EMPLOYMENT DISCRIMINATION IN THE DIGITAL AGE

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In the wake of the #MeToo and Time's Up movements, employers are facing increased public pressure to diversify their workforce and implement best practices to solve persistent gender inequities that limit women's access to positions of power and influence. As one possible approach, many employers have embraced advancements in artificial intelligence (AI) and machine learning technologies to introduce "objective" decision making into the hiring process.[1] While the use of data-driven, predictive analytics hold the promise of eliminating subjective bias throughout the talent acquisition process, there is a tendency in the era of "big data" to have blind faith that these algorithms' systems are fair and objective simply because they are based on "magical mathematical formulas." This is a deeply misguided misconception: these algorithms are designed by inevitably flawed humans who, even with the best of intentions, may use inaccurate, biased, or incomplete data sets that can encode prejudice into the models.[2] Often, the data is based on historical hiring data at a company, which can serve to replicate prior interpersonal, institutional bias.

For example, in 2014, Amazon started to develop an algorithmic recruiting tool to review resumes in order to automate the search for top talent.[3] The tool was trained with data from resumes of persons hired in the past ten years at the company, who unsurprisingly, were predominately men.[4] As a result, the algorithm preferred only male applicants and penalized graduates of all-women colleges or resumes that included phrase like, "Society for Women Scientists."[5] The tool was shelved after the company realized it could not be sure the algorithm would not continue to develop other discriminatory ways of sorting candidates. In another highly publicized episode, a resume screening vendor revealed its algorithm found being named "Jared" and playing high school lacrosse were the strongest predictive indicators of success. Despite this correlation in the data, those criteria are in no way causally related to job performance.

Given these examples, it's no surprise these technologies raise legitimate concerns about the risk of replicating historical bias and violating antidiscrimination laws, such as Title VII of the Civil Rights Act of 1964, the Age Discrimination in Employment Act ("ADEA"), and the Americans with Disabilities Act ("ADA"). Under federal law, plaintiffs must show either disparate treatment ("smoking gun" evidence of explicit, intentional discrimination) or disparate impact (statistical proof of discrimination against a certain group of applicants, such as women,

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[1] Jennifer Zaino, *Can AI Improve Diversity in the Workplace?,* BIZTECH (Sept. 10, 2019), https://biztechmagazine.com/article/2019/09/can-ai-improve-diversity-workplace.

[2] *See generally*, CATHY O'NEIL, WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY 3 (2016) (offering an analysis of the moral and ethical risks of "big data," and the opaque, complex modeling systems that are increasingly managing our lives).

[3] Jeffrey Dastin, *Amazon Scraps Secret AI Recruiting Tool That Showed Bias Against Women*, BUSINESS NEWS (Oct. 9, 2018), https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G.

[4] *Id.*

[5] *Id.*

who were disproportionately rejected).[6] Disparate impact claims arise frequently in the context of a test or selection procedure. In 1978, the Civil Service Commission, the Department of Labor, the Department of Justice, and the Equal Employment Opportunity Commission promulgated the Uniform Guidelines on Employee Selection Procedures ("Uniform Guidelines") to provide employers with a set of principles to determine whether a test or selection procedure is non-discriminatory, including the appropriate means of validation when the selection procedure adversely affects a protected group.[7] In addition, both Title VII[8] and the ADEA[9] forbid discrimination in advertising.

Given the fact these laws were adopted in an era of small data, their applicability to modern predictive hiring technologies remains ambiguous and in need of reform to ensure automated platforms do not worsen employment discrimination. First, it is important to understand all of the various ways that employers are using these technologies. A recent survey over 1,000 global talent acquisition professionals found over 70 different recruiting technologies are available on the market today,[10] and they are being deployed at every stage of the hiring process from determining who sees online job advertisements, to screening and predicting an applicant's qualifications and "fit" for a particular role.[11]

For example, these tools include the use of predictive technologies to optimize ad placement, for example, microtargeting advertisements to specific individuals based on social media habits or other online characteristics.[12] In addition, vendors are offering pre-employment hiring screens, which range from basic screening questions[13] to review of resumes with machine learning techniques[14] to predictive assessments using online tests[15] or "neuroscience" web games.[16] Even at the interviewing stage, the use of AI-powered video and audio screens are replacing human contact while capturing data on facial cues, body language, and word choice.[17] In effect, screening algorithms are the modern "gatekeepers of economic opportunity."[18]

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[6] Civil Rights Act of 1964 § 7, 42 U.S.C. § 2000e (2018); Americans with Disabilities Act of 1990 § 1, 42 U.S.C. § 12112(b)(6) (2018); Age Discrimination in Employment Act of 1967, 29 U.S.C. §§ 621-634 (2018).
[7] Uniform Guidelines on Employee Selection Procedures (1978), 29 C.F.R. § 1607 (2019).
[8] Civil Rights Act of 1964, *supra* note 6.
[9] Age Discrimination in Employment Act of 1967, *supra* note 6.
[10] Jon Bischke, *Welcome to the Age of Recruiting Automation*, FORBES (Apr. 19, 2019), https://www.forbes.com/sites/forbestechcouncil/2018/07/12/welcome-to-the-age-of-recruiting-automation/#7c51409c1865.
[11] Miranda Bogen & Aaron Rieke, *Help Wanted: An Examination of Hiring Algorithms, Equity, and Bias*, UPTURN, 13 (Dec. 2018), https://www.upturn.org/static/reports/2018/hiring-algorithms/files/Upturn%20--%20Help%20Wanted%20-%20An%20Exploration%20of%20Hiring%20Algorithms,%20Equity%20and%20Bias.pdf
[12] Louis Matsakis, Facebook's Ad System Might Be Hard-Coded For Discrimination, Wired (April 6, 2019), https://www.wired.com/story/facebooks-ad-system-discrimination/.
[13] *About Us*, MYA, https://mya.com/about (last visited Oct. 1, 2019).
[14] *Resume Screening: A How-To Guide for Recruiters*, IDEAL, https://ideal.com/resume-screening/ (last visited Oct. 1, 2019).
[15] *About Koru*, KORU, https://www.joinkoru.com/about/ (last visited Oct. 1, 2019).
[16] *About Us*, PYMETRICS, https://www.pymetrics.com/about/ (last visited Oct. 1, 2019).
[17] Bogen, *supra* note 11, at 36-37.
[18] Jenny R. Yang & Bapuchandra Kotapati, *Artificial Intelligence and Its Impact on the Future of Employment Equity*, URBAN INSTITUTE (June 13, 2019), https://next50.urban.org/article/artificial-intelligence-and-its-impact-future-employment-equity.

Unfortunately, there is limited transparency on the methodology used and the validation of these algorithmic tools to ensure outcomes are not discriminatory.[19] A "black-box" algorithm can shield an employer from knowing which factors were the basis for a selection decision, which is problematic if they were protected characteristics or proxies for protected characteristics.[20] Moreover, it is unclear under existing law how to validate these algorithmic selection procedures, especially given the possibility of an algorithm's continual revision with machine learning.[21] The usual defense for tests or selection procedures–job relatedness–may also ambiguous in an algorithmic context, as every variable measured during the process is theoretically "related" to the job.[22]

Signaling possible avenues for greater transparency and accountability, there has been recent litigation success to hold actors liable for discriminatory effects of AI-powered technologies, specifically discriminatory advertisement placement. For example, earlier this year, Facebook settled a class action lawsuit for failing to prevent discrimination on the basis of race, age, and gender in employment, housing, and credit advertisement.[23] As a part of the settlement agreement, Facebook will no longer allow advertisers to target ads based on users' age, gender, race, categories associated with membership in protected groups, zip codes, or geographic areas less than a 15-mile radius.[24] The company also agreed to study the potential for unintended biases in its algorithmic modeling.[25] In addition, in 2017, the Illinois attorney general opened an age discrimination investigation into online hiring platforms using Jobr, a resume building tool with a "drop-down menu that prevented applicants from listing their college graduation year or year of a first job before 1980."[26]

These investigations and settlements are just the tip of the iceberg as regulators and civil rights advocates become increasingly aware of these tools and their possible discriminatory effects. More litigation is likely to come in the not too distant future. Therefore, it is important for employers to recognize that AI will not by itself guarantee fairer and more diverse employment outcomes. In order to capitalize on the available benefits of these technologies, we must better identify clear legal rules and ethical principles for their application.[27] Only with transparent design and a clear commitment to ongoing evaluation and monitoring can these data-driven, predictive systems achieve their intended purpose: to expand opportunity for historical excluded groups.

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[19] Bogen, *supra* note 11, at 46.

[20] *See* Solon Barocas and Andrew D. Selbst, Big Data's Disparate Impact, 104 California L. Rev. 671 (2016).

[21] *See* Manish Raghavan et al., *Mitigating Bias in Algorithmic Hiring: Evaluating Claims and Practices,* 8 (June 21, 2019), https://arxiv.org/abs/1906.09208#.

[22] *See* Pauline Kim, *Data Driven Discrimination at Work*, 58 WM & MARY L. REV. 857-936, 866 (2017) (arguing "[i]n the case of workforce analytics, the data algorithm by definition relies on variables that are correlated in some sense with the job. . . .[t]he more important question in the context of data mining is what does the correlation mean?").

[23] Outten & Golden, LLP, *Facebook Agrees to Sweeping Reforms to Curb Discriminatory Ad Targeting Practice* (Mar. 19, 2019), https://www.outtengolden.com/news/facebook-agrees-sweeping-reforms-curb-discriminatory-ad-targeting-practices.

[24] *Id.*

[25] *Id.*

[26] Ifeoma Ajunwa, *Beware of Automated Hiring*, N.Y. TIMES: OPINION (Oct. 8, 2019), https://www.nytimes.com/2019/10/08/opinion/ai-hiring-discrimination.html.

[27] For additional information on proposed legal solutions, I would recommend: Pauline Kim, *supra* note 22; Pauline Kim and Sharion Scott, Discrimination in Online Employment Recruiting, ST. LOUIS U. L. J. 63(1), 2019; Ifeoma Ajunwa, The Paradox of Automation as Anti-Bias Intervention, 41 CARDOZO L. REV. (2020 Forthcoming).