the use of AI in recruitment is already on the rise, with 98% of Britain's Fortune 500 companies using automated hiring systems (AHSs) to onboard employees (Graham et al. 2020). In 2019, 99% of Fortune 500 companies used Applicant Tracking Systems (ATS) such as Workday, Taleo, SuccessFactors, BrassRing, and iCIMS (Hu 2019), to recruit and onboard new employees. While ATS have been around for a long time, they are increasingly equipped with AI-driven tools, such as resume screeners and candidate rankers (Manatal 2022), adding on to the already full AI-toolbox that recruiters use consisting of natural language processing (NLP) tools to write more "inclusive" job descriptions and ads, targeted advertising for placing job ads on various platforms and in different outlets, AI-driven job and talent search platforms to search for suitable job candidates, video interviewing software, AI-driven personality testing, automated skills assessment, or chatbots.

The latter in particular has been hailed as increasing efficiency in in candidate communication, for example by providing real-time feedback, addressing inquiries, and consistently engaging with the candidates throughout the hiring process (Brishti and Javed 2020). In particular, chatbots are perceived by recruiters as improving accessibility and lowering the application threshold (Koivunen et al. 2022), not least because they can answer a candidate's questions and address their concerns before they even apply (Nawaz and Gomes 2019). Similarly, chatbots have been depicted as a "quick and easy way" to improve efficiency and performance due to their 24/7-availability (Zamora 2017), helping recruiters understand the experience of a candidate, and to automate the more administrative side of recruiting, such as scheduling interviews.

This falls in line with common narratives around increased efficiency and reduced cost in AI-driven recruiting (Singh and Finn 2003; Okolie and Irabor 2017), due to what is perceived as a streamlining of the hiring process, especially in the context of pre-selecting suitable candidates (Derous and De Fruyt 2016). The latter has become more challenging for recruiters as technology has significantly lowered the application threshold and increased the application volumes, leaving HR practitioners with a growing amount of data they must take into account (Guo et al. 2021). This means that recruiters are expected to use technology to increase their productivity but are also facing enlarged workloads *due* to technology. Yet, recruiting professionals see using AI-enabled software as an efficient way of processing candidate data and, thus, as a pathway for introducing or advancing candidates from broader and more diverse pools (L. Li et al. 2021). Invoking the idea of tech neutrality, scholars have also suggested that AI-driven tools are less prone to bias and can be more impartial than human recruiters (Upadhyay and Khandelwal 2018), partially by manipulating AI to avoid bias (Black and van Esch 2020).

3.2 Gender

The second meta theme of *gender* emerges specifically vis-à-vis the STEM labor market and a lack of diversity across STEM jobs. Here, it appears to be undisputed that the "pipeline problem" – i.e., not having sufficient input and retention of STEM students – maps most strongly onto a stark gender divide (Hill, Corbett, and St. Rose 2010; Beede et al. 2011), leading to notoriously small and homogenous talent pools in the STEM fields. For example, in 2019, 73% of all STEM workers in the US were men (US Census Bureau 2021). Various theories percolate around the cause of such strongly sustained gender divisions in the STEM field. These range from a lack of girls' social identity with mathematics (Akin, Santillan, and Valentino 2022) to access to education and educational choices (Hanson and Krywult-Albańska 2020; Bertrand 2020). Scholars have outlined that children display equal interest in mathematics, regardless of gender, in primary and secondary school (Riegle-Crumb et al. 2012) but then diverge in middle school (Akin, Santillan, and Valentino 2022; Seo, Shen, and Alfaro 2019). It has been argued that a deliberate investment in the up-scaling of enrolment of women into STEM programs can have a positive influence on retaining women in STEM-related jobs (Botella et al. 2019). Flowing from these concerns is a present and overwhelming narrative of needing to support women's careers in STEM.

Treated somewhat separate to this body of work is scholarship on the harmful effects of gender stereotyping on education and the composition of the workforce, and the STEM workforce specifically. Here, it has been argued that relative poorer performance of girls and women in mathematics is gender-constructed (Bertrand 2020) which is, for example, evidenced in mathematics teachers' implicit stereotyping having a measurable negative effect on girls' performance in mathematics (Carlana 2019) or in primary school teachers' biases favoring boys, which has been demonstrated to have a positive effect on boys' in-class achievements and enrollments in advanced-level mathematics courses with a corresponding negative effect on girls (Lavy and Sand 2015). These processes reinforce socially inappropriate roles for women and men, with material effects on women's STEM careers, particularly in the academe, as they are considered less able than men by important institutional players such as grant reviewers for the US National Institute of Health (Magua et al. 2017).

It can be argued that gender stereotyping is symptomatic of wider systems of oppression and (gender) inequality that are so infrastructural to the organization of social life that they take hold long before people enter any form of education (Gomez-Herrera and Koeszegi 2022). Historians have shown that these systems materialize in narratives around ability, skill, and power that have excluded women from ascending to more powerful positions alongside the rise of computer, even though "computing", originally, was a high-skill, low reputation role typically occupied by women (Hicks 2017). The knock-on effects of this "gender shift" reinforce the "vicious cycle of digital inequality" in which inequalities and gender stereotypes in society underpin segregation in society and the professions, leading to technologies amplifying (gender) inequality (Gomez-Herrera and Koeszegi 2022). The AI field is a prime example of this dynamic with women accounting for only 22% of all AI and computer science higher degree programs in North America in 2019, and currently only 26% of the data and AI workforce being classified as women (Deloitte 2022).

When putting these findings in context with the composition of the field of human resource management, a field which is currently undergoing rapid technological change, including in recruiting, an equally stark gender divide emerges. In the US, the occupation of "human resource manager" is comprised of over 80% women. The opposite is true for the tech industry that is fueling the AI-fication of recruiting, the “computer and mathematical occupations”, which has an only 26% share of women (U.S. Bureau of Labor Statistics 2021).

3.3 AI Bias

The third and last meta theme that emerges at the intersection of equity in AI, recruiting, and STEM in the fields of computer science, social science, and management scholarship is the theme of *AI bias*. The potentially discriminatory effects of AI in general have, by now, been aptly demonstrated. For the purposes of this paper, these can best be schematized by mapping them onto two dominant AI techniques: computer vision and natural language processing (NLP). Computer vision systems set out to replicate elements of the human vision system and train computers to identify and parts of the complexity of the human vision system and enabling computers to locate and classify objects in images and videos (Mihajlovic 2021). In the context of recruiting, computer vision-based AI is, for example, used in extracting text from the image of a CV, or for the automated analysis of virtual interviews. NLP sets out to model human language by way of combining computational linguistics with statistical analysis, machine learning and deep learning in order to “understand” the meaning of written or spoken speech (IBM n.d.; Yse 2019). NLP used in recruiting includes AI-driven systems used to write job ads, as well as candidate search systems, resume parsers, pre-screening processes, chatbots, and more (Recruiter.com n.d.).

Evidence of intersectional discrimination in computer vision has prominently been proposed by (Buolamwini and Gebru 2018) who demonstrated that facial recognition technologies show disproportionately higher inaccuracy rates for women with darker skin tones. Unevenly distributed false positives in facial recognition technology amplify racial discrimination (Najibi 2020), for example in policing in the United States (Crockford 2020; Perkowitz 2021) and in education. Facial recognition technology used in online proctoring during the Covid-19 pandemic has been shown to be biased against students with certain skin tones and genders (Yoder-Himes et al. 2022). Similarly, word embedding, a framework used in NLP, replicate societal bias and provide pathways for perpetuating sexist tropes (Bolukbasi et al. 2016), as well as perpetuate historic biases more generally (Caliskan 2019).

In the context of recruiting, researchers have found that resume search engines working with text data and demographic features can produce rankings that disadvantage some candidates (Chen et al. 2018). Others have outlined how the automation of hiring by way of algorithmic systems can facilitate and obfuscate employment discrimination (Ajunwa 2019), especially in the context of hiring platforms (Ajunwa and Greene 2019) and algorithmic systems used for workforce management (Ajunwa 2020). Issues of validity in personality-assessment tools used in recruiting have been demonstrated by an interdisciplinary team of scholars conducting a stealth audit (Rhea et al. 2022) while investigative journalists have highlighted how hiring AI increasingly works as “black box” gatekeeper in the hiring process (Schellmann 2022), including in public agencies (Varner 2021). A more nascent body of work examines how recruiters use and make sense, and often only reluctantly embrace, various AI tools (L. Li et al. 2021).

The latter body of work connects to older scholarships on *human* bias in recruiting. For example, well known studies have shown strong bias against African-American-sounding names in the application process (Bertrand and Mullainathan 2004) and underlined the formation of ethnic bias in resume screening (Derous and Ryan 2019) which can lead to job candidates from racial minorities to engage in “résumé whitening” (Kang et al. 2016). Work on gender discrimination in hiring, similarly, has long demonstrated how recruiting bias disproportionately affects women (Birkelund et al. 2022; Barron et al. 2022), particularly women of childbearing age (K. K. Li et al. 2022). Interestingly, the issue of human bias in recruiting has been used as the main argument *for* seemingly “neutral” AI applications in HR more broadly (Raghavan et al. 2020), promising to decrease gender discrimination specifically (Pisanelli 2022), often couched in narratives of “scientism” (Vassilopoulou et al. 2022). More recent studies, however, have shown that these types of claims are misleading, misconstruing AI technology as neutral and misunderstanding the dynamics of gender and race (Drage and Mackereth 2022).

4 DISCUSSION

To provide new avenues for interdisciplinary research on AI, inequality, and recruiting, it is helpful to have a clear understanding of how the three meta themes of productivity, gender, and AI bias emerge at the intersection of technical, social science, and managerial scholarship. However, it is equally important to critically discuss these themes to chart their limitations and make future work more effective.

Whilst the term “bias” has been productive for highlighting both the allocative and the representational harms that AI can cause (Barocas, Hardt, and Narayanan 2021), it also has been critiqued as being conditioned on an inherently normative process and as not being connected well across disciplines (Blodgett et al. 2020). It also tends to skew conversations around AI harm towards training data rather than societal inequalities (Sloane 2019), organizational decision making (Moss and Metcalf 2020; Sloane and Zakrzewski 2022; Rakova et al. 2021), and algorithm and models themselves (O’Neil 2016; Zou and Schiebinger 2018). In the context of recruiting and hiring specifically, a narrow focus on bias also precludes a much needed critical examination of the potentially discriminatory assumptions baked into AI (Sloane, Moss, and Chowdhury 2022), as well as locates bias in either people or technologies, rather than in socio-technical systems. This precludes a closer examination of how socio-technical bias occurs in the hiring funnel. We propose that to address this issue, a closer examination of socio-technical systems is critical. Bias could emerge from these systems because of the interactions and relationships between these social and technical components, not merely between individuals and technologies. Therefore, a practice-based approach that focuses on how technologies are used and made sense of in discretionary decision making is vital. Future research in this area should include investigations into the role of organizational structures, work processes, technological implementation, continuous data input and interpretation and of bias mitigations trainings. Such an investigation will be paramount for enhancing the understanding of harm produced by socio-technical systems in HR.

Similarly, scholars have outlined the limitations of the “pipeline problem”, demonstrating that “improving the pipeline” does not necessarily improve discriminatory workplace cultures in STEM institutions (Rankin 2022), or increase diversity in the workforce (Dickey 2021; Bui and Miller 2016). To the contrary, it has been argued that ramping up the enrollment of women in STEM clusters runs the risk of labeling women as “affirmative enrollments” (Heilman, Block, and Stathatos 1997) or of framing gender as binary or one-dimensional. One could also argue that the gender and racial stereotyping that occurs as a function of social stratification in society is amplified by the representational harm that is propagated through label and unlabeled data that AI models are trained on. Indeed, scholars have demonstrated that demographic information about individuals can be inferred from online data without said individuals explicitly relaying such information (Karimi et al. 2016; Fiscella and Fremont 2006). This highlights the need of technical education of HR and specifically recruiting professionals so that they themselves are literate in the potential generation of bias in socio-technical systems.

Whilst increased productivity has been framed as major driver for AI-adoption in recruiting, we still know very little about e-recruiting in general (Chapman and Gödöllei 2017) and specifically how professional recruiters actually use AI in their professional practice, and if there indeed is an increase in productivity ushered in by AI. What is known, however, is that HR practitioners remain critical of the technology, lacking a trust in data accuracy and decrying an inadequate level of control over algorithmic candidate matches (L. Li et al. 2021). There appears to be a clear need for a more decided engagement of HR professionals in shaping choices around AI in the professional practice of recruiting, not least to circumnavigate what is perceived as threats of largescale automation (Anthony 2021; Charlwood and Guenole 2022).

5 CONCLUSION

This paper has addressed the issue that there still is no comprehensive understanding of how technical, social science, and managerial scholarships around AI bias, recruiting, and inequality in the labor market intersect, particularly vis-à-vis the STEM field. It has reported on a semi-systematic literature review and concluded that currently three overlapping themes dominate: productivity, gender, and AI bias. It has detailed each theme before critically discussing the findings. The key take-away from this study is that the overwhelmingly female and white profession of HR and recruiting is substantially changed through the introduction of AI, which is initiated and driven by the predominantly male and majority white "computer and mathematical occupations" (U.S. Bureau of Labor Statistics 2021). Here, a "gender flipping" (Hicks 2017) occurs that sees men slotted into feminized jobs, here by way of the technology itself, as well as a further racial stratification of the HR industry. Future work should focus further on critically examining this dynamic across an even wider spectrum of disciplines (such gender, critical race, and disability studies) to inform applied AI design, HR management, and policymaking. Such an approach could, for example, be facilitated by way of using social practice theory, or example by way of taking a practice-based approach (Shove, Pantzar, and Watson 2012) (Sloane and Moss 2022).

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