

THE PARADOX OF AUTOMATION AS ANTI-BIAS INTERVENTION

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A received wisdom is that automated decision-making serves as an anti-bias intervention. The conceit is that removing humans from the decision-making process will also eliminate human bias. The paradox, however, is that in some instances, automated decision-making has served to replicate and amplify bias. With a case study of the algorithmic capture of hiring as a heuristic device, this Article provides a taxonomy of problematic features associated with algorithmic decision-making as anti-bias intervention and argues that those features are at odds with the fundamental principle of equal opportunity in employment. To examine these problematic features within the context of algorithmic hiring and to explore potential legal approaches to rectifying them, the Article brings together two streams of legal scholarship: law & technology studies and employment & labor law.

Counterintuitively, the Article contends that the framing of algorithmic bias as a technical problem is misguided. Rather, the Article's central claim is that bias is introduced in the hiring process, in large part, due to an American legal tradition of deference to employers, especially allowing for such nebulous hiring criterion as "cultural fit." The Article observes the lack of legal frameworks to account for the emerging technological capabilities of hiring tools which make it difficult to detect bias. The Article discusses several new approaches to hold liable for employment

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discrimination both employers and makers of algorithmic hiring systems. Particularly related to Title VII, the Article proposes that in legal reasoning corollary to extant tort doctrines, an employer's failure to audit and correct its automated hiring platforms for disparate impact should serve as prima facie evidence of discriminatory intent, for the proposed new doctrine of discrimination per se. The Article also considers approaches separate from employment law, such as establishing consumer legal protections for job applicants that would mandate their access to the dossier of information consulted by automated hiring systems in making the employment decision.

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INTRODUCTION

The automation of decision-making processes via machine learning algorithmic systems presents itself as a legal paradox. On one hand, such automation is often an attempt to prevent unlawful discrimination,¹ but on the other hand, there is evidence that algorithmic decision-making processes may thwart the purposes of antidiscrimination laws such as Title VII of the Civil Rights Act of 1964² and may instead serve to reproduce inequalities at scale.³ Consider the recent discovery that the commerce company, Amazon, had secretly disbanded its algorithmic hiring system.⁴ In October of 2018, the news service, Reuters, reported that Amazon’s engineering team in Edinburgh, Scotland, had created 500 computer models that it used to “trawl through past candidates’ résumés and pick up on about 50,000 key terms.”⁵ Using those selected key terms, “[t]he system would crawl the web to recommend candidates.”⁶ Within a year of using the automated system, however, the engineers observed that

¹ “Advocates applaud the removal of human beings and their flaws from the assessment process.” Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 4 (2014). Algorithms or automated systems are often seen as fair because they are “claimed to rate all individuals in the same way, thus averting discrimination.” *Id.*

² Title VII of the Civil Rights Act of 1964, 42 U.S.C. §§ 2000e–2000e-17 (2018).

³ See, e.g., Solon Barocas & Andrew D. Selbst, *Big Data’s Disparate Impact*, 104 CALIF. L. REV. 671 (2016) (detailing issues of disparate impact associated with algorithmic decision-making); FRANK PASQUALE, *THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION* (2015) (detailing legal issues associated with the non-transparent use of algorithmic decision-making in several societal spheres); Andrew Tutt, *An FDA for Algorithms*, 69 ADMIN. L. REV. 83, 87 (2017) (“This new family of algorithms holds enormous promise, but also poses new and unusual dangers.”); see also VIRGINIA EUBANKS, *AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR* (2018); SAFIYA UMOJA NOBLE, *ALGORITHMS OF OPPRESSION: HOW SEARCH ENGINES REINFORCE RACISM* (2018); CATHY O’NEIL, *WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY* (2016); cf. Sandra G. Mayson, *Bias In, Bias Out*, 128 YALE L.J. 2218 (2019) (arguing that the problem of disparate impact in predictive risk algorithms lies not in the algorithmic system but in the nature of prediction itself).

⁴ Isobel Asher Hamilton, *Amazon Built an AI Tool to Hire People but Had to Shut It Down Because It Was Discriminating Against Women*, BUS. INSIDER (Oct. 10, 2018, 5:47 AM), www.businessinsider.com/amazon-built-ai-to-hire-people-discriminated-against-women-2018-10 [https://perma.cc/9W55-RZYP].

⁵ *Id.*

⁶ *Id.*

the results of the automated hiring system were unfavorable to women applicants; the automated hiring system preferred men.⁷

A potential cause: The computer models were trained on predominantly male resumes, with the result that the system concluded that men were preferred candidates; thus, it “downgraded résumés containing the word ‘women’s’ and filtered out candidates who had attended two women-only colleges.”⁸ As legal scholars such as Professor Sandra Mayson and others have demonstrated, such algorithmic bias is not limited to gender; algorithmic decision-making can also produce disparate racial impact, especially in the criminal justice system.⁹ Amazon’s story of negative discrimination against protected classes as an (un)intended outcome of automated decision-making is not singular. Recent books, like *Algorithms of Oppression*, have detailed the racially-biased impact of algorithms on information delivery on the internet,¹⁰ and others, like *Automating Inequality*, have outlined the biased results of algorithms in criminal justice and public welfare decision-making,¹¹ yet, with the exception of the work of a few legal scholars,¹² the role of

⁷ *Id.*

⁸ *Id.* Ironically, as the use of an automated hiring system revealed the gender disparity here in concrete numbers, this meant that such disparities could potentially be addressed by employment antidiscrimination law. Contrast this to what the legal scholar Professor Jessica Fink has identified as the more nebulous “gender sidelining,” a workplace dynamic in which, for example, “[w]omen often lack access to important opportunities or feel subjected to greater scrutiny than their male peers.” Jessica Fink, *Gender Sidelining and the Problem of Unactionable Discrimination*, 29 STAN. L. & POL’Y REV. 57, 57 (2018).

⁹ More often, legal scholars have considered algorithmic racial inequities in the context of the criminal justice system. *See, e.g.*, Mayson, *supra* note 3 (arguing that the problem of disparate impact in predictive risk algorithms lies not in the algorithmic system but in the nature of prediction itself); Aziz Z. Huq, *Racial Equity in Algorithmic Criminal Justice*, 68 DUKE L.J. 1043 (2019); Aziz Z. Huq, *The Consequences of Disparate Policing: Evaluating Stop and Frisk as a Modality of Urban Policing*, 101 MINN. L. REV. 2397, 2408 (2017); Andrew Guthrie Ferguson, *Big Data and Predictive Reasonable Suspicion*, 163 U. PA. L. REV. 327 (2015).

¹⁰ *See* NOBLE, *supra* note 3.

¹¹ *See* EUBANKS, *supra* note 3.

¹² *See, e.g.*, Stephanie Bornstein, *Antidiscriminatory Algorithms*, 70 ALA. L. REV. 519, 570 (2018) [hereinafter Bornstein, *Antidiscriminatory Algorithms*]; Stephanie Bornstein, *Reckless Discrimination*, 105 CALIF. L. REV. 1055, 1056 (2017) [hereinafter Bornstein, *Reckless Discrimination*]; Pauline T. Kim, *Data-Driven Discrimination at Work*, 58 WM. & MARY L. REV. 857, 908 (2017); Matthew T. Bodie, Miriam A. Cherry, Marcia L. McCormick & Jintong Tang, *The Law and Policy of People Analytics*, 88 U. COLO. L. REV. 961 (2017); Charles A. Sullivan, *Employing*

algorithms in perpetuating inequality in the labor market has been relatively overlooked in legal scholarship.¹³

Often, when legal scholars raise the topic of bias in algorithmic systems, a common retort is: “What’s new?”¹⁴ This rhetorical question is meant to convey the sentiment that bias in algorithmic systems cannot be a novel topic of legal inquiry because it has a pre-existing corollary, bias in human decision-making. However, scholars such as Professor Jack Balkin have exposed this retort as a facile dismissal of what are legitimate lines of scholarly legal inquiry.

[T]o ask “What is genuinely new here?” is to ask the wrong question. If we assume that a technological development is important to law only if it creates something utterly new, and we can find analogues in the past—as we always can—we are likely to conclude that because the development is not new, it changes nothing important. That is the wrong way to think about technological change and public policy, and in particular, it is the wrong way to think about the Internet and digital technologies. Instead of focusing on novelty, we should focus on salience. What elements of the social world does a new technology make particularly salient that went relatively unnoticed before? What features of human activity or of the human condition does a technological change foreground, emphasize, or problematize? And what are the consequences for human freedom of making this aspect more important, more pervasive, or more central than it was before?¹⁵

AI, 63 VILL. L. REV. 395 (2018); James Grimmelman & Daniel Westreich, *Incomprehensible Discrimination*, 7 CALIF. L. REV. ONLINE 164 (2017).

¹³ Going beyond the specific role of algorithms, some scholars have argued that workplaces in the United States are essentially allowed to operate as self-contained, self-governing bodies, without much scrutiny or oversight from regulatory bodies in regard to how the workplace is structured and organized. See ELIZABETH ANDERSON, *PRIVATE GOVERNMENT: HOW EMPLOYERS RULE OUR LIVES (AND WHY WE DON’T TALK ABOUT IT)* (2017) (making the argument that workplaces have become authoritarian private governments with little protection for the worker from the state).

¹⁴ See, e.g., Joseph H. Sommer, *Against Cyberlaw*, 15 BERKELEY TECH. L.J. 1145, 1148 (2000) (“[F]ew of the legal issues posed by the new informatics technologies are novel.”).

¹⁵ Jack M. Balkin, *Digital Speech and Democratic Culture: A Theory of Freedom of Expression for the Information Society*, 79 N.Y.U. L. REV. 1 (2004).

Other legal scholars have made similar points. As Professor Katyal notes: “the true promise of AI does not lie in the information we reveal to one another, but rather in the questions it raises about the interaction of technology, property, and civil rights.”¹⁶ My scholarly agenda has focused on examining the myriad ways in which new computing technologies bring to high relief existing societal biases and continued inequities, particularly in the employment sphere. In past work, I have parsed how online platforms might contribute to age discrimination in the labor market,¹⁷ and I have noted how wearable technologies deployed to manage the workplace prompt novel legal questions and suggest a new agenda for employment and labor law scholarship.¹⁸ I have also conducted an empirical study of work algorithms, which involved a critical discourse analysis and affordance critique of the advertised features and rhetoric behind automated hiring systems as gleaned through 135 archival texts, tracing the timeline of the development of hiring platforms from 1990–2006.¹⁹ That study concluded that while one purported *raison d’être* and advertised purpose of automated hiring systems was to reduce hirer bias—“replacing messy human decisions with a neutral technical process”²⁰—the reality remained that “algorithmic specification of ‘fit’ can itself become a vehicle for bias.”²¹

Deploying a case study of the algorithmic capture of hiring as a heuristic device, this Article makes several important contributions to

¹⁶ Sonia K. Katyal, *Private Accountability in the Age of Artificial Intelligence*, 66 UCLA L. REV. 54, 54 (2019).

¹⁷ Ifeoma Ajunwa, *Age Discrimination by Platforms*, 40 BERKELEY J. EMP. & LAB. L. 1 (2019).

¹⁸ Ifeoma Ajunwa, *Algorithms at Work: Productivity Monitoring Applications and Wearable Technology as the New Data-Centric Research Agenda for Employment and Labor Law*, 63 ST. LOUIS U. L.J. 21 (2018).

¹⁹ Ifeoma Ajunwa & Daniel Greene, *Platforms at Work: Automated Hiring Platforms and Other New Intermediaries in the Organization of Work*, in *WORK AND LABOR IN THE DIGITAL AGE* 61 (Steven P. Vallas & Anne Kovalainen eds., 2019).

²⁰ *Id.* “From a diversity perspective, artificial intelligence can be very beneficial . . . because it’s blind to things like color, age, sexual orientation.” Jeff Meredith, *AI Identifying Steady Workers*, CHI. TRIB. (July 16, 2001), <https://www.chicagotribune.com/news/ct-xpm-2001-07-16-0107160013-story.html> [<https://perma.cc/K2D7-J37S>].

²¹ Ajunwa & Greene, *supra* note 19. Consider that Unicru’s instruction manuals for users of its hiring platforms encourages them to “clone your best people” with the identification of existing high-sales employees within client records. A process that would be sure to replicate existing inequalities in the demographics of the workers. Ajunwa & Greene, *supra* note 19.

two streams of legal scholarship: employment & labor law and law & technology studies. First, the Article provides a taxonomy of problematic features associated with algorithmic decision-making as anti-bias intervention and argues that those features contradict the American bedrock principle of equal opportunity in employment. I observe that one faction of law and technology legal scholars has become preoccupied with determining the legal guidelines to ensure fair automated decision-making,²² while in employment and labor law, the concern is preserving equal opportunity for protected classes to obtain a livelihood;²³ these may represent disjointed interests given that technically fair systems may replicate historic inequalities.

Note that consistent with the approach of legal scholars like Professor Benjamin Sachs, I do not see employment law and labor law as “dichotomous, and in a fundamental respect incompatible, regulatory regimes.”²⁴ Rather, any worker gains accomplished via employment law may be leveraged towards collective bargaining, and thus, “employment law can in fact function as a substitute form of labor law—as the locus of workers’ organizational activity and as the legal mechanism that insulates that activity from employer interference.”²⁵ Furthermore, I argue that any clarity this Article affords in regard to combating algorithmic bias in employment decision-making may also be deployed to bargain for better, more probative hiring criteria.

However, law & technology studies and employment & labor law studies, as different schools of legal thought, approach the issue of algorithmic bias in divergent ways; the law & technology approach to bias has, thus far, with a few emerging exceptions, been from an anti-

²² Other scholars have also noted that this faction exists. *See generally* Ferguson, *supra* note 9; Citron & Pasquale, *supra* note 1, at 4; Barocas & Selbst, *supra* note 3.

²³ Cynthia Estlund has argued that Title VII should be understood as an “equal protection clause for the workplace.” Cynthia Estlund, *Rebuilding the Law of the Workplace in an Era of Self-Regulation*, 105 COLUM. L. REV. 319, 331 (2005); *see also* Samuel R. Bagenstos, *The Structural Turn and the Limits of Antidiscrimination Law*, 94 CALIF. L. REV. 1, 40–41 (2006) (arguing that the best explanation for employment discrimination law is its reflection of a broad goal of social change to eliminate group-based status inequalities).

²⁴ Benjamin I. Sachs, *Employment Law as Labor Law*, 29 CARDOZO L. REV. 2685, 2688 (2008).

²⁵ *Id.* at 2689.

classificationist approach,²⁶ wherein the focus is on the improper use of variables for protected classes in the decision-making process.²⁷ In the context of hiring, such an emphasis would revolve around the disparate treatment cause of action under Title VII.²⁸ Whereas employment & labor law literature now mostly focuses on anti-subordination, where the concern is the adverse impact of decision-making on protected groups, which mostly implicates the disparate impact theory under Title VII.²⁹

²⁶ Jack M. Balkin & Reva B. Siegel, *The American Civil Rights Tradition: Anticlassification or Antisubordination?*, 58 U. MIAMI L. REV. 9 (2003) (relating the history of the development and application of the two distinct antidiscrimination threads in American law); see also Jessica L. Roberts, *The Genetic Information Nondiscrimination Act as an Antidiscrimination Law*, 86 NOTRE DAME L. REV. 597, 631 (2011). Roberts notes:

These two versions of the antidiscrimination principle employ differing accounts of the meaning of equality. The antisubordination principle roughly holds that covered entities should not act in a way that reinforces the social status of subjugated groups. Antisubordination would, therefore, permit affirmative action designed to improve the status of a disadvantaged group and forbid facially neutral policies that perpetuate lowered group status, even absent the intent to discriminate. Its complement, the anticlassification principle, maintains that covered entities should not consider certain classes of forbidden traits under any circumstance, adopting a formal equal treatment model of equality.

Id. at 627–28.

²⁷ See, e.g., Joshua A. Kroll, Joanna Huey, Solon Barocas, Edward W. Felten, Joel R. Reidenberg, David G. Robinson & Harlan Yu, *Accountable Algorithms*, 165 U. PA. L. REV. 633 (2017). For a notable exception, see generally Barocas & Selbst, *supra* note 3 (detailing issues of disparate impact associated with algorithmic decision-making).

²⁸ Title VII states:

It shall be an unlawful employment practice for an employer—

(1) to fail or refuse to hire or to discharge any individual, or otherwise to discriminate against any individual with respect to his compensation, terms, conditions, or privileges of employment, because of such individual's race, color, religion, sex, or national origin; or

(2) to limit, segregate, or classify his employees or applicants for employment in any way which would deprive or tend to deprive any individual of employment opportunities or otherwise adversely affect his status as an employee, because of such individual's race, color, religion, sex, or national origin.

42 U.S.C. § 2000e-2(a) (2018).

²⁹ Title VII explicitly prohibits employers from using any “particular employment practice that causes a disparate impact on the basis of race, color, religion, sex, or national origin.” 42 U.S.C. § 2000e-2(k)(1)(A)(i). But see Bradley A. Areheart, *Information Privacy: GINA, Privacy, and Antisubordination*, 46 GA. L. REV. 705, 709 (2012). Areheart argues that “GINA . . . [represents] a turn toward anticlassificationist principles (and a possible turn away from antisubordination

This Article seeks to reconcile this gulf by noting first that machine learning algorithmic systems present opportunities for both disparate treatment and disparate impact discriminatory actions.³⁰ The Article then notes the particular difficulties of proving a disparate impact theory of discrimination when machine learning algorithmic systems have played a role in the employment decision-making process.

As a second contribution, I argue that too often law & technology scholarship displays a too narrow focus on technical definitions of fairness and overlooks the reality that facially neutral variables may still (in)advertently stand in for protected variables, thus meaning that there could still be a disparate impact on protected classes even when machine learning algorithms are technically fair.³¹ As a result of this myopic view, algorithmic bias, particularly in employment, has been framed as a technical problem, rather than as a matter of inadequate law. This offers a facile dismissal of algorithmic bias as a non-novel problem that could be solved by technical tinkering, or even as a non-problem since some argue that algorithmic systems represent an improvement from human decision-making.

To be sure, human managers hold biases that are reflected in unfavorable employment decisions for protected classes, but the impact of one biased human manager is constrained in comparison to the potential adverse reach of algorithms that could be used to exclude millions of job applicants from viewing a job advertisement or to sort thousands of resumes. The new phenomenon of concern here is that due to the “volume, velocity, and variety”³² of data used in automated hiring, any bias introduced in the system will be magnified and multiplied,

norms).” *Id.*; cf. Bornstein, *Antidiscriminatory Algorithms*, *supra* note 12, at 571. Professor Bornstein asserts that in addition to anticlassification and antisubordination theories underlying antidiscrimination law, antistereotyping principles should be considered since algorithmic discrimination can be liable for intentional discrimination as well as disparate impact.

³⁰ See Richard Thompson Ford, *Bias in the Air: Rethinking Employment Discrimination Law*, 66 STAN. L. REV. 1381 (2014) (noting that concepts in employment law such as “intent” and “causation” escape precise definition).

³¹ See generally Barocas & Selbst, *supra* note 3.

³² This refers to the three V’s of big data. David Gewirtz, *Volume, Velocity, and Variety: Understanding the Three V’s of Big Data*, ZDNET: DIY-IT (Mar. 21, 2018, 7:47 AM), <https://www.zdnet.com/article/volume-velocity-and-variety-understanding-the-three-vs-of-big-data> [<https://perma.cc/BH4Z-ALK9>].

greatly dwarfing the impact of any prejudice held by any one human manager.

A few caveats are in order for a useful reading of this Article. First, I remain agnostic as to whether the problems of biased algorithmic decision-making in hiring can or should be neatly classified as either disparate treatment or disparate impact. Rather, in addition to these two established legal theories for liability, I draw from organizational theory to offer my new theory of the automated hiring platform as a *tertius bifrons*.³³ The hope is that such theorization will help provide support for updated legal frameworks³⁴ to better address what I describe as the novel sociological phenomenon of the *algorithmic capture*³⁵ of employment.

Second, perhaps in the same genre as the “what’s new?” question, there’s the question of whether automated decision-making is better than human decision-making. The aim of this Article is not to argue for or against algorithmic decision-making in the workplace; rather, it is to ensure that the law is able to root out and redress any problems associated with that practice, much the same as the law governs human decision-making. Furthermore, I do not believe that an adjudication of whether or not algorithms are less biased than humans³⁶ is necessary to advocate for better laws to curb the demonstrated potential of algorithms to sometimes return biased results. First, an adjudication of whether hiring

³³ See *infra* Section IV.A; see also GEORG SIMMEL, THE SOCIOLOGY OF GEORG SIMMEL 145–69 (Kurt H. Wolff ed., trans., 1950) (establishing the typology of a triad with a “tertius” as broker).

³⁴ I agree with these sentiments set forth by Professor Selmi: “Employment discrimination law has long been ripe for updating. Many of the core cases regarding how discrimination is defined and proved arose in the 1970s in a very different era and were designed to address very different kinds of discrimination.” Michael Selmi, *The Evolution of Employment Discrimination Law: Changed Doctrine for Changed Social Conditions*, 2014 WIS. L. REV. 937, 938 (2014).

³⁵ See *infra* Section II.A.

³⁶ I firmly believe that whether or not hiring algorithms produce more or less biased results than humans cannot be a legal adjudication. As Professor Charles Sullivan has remarked: “And the antidiscrimination statutes don’t really care whether any particular selection device actually improves productivity so long as it does not discriminate.” Sullivan, *supra* note 12, at 398. Rather, determining whether algorithmic systems evince less bias than human managers requires empirical data obtained via rigorous social scientific research. Some legal scholars have argued, based on preliminary studies, that automated hiring systems have “allowed some employers to easily and dramatically reduce the biasing effects of subjectivity from their hiring decisions.” Bornstein, *Reckless Discrimination*, *supra* note 12, at 1056. I argue, however, that since algorithmic hiring systems are a relatively new invention, to assess any bias reduction would require longitudinal studies in several industries, and with adequate controls.

platforms are more or less biased than humans is not a legal one—rather, it is a social scientific one that demands rigorous longitudinal research. Although there is some research, as proffered by Professor Bornstein in her article *Antidiscriminatory Algorithms*,³⁷ showing automated hiring to be less biased, the relative novelty of hiring platforms brings to question the rigor of such studies.

I also do not believe that an actual adjudication of whether hiring platforms are less biased than humans or not is necessary before there can be new legal frameworks specifically designed to govern automated decision-making in hiring. Professor Julie Cohen makes this argument clear in her article, *Law for the Platform Economy*.³⁸ Much like our present laws have been developed to govern human decision-making, we need new legal frameworks to govern emerging new technologies in the workplace. My third and most important point here: to argue for or against automated decision-making versus human decision-making is to create a false binary. It is to willfully forget that the human hand remains present in all automated decision-making.³⁹

A final caveat, this Article operates from the normative standard of a social contract society and asks not just how business efficiency can be achieved through algorithmic decision-making while toeing to the letter of employment antidiscrimination law but, rather, how the societal goal of equality and the spirit of antidiscrimination laws meant to accomplish that goal could be honored, even in the face of the automation of employment decision-making. This Article also affirms worker diversity as a normative business and societal ideal. While much can be said about the ethical benefits of a diverse workforce, particularly in regard to reducing economic inequality and its attendant negative effects,⁴⁰ a diverse workplace also affords business advantage because diverse workplaces evince greater innovation and better decision-making.⁴¹

³⁷ Bornstein, *Antidiscriminatory Algorithms*, *supra* note 12.

³⁸ Julie E. Cohen, *Law for the Platform Economy*, 51 U.C. DAVIS L. REV. 133, 189 (2017).

³⁹ See *infra* Section II.C.

⁴⁰ Some research demonstrates that greater inequality is correlated to violence, incarceration, drug abuse, obesity, teenage pregnancy, and mental health issues. See generally RICHARD WILKINSON & KATE PICKETT, *THE SPIRIT LEVEL: WHY GREATER EQUALITY MAKES SOCIETY STRONGER* (2009).

⁴¹ Sheen S. Levine, Evan P. Apfelbaum, Mark Bernard, Valerie L. Bartelt, Edward J. Zajac & David Stark, *Ethnic Diversity Deflates Price Bubbles*, 111 PROC. NAT'L ACAD. SCI. 18,524 (2014)

Therefore, I push for a Rawlesian⁴² approach to the governance of automated hiring systems, wherein the focus is on institutional approaches to algorithmic decision-making and their impact on society as a whole. In so doing, rather than merely proposing ways to build fairer algorithmic systems as some other legal scholars have done,⁴³ I argue that we should also interrogate what values are given precedence by the turn to algorithmic decision-making and by the legal deference accorded employers in determining hiring criteria.

The Article is then organized as follows: Part I discusses the “algorithmic turn” and three problematic features of big-data-driven algorithmic decision-making: 1) data objectivity, 2) data as oracle, and 3) data-laundering. Part II details the algorithmic capture of the workplace, including the notion that automation in hiring is presented as an anti-bias intervention, and notes several examples of bias in both algorithmic recruitment and hiring. Part III urges a reframing of the problem of algorithmic bias, notably with the argument that bias in algorithmic hiring is not a technical problem but rather a legal one borne from a tradition of deference to employers, especially in regard to non-probative hiring criterion such as “cultural fit.” Based on original theorization of platform authoritarianism and the *tertius bifrons*, Part IV proposes new

(detailing sociological research showing that diverse teams make better decisions and are more innovative); *see also* Katherine W. Phillips, Katie A. Liljenquist & Margaret A. Neale, *Better Decisions Through Diversity*, KELLOGG SCH. MGMT.: KELLOGGINSIGHT (Oct. 1, 2010), https://insight.kellogg.northwestern.edu/article/better_decisions_through_diversity [<https://perma.cc/7NDF-QNS6>] (showing that diverse groups outperform homogenous groups because of both an influx of new ideas and more careful information processing); Sheen S. Levine & David Stark, *Diversity Makes You Brighter*, N.Y. TIMES (Dec. 9, 2015), <https://www.nytimes.com/2015/12/09/opinion/diversity-makes-you-brighter.html> [<https://perma.cc/EW4T-DH7Q>].

⁴² JOHN RAWLS, *A THEORY OF JUSTICE* (1971). Rawls, a social contract philosopher, argued that the competing claims of freedom and equality could be reconciled when decisions about justice are made on the basis of the difference principle behind a “veil of ignorance,” wherein no one individual knows their original position (that is, they could be members of low status groups in society), with the result that the only rational choice is to make decisions that would improve the position of the worst off in society. *Id.*; *see also* Mark Kelman, *Defining the Antidiscrimination Norm to Defend It*, 43 SAN DIEGO L. REV. 735, 737 (2006) (rejecting “the [utilitarian ethics] idea that the antidiscrimination norm’s propriety should be evaluated solely by reference to its impact on a mere subset of experiences or capacities to engage in certain activities, for example, a claim that what is relevant in deciding whether the plaintiff merits protection is the plaintiff’s legitimate sense that, absent protection, he is not treated as a ‘first-class’ citizen”).

⁴³ *See, e.g.*, Kroll, Huey, Barocas, Felten, Reidenberg, Robinson & Yu, *supra* note 27.

legal frameworks for addressing algorithmic discrimination in employment that borrows from tort law to update employment law. Of particular note here, is the idea that intent to discriminate could be implied from the act of negligence⁴⁴ to audit and correct bias in algorithmic hiring systems. Furthermore, Part IV discusses how consumer protection laws might help ensure that the information collection of algorithmic hiring systems does not amplify bias.

I. THE ALGORITHMIC TURN

Derived from the name of a Persian mathematician, al-Khwarizmi,⁴⁵ the word “algorithm” and the mathematical system of problem-solving it stands for has gained prominence in all spheres of social and economic life in the past three decades.⁴⁶ With advancements in computing technologies and the capacity for rapid mining of big data, algorithms now pervade our daily lives and exert influence over many important decisions.⁴⁷ The *algorithmic turn*⁴⁸ is the profusion of algorithmic

⁴⁴ Several other legal scholars have applied the tort law principle of a duty of care to employment discrimination. See, e.g., Ford, *supra* note 30 (arguing that employment law imposes a duty of care on employers to refrain from practices that go against equal opportunity in employment); see also Robert Post, Lecture at the Brennan Center Symposium on Constitutional Law, Prejudicial Appearances: The Logic of American Antidiscrimination Law, in 88 CALIF. L. REV. 1 (2000) (arguing that antidiscrimination law aims to achieve positive interventions in social practices as opposed to solely dictating prohibitions). Other professors have also used a “duty of care” framework to propose remedial measures for employment discrimination. See David Benjamin Oppenheimer, *Negligent Discrimination*, 141 U. PA. L. REV. 899 (1993); Noah D. Zatz, *Managing the Macaw: Third-Party Harassers, Accommodation, and the Disaggregation of Discriminatory Intent*, 109 COLUM. L. REV. 1357 (2009).

⁴⁵ DONALD E. KNUTH, STANFORD DEP’T OF COMPUT. SCI., ALGORITHMS IN MODERN MATHEMATICS AND COMPUTER SCIENCE 2 (1980).

⁴⁶ Google Ngram shows the usage of the word “algorithm” beginning in the 1800s and rapidly growing from the 1980s. Two recently published books document the widespread use of algorithms both in governmental decision-making and in the delivery of search results online. See EUBANKS, *supra* note 3; NOBLE, *supra* note 3.

⁴⁷ See Neil M. Richards & Jonathan H. King, *Big Data Ethics*, 49 WAKE FOREST L. REV. 393, 393 (2014) (noting that “large datasets are being mined for important predictions and often surprising insights”).

⁴⁸ See Philip M. Napoli, *On Automation in Media Industries: Integrating Algorithmic Media Production into Media Industries Scholarship*, 1 MEDIA INDUSTRIES J. 33 (2014). But note that I use algorithmic turn here in a similar fashion as Professor Julie Cohen to denote a fad or trend towards

decision-making in our daily lives, even in the absence of established regulatory or ethical frameworks to guide the deployment of those algorithms.⁴⁹ First, I note that the definition of the term “artificial intelligence” (AI)⁵⁰ varies in legal literature and in popular media,⁵¹ and thus, in this Article, in lieu of “AI,” I employ the more precise terms of “algorithms”⁵² and “machine learning algorithms.”⁵³

business practices that are, at their base, about capitalist control. See Julie E. Cohen, *The Surveillance-Innovation Complex: The Irony of the Participatory Turn*, in *THE PARTICIPATORY CONDITION IN THE DIGITAL AGE* 207, 207–26 (Darin Barney et al. eds., 2016).

⁴⁹ See Harry Surden, *Machine Learning and Law*, 89 WASH. L. REV. 87, 88 (2014) (detailing gaps in the law in regard to machine learning algorithms).

⁵⁰ John McCarthy coined the term “AI” in his 1955 proposal for the 1956 Dartmouth Conference, the inaugural AI conference. See Martin Childs, *John McCarthy: Computer Scientist Known as the Father of AI*, INDEPENDENT (Nov. 1, 2011, 1:00 PM), <https://www.independent.co.uk/news/obituaries/john-mccarthy-computer-scientist-known-as-the-father-of-ai-6255307.html> [<https://perma.cc/CE63-T3NU>].

⁵¹ In most media, “artificial intelligence” and “algorithms” are used interchangeably. Lauri Donahue writes about the process of machine learning, in which an algorithm learns from its experiences and adapts to new sets of information, based on data. See Lauri Donahue, *A Primer on Using Artificial Intelligence in the Legal Profession*, HARV. J.L. & TECH.: JOLT DIG. (Jan. 3, 2018), <https://jolt.law.harvard.edu/digest/a-primer-on-using-artificial-intelligence-in-the-legal-profession> [<https://perma.cc/E3KU-KYNH>]. Donahue uses the terms AI and algorithm interchangeably throughout the article.

⁵² In defining an algorithm, Alan D. Minsk references the *Gottschalk v. Benson* decision, in which the court defined an algorithm as a “‘procedure for solving a given type of mathematical problem’ [An algorithm is] . . . a ‘generalized formulation [for programs] to solve mathematical problems of converting one form of numerical representation to another.’” Alan D. Minsk, *The Patentability of Algorithms: A Review and Critical Analysis of the Current Doctrine*, 8 SANTA CLARA COMPUTER & HIGH TECH. L.J. 251, 257 (1992) (citing *Gottschalk v. Benson*, 409 U.S. 63, 65 (1972)). Minsk also references the *Paine, Webber, Jackson & Curtis, Inc. v. Merrill Lynch, Pierce, Fenner & Smith, Inc.* decision, which defines a mathematical algorithm and a computer algorithm. A mathematical algorithm is a “recursive computational procedure [which] appears in notational language, defining a computational course of events which is self-contained.” *Paine, Webber, Jackson & Curtis, Inc. v. Merrill Lynch, Pierce, Fenner & Smith, Inc.*, 564 F. Supp. 1358, 1366–67 (D. Del. 1983) (“[A] computer algorithm is a procedure consisting of operation[s] to combine data, mathematical principles and equipment for the purpose of interpreting and/or acting upon a certain data input.”). In one of the earliest mentions of algorithms in case law, we find that “algorithm[s] [are] procedure[s] for solving a given type of mathematical problem.” *Diamond v. Diehr*, 450 U.S. 175, 186 (1981) (internal quotation marks omitted).

⁵³ See PEDRO DOMINGOS, *THE MASTER ALGORITHM: HOW THE QUEST FOR THE ULTIMATE LEARNING MACHINE WILL REMAKE OUR WORLD* (2015) (“Every algorithm has an input and an output: the data goes into the computer, the algorithm does what it will with it, and out comes the result. Machine learning turns this around: in goes the data and the desired result and out comes

Consider that an algorithm decides all of the following: the answer to a search one conducts online,⁵⁴ the best romantic prospects provided by a dating website,⁵⁵ what advertisements one sees during a visit to a given website,⁵⁶ one's creditworthiness,⁵⁷ whether or not one should be considered a suspect for a crime,⁵⁸ and whether or not one is qualified for a job.⁵⁹ As I detail in the following Sections, the *algorithmic turn*, as a sociotechnical phenomenon in which we turn to machine learning algorithms for efficiency in decision-making, evinces several features that I ultimately see as problematic in various aspects.

A. Data Objectivity

A common adage is “the numbers speak for themselves,”⁶⁰ and as identified by previous researchers, this demonstrates an unquestioning

the algorithm that turns one into the other. Learning algorithms—also known as learners—are algorithms that make other algorithms.”).

⁵⁴ See, e.g., Latanya Sweeney, *Discrimination in Online Ad Delivery*, 11 ASS'N FOR COMPUTING MACHINERY QUEUE 1 (2013) (detailing a study in which a search of names associated with African-Americans returned results featuring advertisements for arrest records as a result of machine learning by Google's ad algorithm); see also NOBLE, *supra* note 3.

⁵⁵ Leslie Horn, *Here's How OkCupid Uses Math to Find Your Match*, GIZMODO (Feb. 14, 2013, 9:32 AM), <http://gizmodo.com/5984005/heres-how-okcupid-uses-math-to-find-your-match> [<https://perma.cc/8BLF-4ANE>].

⁵⁶ Thorin Klosowski, *How Facebook Uses Your Data to Target Ads, Even Offline*, LIFEHACKER (Apr. 11, 2013, 11:00 AM), <http://lifehacker.com/5994380/how-facebook-uses-your-data-to-target-ads-even-offline> [<https://perma.cc/J44C-HKFV>] (explaining how Facebook uses your likes (in addition to those of your friends) to tailor ads or target you for specific advertisements).

⁵⁷ PASQUALE, *supra* note 3.

⁵⁸ Ferguson, *supra* note 9 (noting that, although in the past, determining who was a suspect was a more individualized process, police can now rely on large datasets to make probabilistic determinations of criminal activity).

⁵⁹ Claire Cain Miller, *Can an Algorithm Hire Better than a Human?*, N.Y. TIMES: UPSHOT (June 25, 2015), <http://www.nytimes.com/2015/06/26/upshot/can-an-algorithm-hire-better-than-a-human.html> [<https://perma.cc/2UDA-X2RE>]; Sarah Green Carmichael, *Hiring C-Suite Executives by Algorithm*, HARV. BUS. REV. (Apr. 6, 2015), <https://hbr.org/2015/04/hiring-c-suite-executives-by-algorithm> [<https://perma.cc/RL3S-7B4C>] (detailing how established headhunting firms like Korn Ferry are incorporating algorithms into their work, too).

⁶⁰ The author concludes: “With enough data, the numbers speak for themselves.” See, e.g., Chris Anderson, *The End of Theory: The Data Deluge Makes the Scientific Method Obsolete*, WIRED (June 23, 2008, 12:00 PM), <https://www.wired.com/2008/06/pb-theory> [<https://perma.cc/675W-PDFT>].

belief in data objectivity, particularly regarding large numbers of data.⁶¹ This, in turn, becomes a problematic feature of algorithmic systems—as their decision-making relies on algorithms trained on a corpus of data, the belief in data objectivity then often results in an uncritical acceptance of decisions derived from such algorithmic systems.⁶² In the article, *Think Again: Big Data*,⁶³ Professor Kate Crawford disputes the reverence accorded to big data. First, she argues that numbers do not speak for themselves even with enough data because “data sets . . . are still objects of human design,”⁶⁴ which means that big data is not free from “skews, gaps, and faulty assumptions.”⁶⁵ Biases can exist in big data as much as they do in the real world with individual perceptions.⁶⁶

For one, Professor Crawford notes the “signal problems”⁶⁷ associated with big data, which arise when citizens or subgroups are underrepresented due to unequal creation or collection of data. She also observes that more data does not necessarily improve transparency or accountability; rather, mechanisms to aid the better interpretation of data are more important.⁶⁸ Moreover, Professor Crawford argues that although many believe that big data cause “less discrimination against minority groups because raw data is somehow immune to social bias”⁶⁹ and help people avoid group-based discrimination at a mass level,⁷⁰ big data may, in fact, contribute to the segregating of individuals into groups because of its “ability to make claims about how groups behave differently,”⁷¹ an action forbidden by anti-classificationist laws.

⁶¹ Danah Boyd & Kate Crawford, *Critical Questions for Big Data*, 15 INFO., COMM. & SOC'Y 662 (2012).

⁶² See, e.g., Anderson, *supra* note 60 (arguing that “[c]orrelation is enough” and that the scientific method is now defunct).

⁶³ Kate Crawford, *Think Again: Big Data*, FOREIGN POL'Y (May 10, 2013, 12:40 AM), <https://foreignpolicy.com/2013/05/10/think-again-big-data> [<https://perma.cc/T4F4-V54J>].

⁶⁴ *Id.*

⁶⁵ *Id.*

⁶⁶ *Id.*

⁶⁷ *Id.*

⁶⁸ *Id.*

⁶⁹ *Id.*

⁷⁰ *Id.*

⁷¹ *Id.*

These sentiments are echoed by the legal scholar Professor Anupam Chander, who, in disavowal of data objectivity, argues for “algorithmic affirmative action.”⁷² Chander emphasizes that although algorithms are perceived as fair because computers are logical entities, their results may still bear the traces of real-world discrimination. He argues that “[a]lgorithms trained or operated on a real-world data set that necessarily reflects existing discrimination may well replicate that discrimination.”⁷³ This means that because data are historically biased towards certain groups or classes, discriminatory results may still emerge from automated algorithms that are designed in racial- or gender-neutral ways.⁷⁴ Also, discriminatory results can occur even when decision-makers are not motivated to discriminate: “Because race or gender might be statistically associated with an unobservable trait—such as worker productivity^[75] or propensity to remain in the labor market—profit-maximizing employers might discriminate on the basis of race or gender, using the observable characteristics as proxies for the unobservable traits.”⁷⁶ Thus, in addition to the problem of intentional discrimination, “automated algorithms offer a perhaps more ubiquitous risk: replicating real-world inequalities.”⁷⁷

⁷² See Anupam Chander, *The Racist Algorithm?*, 115 MICH. L. REV. 1023, 1041 (2017).

⁷³ *Id.* at 1036.

⁷⁴ See *id.* at 1036–37.

⁷⁵ It is important to clarify that neither I nor Professor Chander are denying that employers have a vested interest in worker productivity. The issue here is *how* productivity is observed and whether statistics for productivity are ever wholly objective and not tainted for bias when it comes to protected categories.

⁷⁶ Chander, *supra* note 72, at 1038.

⁷⁷ Chander’s call for algorithmic affirmative action is rooted in the idea that it is necessary to design algorithms in race- and gender-conscious ways to account for discrimination already embedded in the data. *Id.* at 1039. This action goes along with what the Obama Administration offered as an approach to handle big data: “[w]e need to develop a principle of ‘equal opportunity by design’—designing data systems that promote fairness and safeguard against discrimination from the first step of the engineering process and continuing throughout their lifespan.” EXEC. OFFICE OF THE PRESIDENT, BIG DATA: A REPORT ON ALGORITHMIC SYSTEMS, OPPORTUNITY, AND CIVIL RIGHTS 5–6 (2016), https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/2016_0504_data_discrimination.pdf [<https://perma.cc/9XQT-9VYQ>].

B. *Data as Oracle*

Concomitant with the belief in data objectivity is the uncritical acquiescence to data-driven algorithmic decision-making as the final arbiter on any given inquiry. Thus, the results of algorithmic systems are heeded as oracular proclamations; they are accepted at face value without any attempt to analyze or further interpret them. In the article, *Critical Questions for Big Data*,⁷⁸ the authors offer six provocations to conversations about big data issues. They define big data as “a cultural, technological, and scholarly phenomenon”⁷⁹ that rests on the interplay of technology, which “maximiz[es] computation power and algorithmic accuracy to gather, analyze, link, and compare large data sets,”⁸⁰ and analysis, which “identif[ies] patterns in order to make economic, social, technical, and legal claims.”⁸¹ Furthermore, they note that this analysis carries with it a mythology, notably the prevalent belief that large data sets offer better intelligence and knowledge, and could algorithmically “generate insights that were previously impossible, [imbued] with the aura of truth, objectivity, and accuracy.”⁸²

What I term the phenomenon of data as oracle is best illustrated by Chris Anderson, who proposes that, because of big data, the scientific method is now defunct.⁸³ According to his article, the scientific approach has traditionally consisted of three parts—hypothesize, model, and test.⁸⁴ As scientists know that correlation is not causation, they understand that no conclusions should be based simply on correlation.⁸⁵ Anderson argues, however, that this approach to science is becoming obsolete with big data because petabytes of data allow people to conclude that “[c]orrelation is enough.”⁸⁶ He places such trust in data and algorithms that he believes that people can now “throw the numbers into the biggest

⁷⁸ Boyd & Crawford, *supra* note 61.

⁷⁹ *Id.* at 663.

⁸⁰ *Id.*

⁸¹ *Id.*

⁸² *Id.*

⁸³ See Anderson, *supra* note 60.

⁸⁴ *Id.*

⁸⁵ *Id.*

⁸⁶ *Id.*

computing clusters the world has ever seen and let statistical algorithms find patterns where science cannot.”⁸⁷

There is a danger, however, with treating algorithmic systems driven by big data as oracles given that “[i]nterpretation is at the center of data analysis”⁸⁸ and that without proper interpretation the decision-making of algorithmic systems could devolve to apophenia, which results in “seeing patterns where none actually exist, simply because enormous quantities of data can offer connections that radiate in all directions.”⁸⁹ Thus, when approaching a data set and designing algorithmic systems on that data set, researchers or interpreters should understand not only the limits of the data set but also of which questions they can ask of a data set and appropriate interpretations.⁹⁰

To illustrate the problem of apophenia for employment decision-making, consider this hypothetical example. Company A decides to use an unsupervised machine learning algorithm to create a profile of the ideal worker. As training data, Company A selects resumes of ten people it considers high performers and trains its algorithm on this corpus of resumes. It turns out that not only are the top ten performers men, but they all listed rock climbing as a hobby on their resumes. The machine learning algorithm thus deduces that the criteria for a good worker includes not only being male but also being a rock climber. Now, if the job position required above average upper body strength, then perhaps this determination could be taken at face value. But what if not? If the job advertised had no relation to upper body strength or really any of the skills or characteristics of a rock climber, then the correct move is not to treat this result as oracular truth, but rather to recognize it as the biased result of a severely limited training data set.

If that hypothetical example seemed risible, then consider this real-life case. Mark J. Girouard, an employment attorney, recounts what

⁸⁷ *Id.*

⁸⁸ Boyd & Crawford, *supra* note 61, at 668.

⁸⁹ *Id.*

⁹⁰ *Id.* at 670. Professor Jim Greiner exposes the same type of problem in civil rights litigation, when the use of regression analysis can prompt unjustified casual inferences. See D. James Greiner, *Causal Inference in Civil Rights Litigation*, 122 HARV. L. REV. 533 (2008).

transpired when one of his clients audited⁹¹ a resume screening tool.⁹² The results: “After an audit of the algorithm, the resume screening company found that the algorithm found two factors to be most indicative of job performance [for applicants]: their name was Jared, and whether they played high school lacrosse.”⁹³ As Girouard recounted, ultimately, the client chose not to use the tool because although there might be a statistically significant correlation between the data points, it was difficult to argue that they were actually important to job performance.⁹⁴

C. *Data-laundering*

Perhaps an opposite problem to seeing patterns where there are none is the potential for large data sets to be deployed to create patterns based on faulty threads of causation, all with the goal of masking intentional discrimination. I term this feature “data-laundering,” that is, the use of data to “launder” or disguise intentional discrimination. In their seminal article, Barocas and Selbst argue that existing law mostly fails to address the discrimination that comes from data mining because some instances of discriminatory data mining will not generate legal liability under Title VII.⁹⁵ Based on the idea that data mining is “*always* a form of statistical . . . discrimination,”⁹⁶ the authors describe five mechanisms by which discriminatory outcomes might occur. The five mechanisms are: 1) defining the target variable, 2) labeling and collecting training data, 3) using feature selection, 4) using proxies, and 5) masking. Notably, the authors argue “the definition of the target variable and its associated class labels will determine what data mining happens to

⁹¹ This real-life case highlights exactly why I make the case in another law review article that there ought to be an auditing imperative for hiring algorithms. Ifeoma Ajunwa, *Automated Employment Discrimination*, 34 HARV. J.L. & TECH. (forthcoming 2021).

⁹² See Dave Gershgorn, *Companies Are on the Hook if Their Hiring Algorithms Are Biased*, QUARTZ (Oct. 22, 2018), <https://qz.com/1427621/companies-are-on-the-hook-if-their-hiring-algorithms-are-biased> [<https://perma.cc/69NT-AA55>].

⁹³ *Id.*

⁹⁴ See *id.*

⁹⁵ See Barocas & Selbst, *supra* note 3, at 675.

⁹⁶ *Id.* at 677.

find,”⁹⁷ and concerns with discrimination enter at this stage because whatever choices are selected will influence whether there are adverse impacts on protected classes.⁹⁸

Secondly, labeling and collection of training data is important because the effectiveness of data mining is dependent on the quality of the data from which it draws lessons.⁹⁹ Data should serve as a good sample of a protected group in order for data mining to be a nondiscriminatory basis for future decision-making.¹⁰⁰ This is not always the case, however, and in an act of data-laundering, the decision-maker may choose to use data known to be incomplete or inaccurate. Next, the authors indicate that organizations “make choices about what attributes they observe and subsequently fold into their analyses”¹⁰¹ through the process of feature selection. This could result in a discriminatory impact on legally protected classes if the factors that “better account for pertinent statistical variation among members of a protected class are not well represented in the set of selected features.”¹⁰²

For example, making an employment decision based on an individual’s criminal record would have a disparate impact on protected racial groups given that mass incarceration has disproportionately impacted racial minorities in the United States.¹⁰³ Similarly, I would note that using a lack of gaps in employment as a hiring criterion could negatively impact women candidates as women disproportionately leave the workplace to shoulder the family burden of child or elderly care. Thus, as the authors note, the existence of proxies could also be a mechanism that drives discrimination if “the criteria that are genuinely

⁹⁷ *Id.* at 680.

⁹⁸ *Id.*

⁹⁹ *Id.* at 687.

¹⁰⁰ *Id.*

¹⁰¹ *Id.* at 688.

¹⁰² *Id.*

¹⁰³ *Id.* at 690; *see also* MICHELLE ALEXANDER, *THE NEW JIM CROW: MASS INCARCERATION IN THE AGE OF COLORBLINDNESS* (2010) (observing how mass incarceration in the United States is a warehousing of the redundant labor population of Black American males and resembles a return to Jim Crow era); Devah Pager, *The Mark of a Criminal Record*, 108 AM. J. SOC. 937 (2003) (describing the racial disparities present in the use of criminal records in the hiring process); Ifeoma Ajunwa, *The Modern Day Scarlet Letter*, 83 FORDHAM L. REV. 2999 (2015) (arguing that Black women are the most disadvantaged by the collateral consequences of conviction).

relevant in making rational and well-informed decisions also happen to serve as reliable proxies for class membership.”¹⁰⁴ As Barocas and Selbst explain, decision-makers with prejudicial values can mask their intentional discrimination as accidental by exploiting the mechanisms above because the data mining process helps conceal the fact that those decision-makers considered class membership.¹⁰⁵

II. ALGORITHMIC CAPTURE OF HIRING AS CASE STUDY

Given the described problems associated with algorithmic decision-making, the algorithmic capture of hiring is cause for concern. I use the term *algorithmic capture* to describe the combined effect of the belief that algorithms are more efficient and fairer¹⁰⁶ and the abdication of human accountability for undesirable outcomes as a result of employing machine learning algorithms as part of a decision-making process. Thus, my focus here is on algorithmic work tools that are implicated in automating the hiring process and thus in revolutionizing the workplace.¹⁰⁷ Although there are several types of algorithmic hiring systems, I see them as falling into two groups: 1) what I term “off-the shelf” algorithms that employers can purchase or license, or 2) what I term “bespoke” algorithms that employers can have a software developer create to their custom specifications. While I would concede that intent and liability might be analyzed differently for the employer depending on the type of algorithm in question, ultimately, differences in hiring algorithms are less important than the fact that although AI in the form of machine learning algorithms has automated many work functions previously thought reserved for human judgment,¹⁰⁸ there have been scant new regulations to ensure that

¹⁰⁴ Barocas & Selbst, *supra* note 3, at 691.

¹⁰⁵ *Id.* at 692–93.

¹⁰⁶ Boyd & Crawford, *supra* note 61 (noting the aura of efficiency associated with big data-driven algorithms).

¹⁰⁷ ERIK BRYNJOLFSSON & ANDREW MCAFEE, *THE SECOND MACHINE AGE: WORK, PROGRESS, AND PROSPERITY IN A TIME OF BRILLIANT TECHNOLOGIES* (2014) (arguing that akin to how the Industrial Revolution changed the path of human invention, the artificial intelligence age will similarly revolutionize work as we know it).

¹⁰⁸ See Harry Surden, *Computable Contracts*, 46 U.C. DAVIS L. REV. 629, 646 (2012) (discussing how computer algorithms may find it difficult to decipher language changes that are readily comprehensible to humans). *But see, e.g.*, Erin Winick, *Lawyer-Bots Are Shaking Up Jobs*, MIT

these new technological developments will conform to the normative ideal of equal economic opportunity for all, which is the bedrock of our democratic society.

The automation of the hiring process represents a particularly important technological trend and one that requires greater legal attention given its potential for employment discrimination. Whereas once, an applicant could rely on their interpersonal skills to make a favorable first impression on the hiring manager, these days the hiring algorithm is the initial hurdle to clear to gain employment.¹⁰⁹ This is particularly true for the U.S. low-wage and hourly workforce, as a co-author and I found through a survey of the top twenty private employers in the *Fortune 500* list (comprised of mostly retail companies).¹¹⁰ That survey indicated that job applications for such retail jobs must be submitted online, where they will first be sorted by automated hiring platforms powered by algorithms.¹¹¹

The algorithmic capture of the hiring process also goes beyond the hourly workforce, as white collar and white shoe firms are increasingly turning to hiring automation.¹¹² In 2016, the investment firm Goldman Sachs announced a key change to its process for hiring summer interns

TECH. REV. (Dec. 12, 2017), <https://www.technologyreview.com/s/609556/lawyer-bots-are-shaking-up-jobs> [<https://perma.cc/246J-KGWP>]; Carl Benedikt Frey & Michael A. Osborne, *The Future of Employment: How Susceptible Are Jobs to Computerisation?*, 114 TECHNOLOGICAL FORECASTING & SOC. CHANGE 254, 268 (2017) (“While computerisation has been historically confined to routine tasks involving explicit rule-based activities, algorithms for big data are now rapidly entering domains reliant upon pattern recognition and can readily substitute for labour in a wide range of non-routine cognitive tasks.”); ERIC SIEGEL, PREDICTIVE ANALYTICS: THE POWER TO PREDICT WHO WILL CLICK, BUY, LIE, OR DIE (2013).

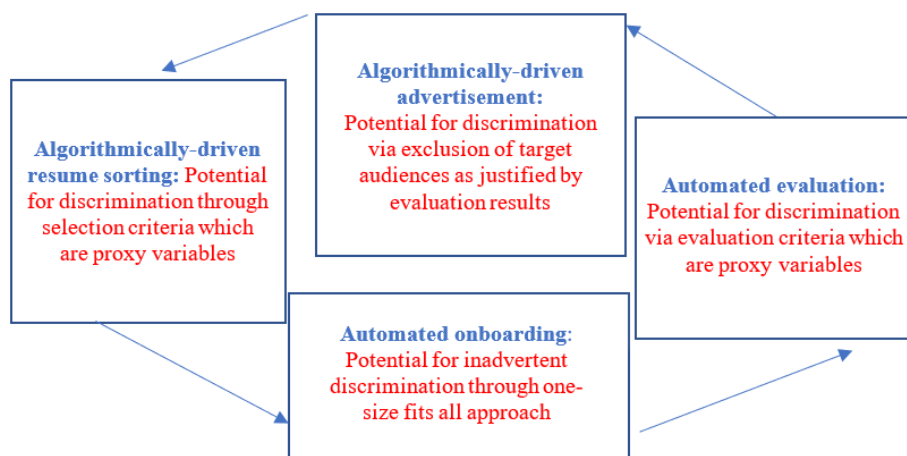
¹⁰⁹ See LINDA BARBER, INST. FOR EMP’T STUDIES, E-RECRUITMENT DEVELOPMENTS (2006), <https://www.employment-studies.co.uk/system/files/resources/files/mp63.pdf> [<https://perma.cc/KZ89-MCRC>] (noting that nearly all Global 500 companies use e-recruitment and hire screening algorithmic tools).

¹¹⁰ Ajunwa & Greene, *supra* note 19.

¹¹¹ *Id.*

¹¹² See, e.g., Richard Feloni, *Consumer-Goods Giant Unilever Has Been Hiring Employees Using Brain Games and Artificial Intelligence—And It’s a Huge Success*, BUS. INSIDER (June 28, 2017, 9:30 AM), <http://www.businessinsider.com/unilever-artificial-intelligence-hiring-process-2017-6> [<https://perma.cc/TBG2-RF8K>]; Louis Efron, *How A.I. Is About to Disrupt Corporate Recruiting*, FORBES (July 12, 2016, 1:57 PM), <https://www.forbes.com/sites/louisefron/2016/07/12/how-a-i-is-about-to-disrupt-corporate-recruiting/#75ae172d3ba2> [<https://perma.cc/G5L3-AAWX>].

and first-year analysts.¹¹³ Candidates now have their resumes scanned—ostensibly by machine learning algorithms, in search of keywords and experiences that have been prejudged to be “good barometers of a person’s success at Goldman.”¹¹⁴ Goldman Sachs has also considered the addition of personality tests as part of its hiring program.¹¹⁵ The world’s largest hedge fund has taken the automation gambit the furthest, as starting in 2016, it is building an algorithmic model that would automate all management, including hiring, firing, and other managerial decision-making processes.¹¹⁶ Thus, automated hiring represents an ecosystem in which, if left unchecked, a closed loop system forms—with algorithmically-driven advertisement determining which applicants will send in their resumes, automated sorting of resumes leading to automated onboarding and eventual automated evaluation of employees, and the results of said evaluation being looped back into criteria for job advertisement and selection.



¹¹³ Mary Thompson, *Goldman Sachs Is Making a Change to the Way It Hires*, CNBC (June 23, 2016, 3:01 PM), <https://www.cnbc.com/2016/06/23/goldman-sachs-is-making-a-change-to-the-way-it-hires.html> [<https://perma.cc/3Y2X-3RMD>].

¹¹⁴ *Id.*

¹¹⁵ *Id.*

¹¹⁶ Rob Copeland & Bradley Hope, *The World’s Largest Hedge Fund Is Building an Algorithmic Model from Its Employees’ Brains*, WALL ST. J. (Dec. 22, 2016, 1:14 PM), <https://www.wsj.com/articles/the-worlds-largest-hedge-fund-is-building-an-algorithmic-model-of-its-founders-brain-1482423694> [<https://perma.cc/Z5MQ-5LRV>].

As algorithmic technological advances present us with unprecedented legal challenges,¹¹⁷ the use of machine learning algorithms in decision-making hiring processes represents a particularly sensitive legal issue because of the potential to create or exacerbate economic inequality. Yet, even with headline-making cases of bias, the issue of how to govern algorithmic systems remains a thorny one. In her article, *Law for the Platform Economy*, Professor Julie Cohen notes that much of the conduct of platforms is simply “intractable using conventional regulatory methodologies.”¹¹⁸ For instance:

to enforce existing antidiscrimination laws effectively, the various agencies with enforcement authority need the ability to detect and prove discrimination, yet that task is increasingly difficult when decisions about lending, employment, and housing are made via complex algorithms used to detect patterns in masses of data and the data itself reflects preexisting patterns of inequality.¹¹⁹

Professor Cohen concludes that these phenomena combine to constitute a space “devoid of protections for vital human freedoms, even as the activities conducted in that space become more and more fundamental to the exercise of those freedoms.”¹²⁰

In his article, Professor Anupam Chander analogizes the process of “baby-proofing” to the concept of “future-proofing.”¹²¹ To the question “[d]oes the idea of ‘future-proofing’ law refer to a need to protect the . . . future from the . . . legal system? Or, does it refer to a need to protect . . . rule of law from the . . . future?” Professor Cohen responds

¹¹⁷ These legal challenges exist precisely because even with computing advancements that allow computers to perform non-routine cognitive tasks, as noted by the legal scholar Cass Sunstein, “at the present state of the art artificial intelligence cannot engage in analogical reasoning or legal reasoning.” Kevin Ashley, Karl Branting, Howard Margolis & Cass R. Sunstein, *Legal Reasoning and Artificial Intelligence: How Computers “Think” like Lawyers*, 8 U. CHI. L. SCH. ROUNDTABLE 1, 19 (2001); see Surden, *supra* note 49, at 88 (detailing gaps in the law in regards to machine learning algorithms); see also Barocas & Selbst, *supra* note 3, at 673–74 (detailing issues of disparate impact associated with algorithmic decision-making).

¹¹⁸ Cohen, *supra* note 38, at 189.

¹¹⁹ *Id.* at 190.

¹²⁰ *Id.* at 199.

¹²¹ See *id.* at 203.

that neither alone is quite accurate.¹²² This is because the law and technological development are co-constitutive. Professor Cohen argues that “legal institutions should change to meet the demands of the times, and so it is only logical that the ascendancy of platforms should produce new legal relationships and new institutional settlements.”¹²³ She reinforces that it is time to pay attention to the best paths for institutional evolution and the “extent to which legal institutions should bend to the service of emergent economic power.”¹²⁴

I echo Professor Cohen’s sentiments here, particularly in cautioning against a techno-correctionist view of algorithmic bias that focuses on technical fairness in lieu of examining assumptions undergirding the criteria chosen for automated decision-making. But in order to engender new legal frameworks, we must first grasp the true nature of the issue. In the following Sections, I detail how the move towards the automation of decision-making came about as an anti-bias intervention and the ways in which machine learning algorithms involved in hiring have been found to return discriminatory results and raise new legal quandaries.

A. *Algorithms as Anti-Bias Intervention*

The paradox of the algorithmic capture of hiring is that, despite proof of algorithmic bias, some perceive the move to automated decision-making as an anti-bias intervention. That is, the increasing use of algorithms in employment decision-making is seen as an improvement in comparison to decisions made solely by humans. In *Want Less-Biased Decisions? Use Algorithms*,¹²⁵ the author challenges many scholars’ concern that “algorithms are often opaque, biased, and unaccountable tools being wielded in the interests of institutional power.”¹²⁶ He notes that although these critiques have helped people to avoid abusing algorithms, there is a pattern among the critiques, “which is that they

¹²² *See id.*

¹²³ *See id.* at 204.

¹²⁴ *Id.*

¹²⁵ Alex P. Miller, *Want Less-Biased Decisions? Use Algorithms*, HARV. BUS. REV. (July 26, 2018), <https://hbr.org/2018/07/want-less-biased-decisions-use-algorithms> [https://perma.cc/RX6F-6QDB].

¹²⁶ *Id.*

rarely ask how well the systems they analyze would operate without algorithms.”¹²⁷

Miller cites multiple studies of algorithmic decision-making that support the notion that “[a]lgorithms are less biased and more accurate than the humans they are replacing.”¹²⁸ For instance, one study found that a job-screening algorithm “actually favored ‘nontraditional’ candidates”¹²⁹ much more than human screeners did, “exhibit[ing] significantly less bias against candidates that were underrepresented at the firm.”¹³⁰ Other algorithmic studies related to credit applications, criminal justice, public resource allocations, and corporate governance all concluded that “[a]lgorithms are less biased and more accurate than the humans they are replacing.”¹³¹

In each of the examples he notes, Miller argues that the algorithm programmers “trained their algorithms on past data that is surely biased by historical prejudices.”¹³² Miller asserts that while this fact might be alarming to many, because of the widespread belief that algorithms are negatively affected by a biased data set, “the humans [algorithms] are replacing are significantly more biased.”¹³³ He argues that a number of psychological and other studies in judgment and decision have demonstrated that “humans are remarkably bad judges of quality in a wide range of contexts”¹³⁴ and that “very simple mathematical models outperform supposed experts at predicting important outcomes.” Thus, since humans are significantly bad at making decisions, “replacing them with algorithms both increased accuracy and reduced institutional biases.”¹³⁵ Miller refers to this as a “[p]areto improvement, where one policy beats out the alternative on every outcome [people] care about.”¹³⁶ He also emphasizes that there is no trade-off between productivity and fairness when using algorithms because “[a]lgorithms deliver more-

¹²⁷ *Id.* (emphasis omitted).

¹²⁸ *Id.*

¹²⁹ *Id.* (emphasis omitted).

¹³⁰ *Id.*

¹³¹ *Id.*

¹³² *Id.*

¹³³ *Id.* (emphasis omitted).

¹³⁴ *Id.*

¹³⁵ *Id.* (emphasis omitted).

¹³⁶ *Id.*

efficient and more-equitable outcomes.”¹³⁷ Miller thus insists that even if technology cannot fully solve the social ills of institutional bias and discrimination, it is worthwhile to “accept that—in some instances—algorithms will be part of the solution for reducing institutional biases”¹³⁸ because the perils of human bias are far worse.

Similarly, the legal scholar Professor Stephanie Bornstein, in her article *Antidiscriminatory Algorithms*,¹³⁹ challenges the current focus on ensuring that algorithmically derived decision-making results are not discriminatory. She emphasizes the original intent of technology, which is “to improve upon human decision-making by suppressing biases to make the most efficient and least discriminatory decisions.”¹⁴⁰ Deploying the example of Amazon’s hiring algorithm and LinkedIn’s survey results,¹⁴¹ Professor Bornstein notes that “[a]lgorithmic decision-making offers unprecedented potential to reduce the stereotypes and implicit biases that often infect human decisions.”¹⁴² However, Professor Bornstein acknowledges that despite the promise of algorithms to reduce bias in decision-making, there are concerns about algorithmic discrimination and the risk of reproducing existing inequality¹⁴³ because the effectiveness of algorithms and decision-making greatly relies on what data is used and how.¹⁴⁴ Yet, Professor Bornstein believes that if algorithms are handled properly, they can still “suppress, interrupt, or remove protected class stereotypes from decisions.”¹⁴⁵

As noted earlier, my aim is not to adjudicate whether algorithms are less biased than humans,¹⁴⁶ and I do not believe that such a determination is necessary to observe the inadequacy of current laws to govern machine learning algorithms or to conceive of better legal frameworks. Therefore, although in many respects the algorithmic turn to hiring is purportedly driven by a desire for fairness and efficiency—for example, Goldman

¹³⁷ *Id.* (emphasis omitted).

¹³⁸ *Id.*

¹³⁹ Bornstein, *Antidiscriminatory Algorithms*, *supra* note 12.

¹⁴⁰ *Id.* at 520.

¹⁴¹ *Id.* at 521–23.

¹⁴² *Id.* at 523.

¹⁴³ *Id.*

¹⁴⁴ *Id.* at 570.

¹⁴⁵ *Id.*

¹⁴⁶ *See supra* note 36 and accompanying text.

Sachs's hiring changes were prompted by a desire for a more diverse candidate pool¹⁴⁷—as these machine learning algorithms may have the (un)intended effects of perpetuating structural biases or could have a disparate impact on protected categories,¹⁴⁸ the law should evolve more robust governing mechanisms to guard against those outcomes. In the next Section, I detail how bias may still creep into algorithmic decision-making systems in the context of recruitment and hiring.

B. *The Fault in the Machine*

Albeit that it is well documented that humans evince bias in employment decision-making,¹⁴⁹ one cannot overlook that algorithmic systems of decision-making, too, might enable, facilitate, or amplify such biases. The cases below demonstrate that this is true both in the recruitment and hiring of job candidates. Consider also that it is exactly because Facebook has automated algorithms that are able to distinguish (with some degree of accuracy) between men and women that it is able to select only men for job ads, and the inscrutable workings of this algorithms also allows this discrimination to go undetected for some time. It is impossible to do the same with an advertisement in a physical newspaper. Thus, it is the very design of automated platform that is both enabling and facilitating discrimination here. Therefore, this Article builds on the work of Professor Olivier Sylvain, who has noted that the design of automated intermediaries, has “enabled a range of harmful expressive acts, including violations of housing and employment laws.”¹⁵⁰

¹⁴⁷ See Thompson, *supra* note 113.

¹⁴⁸ See Surden, *supra* note 49, at 88 (detailing gaps in the law in regards to machine learning algorithms); Barocas & Selbst, *supra* note 3 (detailing issues of disparate impact associated with algorithmic decision-making).

¹⁴⁹ See *infra* Section III.A.

¹⁵⁰ Olivier Sylvain, *Discriminatory Designs on User Data*, KNIGHT FIRST AMEND. INST. COLUM. U. (Apr. 1, 2018), <https://knightcolumbia.org/content/discriminatory-designs-user-data> [<https://perma.cc/5QXR-QFB9>] [hereinafter Sylvain, *Discriminatory Designs on User Data*]; see also Olivier Sylvain, *Intermediary Design Duties*, 50 CONN. L. REV. 203 (2018).

1. Recruitment

A recent *ProPublica* investigation revealed that Facebook allowed advertisers (both for jobs and for housing) to exclude audiences by ethnic group.¹⁵¹ In what investigators described as a modern form of Jim Crow,¹⁵² Facebook had developed a feature it termed “Ethnic Affinities”—essentially, a method for advertisers to use demographic data to algorithmically target who will receive certain Facebook ads.¹⁵³ For example, one page on Facebook for Business, titled *U.S. Hispanic Affinity on Facebook*, boasts of the potential for advertisers to reach up to 26.7 million Facebook users of “Hispanic Affinity.”¹⁵⁴ From this specific ethnic affinity, advertisers can choose to narrow in on bilingual users, those who are “Spanish dominant,” or those who are “English dominant,” in order to “refine [their] audience.”¹⁵⁵

Although, ostensibly, this algorithmic feature might help business owners refine their audiences and target ads to individuals who might be more likely customers, the use of Affinity Groups as an ad distribution tool holds high potential for unlawful discrimination. In demonstration of this discriminatory potential, *ProPublica* reporters were able to buy dozens of rental house ads on Facebook that excluded “African Americans, mothers of high school kids, people interested in wheelchair ramps, Jews, expats from Argentina and Spanish speakers.”¹⁵⁶

Following on the heels of this *ProPublica* investigation, a 2017 class action lawsuit against Facebook contended that Facebook Business tools

¹⁵¹ Julia Angwin & Terry Parris Jr., *Facebook Lets Advertisers Exclude Users by Race*, PROPUBLICA (Oct. 28, 2016, 1:00 PM), <https://www.propublica.org/article/facebook-lets-advertisers-exclude-users-by-race> [<https://perma.cc/D3E8-5WVQ>].

¹⁵² *Id.*

¹⁵³ See *About Reaching New Audiences*, FACEBOOK FOR BUS., https://www.facebook.com/business/help/717368264947302?helpref=page_content [<https://perma.cc/ERU9-YB2N>].

¹⁵⁴ See *U.S. Hispanic Affinity on Facebook*, FACEBOOK FOR BUS., <https://www.facebook.com/business/a/us-hispanic-affinity-audience> [<https://web.archive.org/web/20190106063038/https://www.facebook.com/business/a/us-hispanic-affinity-audience>].

¹⁵⁵ See *id.*

¹⁵⁶ Jessica Guynn, *Facebook Halts Ads that Exclude Racial and Ethnic Groups*, USA TODAY (Nov. 29, 2017, 11:32 AM), <https://www.usatoday.com/story/tech/2017/11/29/facebook-stop-allowing-advertisers-exclude-racial-and-ethnic-groups-targeting/905133001> [<https://perma.cc/6QS5-PA9Q>].

both “enable and encourage discrimination by excluding African Americans, Latinos, and Asian Americans—but not white Americans—from receiving advertisements for the Relevant Opportunities.”¹⁵⁷ In an amended complaint, another class action also alleged that “Facebook offers a feature that is legally indistinguishable from word-of-mouth hiring, which has long been considered a discriminatory and unlawful employment practice.”¹⁵⁸ This allegation references Facebook’s “Lookalike Audiences” feature, in which employers and employment agencies provide a list of their existing workers to Facebook, and Facebook uses that list to then create its own list of Facebook users who are demographically similar to the existing workers.¹⁵⁹ Then, the employer or employment agency uses the new “Lookalike Audience” list created by Facebook as the population to receive its employment ads.¹⁶⁰ Such a feature would help to perpetuate any existing historical racial, gender, and other demographic imbalances of employees already present in a given corporation.

Seemingly in response to the publicity from the *ProPublica* investigations, Facebook began temporarily blocking advertisers from excluding audiences by race in late 2017.¹⁶¹ In March of 2019, the Communications Workers of America, along with the ACLU and the law firm of Outten & Golden LLP, reached a settlement with Facebook in which the corporation agreed to make “changes to its paid advertising platform to prevent discrimination in employment, housing, and credit advertising.”¹⁶²

¹⁵⁷ First Amended Complaint at 1, *Mobley v. Facebook, Inc.*, No. 16-cv-06440-EJD (N.D. Cal. Feb. 13, 2017).

¹⁵⁸ See First Amended Class and Collective Action Complaint at 22, *Bradley v. T-Mobile U.S., Inc.*, No. 17-cv-07232-BLF (N.D. Cal. May 29, 2018), <https://www.onlineagediscrimination.com/sites/default/files/documents/og-cwa-complaint.pdf> [<https://perma.cc/JGU8-DSKT>].

¹⁵⁹ See *id.*

¹⁶⁰ See *id.*; see generally *About Lookalike Audiences*, FACEBOOK FOR BUS., <https://www.facebook.com/business/help/164749007013531> [<https://perma.cc/4HXW-K5DM>].

¹⁶¹ See Guynn, *supra* note 156.

¹⁶² *CWA Secures Agreement with Facebook on Sweeping Reforms to Curb Discrimination*, COMM. WORKERS AM. (Mar. 21, 2019), <https://cwa-union.org/news/cwa-secures-agreement-facebook-on-sweeping-reforms-curb-discrimination> [<https://perma.cc/Q842-R5ZQ>]. Here are some of the reforms Facebook agreed to:

Create a separate portal for such ads with a much more limited set of targeting options so that advertisers cannot target ads based on Facebook users’ age, gender, race, or

2. Hiring

Job recruitment algorithms on platforms like Facebook are, however, not the sole problem. Algorithms that quickly sort job applicants based on pre-set criteria may also (inadvertently) be unlawfully discriminatory. In her book, *Weapons of Math Destruction*, Cathy O’Neil poignantly illustrates how personality tests may serve to discriminate against one protected class, job applicants suffering from mental disabilities.¹⁶³ In one class action, the named plaintiff, Kyle Behm, a college student with a near-perfect SAT score and who had been diagnosed with bipolar disorder, found himself repeatedly rejected for minimum wage jobs at supermarkets and retail stores that all used a personality test that had been modeled on the “Five Factor Model” test used to diagnose mental illness.¹⁶⁴ Thus, personality tests, as part of automated hiring systems, could be seen as a covert method for violating antidiscrimination law—specifically, the Americans with Disabilities Act.¹⁶⁵ In addition, other test questions, such as the length of commute

categories that are associated with membership in protected groups, or based on zip code or a geographic area that is less than a 15-mile radius, and cannot consider users’ age, gender, or zip code when creating “Lookalike” audiences for advertisers

Implement a system of automated and human review to catch advertisements that aren’t correctly self-certified as these types of ads

Require all advertisers creating such ads to certify compliance with anti-discrimination laws, and provide education for advertisers on those laws

Study the potential for unintended biases in algorithmic modeling on Facebook

Meet with plaintiffs and their counsel every six months for three years to enable them to monitor the implementation of the reforms that Facebook is undertaking.

Press Release, Commc’ns Workers of Am., Facebook Agrees to Sweeping Reforms to Curb Discriminatory Ad Targeting Practices (Mar. 19, 2019), <https://cwa-union.org/news/releases/facebook-agrees-sweeping-reforms-curb-discriminatory-ad-targeting-practices> [<https://perma.cc/6L6X-UVBK>].

¹⁶³ O’NEIL, *supra* note 3.

¹⁶⁴ *Id.*

¹⁶⁵ Titles I and V of the Americans with Disabilities Act of 1990, Pub. L. No. 101-336, 104 Stat. 327 (codified as amended at 42 U.S.C. §§ 12111–12117, 12201–12213 (2018)), grant mentally ill workers equal opportunity in employment. *See, e.g.*, Press Release, U.S. Equal Emp’t Opportunity Comm’n, Worker with Bipolar Disorder to Receive \$91,000 in Disability Discrimination Case Settled by EEOC (Mar. 18, 2003), <https://www.eeoc.gov/eeoc/newsroom/release/3-18-03b.cfm> [<https://perma.cc/94ZS-NBYW>]; *see also* *Depression, PTSD, & Other Mental Health Conditions in*

time, could be seen as covertly discriminating against those from under-resourced neighborhoods which lack a reliable transportation infrastructure.¹⁶⁶

In addition to personality tests, companies are using other algorithmic processes to screen applicants. For example, the company HireVue offers virtual interviews with individual applicants. HireVue's innovative hiring tool identifies facial expression, vocal indications, word choice, and more.¹⁶⁷ The problem is that “[s]peech recognition software can perform poorly” and “[f]acial analysis systems can struggle to read the faces of women with darker skin.”¹⁶⁸ Some skeptics express their concerns about the legitimacy of using physical features and facial expressions that have no causal link with workplace success to make hiring decisions.¹⁶⁹

Another example of automated hiring is the use of algorithms to conduct social media background checks. Such checks are fraught with issues for several reasons. First, they “presume that a person’s online behaviors, like some use of foul language, are relevant to their professional activities.”¹⁷⁰ Second, they have “limited ability to parse the nuanced meaning of human communication.”¹⁷¹ In addition, such checks could “surface details about an applicant’s race, sexual identity, disability,

the Workplace: Your Legal Rights, U.S. EQUAL EMP. OPPORTUNITY COMMISSION, https://www.eeoc.gov/eeoc/publications/mental_health.cfm [<https://perma.cc/5QDA-Y2HD>].

¹⁶⁶ Debra Cassens Weiss, *Do Job Personality Tests Discriminate? EEOC Probes Lawyer’s Complaint, Filed on Behalf of His Son*, A.B.A. J. (Sept. 30, 2014, 8:08 AM), http://www.abajournal.com/news/article/do_job_personality_tests_discriminate_eeoc_probes_lawyers_complaint_filed_o [<https://perma.cc/B3X3-YX9E>].

¹⁶⁷ Hilke Schellmann & Jason Bellini, *Artificial Intelligence: The Robots Are Now Hiring*, WALL STREET J. (Sept. 20, 2018, 5:30 AM), <https://www.wsj.com/articles/artificial-intelligence-the-robots-are-now-hiring-moving-upstream-1537435820> [<https://perma.cc/4GHT-NTYB>].

¹⁶⁸ MIRANDA BOGEN & AARON RIEKE, UPTURN, HELP WANTED: AN EXAMINATION OF HIRING ALGORITHMS, EQUITY, AND BIAS 37 (2018), <https://www.upturn.org/reports/2018/hiring-algorithms> [<https://perma.cc/277F-ZG97>]; see also Joy Buolamwini & Timnit Gebru, *Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification*, 81 PROC. MACHINE LEARNING RES. 1 (2018).

¹⁶⁹ See BOGEN & RIEKE, *supra* note 168.

¹⁷⁰ *Id.*

¹⁷¹ *Id.*

pregnancy, or health status, which employers should not consider during the hiring process.”¹⁷²

Finally, as the last step of the hiring process, employers make offers to applicants using automated hiring systems. For example, there exist software programs that predict the probability that a candidate will accept a given job offer and that suggest what the employer could do to increase those chances. For example, these programs allow the employer to “adjust salary, bonus, stock options, and other benefits to see in real time how the prediction changes.”¹⁷³ The worry remains that such programs might amplify pay gaps for white women and racial minorities because the data commonly include “ample proxies for a worker’s socioeconomic and racial status, which could be reflected in salary requirement predictions.”¹⁷⁴ They might also undermine laws that bar employers from considering candidates’ salary histories.¹⁷⁵

C. *Exposing the Mechanical Turk*

Even as incidences of algorithmic bias come to light,¹⁷⁶ an important feature of algorithms is that they tend to obscure the role of the human hand in setting parameters for solving any given problem, with the final

¹⁷² *Id.*

¹⁷³ *Id.* at 40.

¹⁷⁴ *See id.* (internal footnote omitted).

¹⁷⁵ *See id.*

¹⁷⁶ It is important to note here, as I discuss more fully in another article, Ajunwa, *supra* note 91, that U.S. law actively works to prevent instances of algorithmic bias from coming to light. One reason is that the intellectual property law regime allows automated systems to fall under trade secret or copyright law, which means that their creators are able to keep secret the exact workings of these automated systems. Congress enacted the Digital Millennium Copyright Act (DMCA) in 1998. Pub. L. No. 105-304, 112 Stat. 2860 (1998) (codified as amended in sections of 17 and 28 U.S.C.). Section 1201 of the DMCA creates liability for hacking or reverse engineering an automated system protected under copyright law. 17 U.S.C. § 1201 (2018); *see also* Maayan Perel & Niva Elkin-Koren, *Accountability in Algorithmic Copyright Enforcement*, 19 STAN. TECH. L. REV. 473 (2016) (noting the chilling effect on researchers who would like to reverse engineer automated processes, given the potential to incur liabilities). Another reason is that these systems also receive intellectual property law protections without having demonstrated their utility to society. *Cf.* Christopher Buccafusco, Mark A. Lemley & Jonathan S. Masur, *Intelligent Design*, 68 DUKE L.J. 75 (2018) (noting that designers are “able to obtain powerful IP protection over the utilitarian aspects of their creations without demonstrating that they have made socially valuable contributions” and concluding that “[t]his is bad for competition and bad for consumers”).

result attributed solely to the machine.¹⁷⁷ Consider that proponents of automations have always tended to downplay or deny the role of the human mastermind.¹⁷⁸ As an early example, consider the “Mechanical Turk” also known as the “chess Turk,” which was a chess-playing machine constructed in the late eighteenth century.¹⁷⁹ Although the Mechanical Turk was presented as an automaton chess-playing machine that was capable of beating the best human players, the secret of the machine was that it contained a human man, concealed inside its chambers.¹⁸⁰ The hidden chess master controlled the machine while the seemingly automated machine beat notable statesmen, like Napoleon Bonaparte and Benjamin Franklin, at chess.¹⁸¹ Thus, the Mechanical Turk operated on obfuscation and subterfuge and sought to reserve the glory of the win to the machine.¹⁸²

With the growing allure of AI as a venture-capital-generating marketing ploy,¹⁸³ modern day corporations have been discovered

¹⁷⁷ Surden, *supra* note 49, at 115; Jatinder Singh, Ian Walden, Jon Crowcroft & Jean Bacon, *Responsibility & Machine Learning: Part of a Process* (Oct. 27, 2016) (unpublished manuscript), <http://dx.doi.org/10.2139/ssrn.2860048> [<https://perma.cc/6SLY-2QK9>] (arguing that machines can learn to operate in ways beyond their programming levels, meaning that the responsibility for problems created by the algorithms cannot lie solely with the algorithms creators or the algorithms themselves).

¹⁷⁸ Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 GEO. L.J. 1147, 1207 (2017) (noting that machine-learning technology is not yet fully understood and that most people simply “lack . . . [the] interpretive ability to . . . show[] that X causes Y” on a machine-learning platform).

¹⁷⁹ TOM STANDAGE, *THE TURK: THE LIFE AND TIMES OF THE FAMOUS EIGHTEENTH-CENTURY CHESS-PLAYING MACHINE* (2002).

¹⁸⁰ 4 RICKY JAY, *The Automaton Chess Player, the Invisible Girl & the Telephone*, in JAY’S JOURNAL OF ANOMALIES 147, 147–62 (2000).

¹⁸¹ *Id.*

¹⁸² See PASQUALE, *supra* note 3 (arguing that algorithms operate on obfuscation). Conversely, Amazon’s Mechanical Turk program does the opposite. The program allows businesses or individual clients to assign human intelligence tasks, that is, tasks that are difficult or impossible for machines to complete (like sorting photographs, writing product descriptions, completing surveys, etc.) to humans. Amazon explicitly bans the use of automated bots to complete such tasks. See AMAZON MECHANICAL TURK, <https://www.mturk.com> [<https://perma.cc/6SHT-F88U>].

¹⁸³ See Ellen Huet, *The Humans Hiding Behind the Chatbots*, BLOOMBERG (Apr. 18, 2016, 8:00 AM), <https://www.bloomberg.com/news/articles/2016-04-18/the-humans-hiding-behind-the-chatbots> [<https://perma.cc/GV6F-PZ28>] (“The incentive to play up automation is high. Human-assisted AI is ‘the hottest space to be in right now,’ said Navid Hadzaad, who founded bot-and-human concierge service GoButler. Startups in this arena have together raised at least \$50 million

operating their own versions of the Mechanical Turk. Consider, for example, that the humans on the Amazon Mechanical Turk crowd-sourcing work platform consider themselves the “AI behind the AI.”¹⁸⁴ On this internet-based platform, human workers are recruited to accomplish mundane tasks that are difficult for algorithms to tackle. These tasks, referred to as “human intelligence tasks” (or HITs), include: “transcribing audio clips; tagging photos with relevant keywords; copying photocopied receipts into spreadsheets.”¹⁸⁵ While the work on Amazon Turk and its notoriously low pay is no secret, a Bloomberg exposé revealed that several corporations were disingenuously passing off the labor of human workers as that of AI.¹⁸⁶

Even when corporations are not attempting to pass off human workers as AI, it is important to understand that there is always a human behind the AI. Modern day algorithms operate in ways similar to the Mechanical Turk in that the human decisions behind the creation of algorithms operated by businesses are generally considered trade secrets that are jealously guarded and protected from government oversight.¹⁸⁷

in venture capital funding in the past two years. But companies with a wide variety of strategies all use similar and vague marketing language and don't often divulge operational details.”). For example, in May of 2018, to much publicity, Google debuted an uncanny digital assistant which is able to call for reservations and fool humans on the telephone with its natural speech, complete with human-like pauses and interjections. Chris Welch, *Google Just Gave a Stunning Demo of Assistant Making an Actual Phone Call*, VERGE (May 8, 2018, 1:54 PM), <https://www.theverge.com/2018/5/8/17332070/google-assistant-makes-phone-call-demo-duplex-io-2018> [<https://perma.cc/UTD3-BWYU>].

¹⁸⁴ Miranda Katz, *Amazon's Turker Crowd Has Had Enough*, WIRED (Aug. 23, 2017, 6:55 AM), <https://www.wired.com/story/amazons-turker-crowd-has-had-enough> [<https://perma.cc/RJ6E-K7B7>].

¹⁸⁵ Sarah O'Connor, *My Battle to Prove I Write Better than an AI Robot Called 'Emma,'* FIN. TIMES (May 4, 2016), <https://www.ft.com/content/92583120-0ae0-11e6-b0f1-61f222853ff3> [<https://perma.cc/U33Q-3F8T>].

¹⁸⁶ See Huet, *supra* note 183 (“A handful of companies employ humans pretending to be robots pretending to be humans. In the past two years, companies offering do-anything concierges (Magic, Facebook's M, GoButler); shopping assistants (Operator, Mezi); and e-mail schedulers (X.ai, Clara) have sprung up. The goal for most of these businesses is to require as few humans as possible. People are expensive. They don't scale. They need health insurance. But for now, the companies are largely powered by people, clicking behind the curtain and making it look like magic.”).

¹⁸⁷ See Frank Pasquale, *Restoring Transparency to Automated Authority*, 9 J. ON TELECOMM. & HIGH TECH. L. 235 (2011); *supra* note 176; see also Perel & Elkin-Koren, *supra* note 176 (noting the chilling effect on researchers who would like to reverse engineer automated processes, given the potential to incur liabilities).

But while algorithms might remove some decisions from a human entity, humans must still make the initial decisions as to what data to train the algorithm on and as to what factors are deemed relevant or irrelevant.¹⁸⁸ Even more importantly, the decisions for what data is important in the training data—decisions that are then matched as closely as possible by the algorithm—are also made by humans.¹⁸⁹ For example, if a hiring algorithm is trained on a corpus of resumes, a human must still make consequential decisions as to what variables from the resumes should matter and which ones should be disregarded by the algorithm. Thus, akin to Mary Shelley’s conclusion in *Frankenstein’s Monster*, the creators of runaway algorithms should not be permitted to disavow their creations; rather those makers, like Dr. Frankenstein, must bear the ultimate liability for any harm wrought by their creations.

III. *EX MACHINA*: A LEGAL PROBLEM, NOT A TECHNICAL PROBLEM

The framing of the problem of algorithmic bias becomes important when deciding to whom to allocate liability. I contend that the current framing of algorithmic bias as a technical problem rather than as a legal problem is misguided.¹⁹⁰ As a consequence of this erroneous framing of algorithmic bias as a solely technical problem, ineffective technosolutionist approaches have proliferated. I argue that a reframing of the

¹⁸⁸ Even when automated feature selection methods are used, the final decision to use or not use the results, as well as the choice of feature selection method and any fine-tuning of its parameters, are choices made by humans. For more on feature selection see, e.g., GARETH JAMES, DANIELA WITTEN, TREVOR HASTIE & ROBERT TIBSHIRANI, *AN INTRODUCTION TO STATISTICAL LEARNING WITH APPLICATIONS IN R* (2017).

¹⁸⁹ See, e.g., the way that hiring startup Jobaline verifies their technique by using the ratings that people listening give voice snippets of job candidates. Ying Li et al., *Predicting Voice Elicited Emotions*, *PROC. 21ST ACM SIGKDD INT’L CONF. ON KNOWLEDGE DISCOVERY & DATA MINING* 1969 (2015).

¹⁹⁰ Professor Sandra Mayson also makes this argument in regard to algorithmic decision-making in the criminal justice field. Mayson, *supra* note 3 (arguing that the problem of disparate impact in predictive risk algorithms lies not in the algorithmic system but in the nature of prediction itself). Professors Paul Ohm and Blake Reid also make the argument that any coding decision will necessarily demand a legal conclusion: “Given the intrinsic malleability of code, every coding endeavor will implicate a growing number of regulations, subjecting coders to a complex and entangled set of requirements, prohibitions, and obligations.” Paul Ohm & Blake Reid, *Regulating Software When Everything Has Software*, 84 *GEO. WASH. L. REV.* 1672 (2016).

issues of bias in algorithmic hiring as legal in nature is necessary to plumb the true depths of the problem. In the following Sections, I describe how the biased results of algorithmic hiring systems are not merely technical deficiencies, rather, they reveal legal anachronisms, such as an American tradition of deference to the employer and what amounts to a legal shrug when it comes to addressing the nebulous concept of “cultural fit” as hiring criterion.

A. *A Legal Tradition of Employer Deference*

As previous scholars have noted, the social phenomenon in which organizations both respond to and construct the law that regulates them “renders law ‘endogenous’; the content and meaning of law is determined within the social field that it is designed to regulate.”¹⁹¹ It is no surprise then that American law has historically given much deference to employers vis-à-vis the employment bargain.¹⁹² In an empirical legal study, Professors Clermont and Schwab found:

¹⁹¹ Lauren B. Edelman, Christopher Uggen & Howard S. Erlanger, *The Endogeneity of Legal Regulation: Grievance Procedures as Rational Myth*, 105 AM. J. SOC. 406, 407 (1999).

¹⁹² Perhaps the most emblematic example of the American legal system’s deference to employers is the case of *Lochner v. New York*, 198 U.S. 45 (1905), which held that any limit on the number of hours (in excess of sixty hours) that employees of a bakery could work was unconstitutional. Although that particular decision has since been overturned, there is a wealth of scholarship noting the continued deference to employers. See Cynthia L. Estlund, *The Ossification of American Labor Law*, 102 COLUM. L. REV. 1527, 1527 (2002) (noting that the “ossification of labor law” is due, in part, to a lack of “democratic renewal”); see also Franita Tolson, *The Boundaries of Litigating Unconscious Discrimination: Firm-Based Remedies in Response to a Hostile Judiciary*, 33 DEL. J. CORP. L. 347 (2008). Courts want to avoid turning Title VII into a rule by which employers could be held liable for “perceived slights” towards employees. *Id.*; see also Kevin M. Clermont & Stewart J. Schwab, *How Employment Discrimination Plaintiffs Fare in Federal Court*, 1 J. EMPIRICAL LEGAL STUD. 429 (2004) (claiming that employment discrimination plaintiffs (unlike many other plaintiffs) have always done substantially worse in judge trials than in jury trials); Michael J. Zimmer, *The New Discrimination Law: Price Waterhouse Is Dead, Whither McDonnell Douglas?*, 53 EMORY L.J. 1887, 1944 (2004) (“The 5.8 percent reversal rate of defendant trial victories is smaller in employment discrimination cases than any other category of cases except prisoner habeas corpus trials.”); see also Ruth Colker, *The Americans with Disabilities Act: A Windfall for Defendants*, 34 HARV. C.R.-C.L. L. REV. 99, 100 (1999) (looking at reported decisions from 1992–1998 and finding that defendants prevailed in more than ninety-three percent of the cases decided at the trial court level and were more likely to be affirmed on appeal); Theodore Eisenberg, *Litigation Models and Trial Outcomes in Civil Rights and Prisoner Cases*, 77 GEO. L.J. 1567, 1577 (1989) (noting that only

Employment discrimination plaintiffs . . . manage many fewer happy resolutions early in litigation, and so they have to proceed toward trial more often. They win a lower proportion of cases during pretrial and at trial. Then, more of their successful cases are appealed. On appeal, they have a harder time upholding their successes and reversing adverse outcomes.¹⁹³

Likewise, after Professor Wendy Parker's empirical study of 659 cases alleging racial discrimination in employment, she concluded that judges operate under the assumption that those types of claims are generally without merit.¹⁹⁴ For cases alleging implicit bias, Professor Franita Tolson has also noted that courts will find in favor of the employee in only the most extreme cases because the courts have "statutory concerns and . . . [believe] that they are not qualified to resolve these claims."¹⁹⁵

Professor Selmi echoes these conclusions and observes:

When it comes to race cases, which are generally the most difficult claim for a plaintiff to succeed on, courts often seem mired in a belief that the claims are generally unmeritorious, brought by whining plaintiffs who have been given too many, not too few, breaks along the way. These biases, as well as others, inevitably influence courts' treatment of discrimination cases, and help explain why the cases are so difficult to win.¹⁹⁶

Professor Selmi also notes that judges display a similar bias against employees in sex employment discrimination cases as judicial activism has created an affirmative defense for employers "out of whole cloth, as there was very little precedent for the defense . . . [and] may signal a shift in judicial attitudes that portends more difficulty for plaintiffs to recover in cases of sexual harassment . . ."¹⁹⁷

claims filed by prisoners have a lower success rate than that of employment discrimination plaintiffs).

¹⁹³ Clermont & Schwab, *supra* note 192.

¹⁹⁴ Wendy Parker, *Lessons in Losing: Race Discrimination in Employment*, 81 NOTRE DAME L. REV. 889, 893 (2006).

¹⁹⁵ See Tolson, *supra* note 192, at 378.

¹⁹⁶ Michael Selmi, *Why Are Employment Discrimination Cases So Hard to Win?*, 61 LA. L. REV. 555, 556–57 (2001).

¹⁹⁷ *Id.* at 569.

In addition to this legal deference in contested cases of employment discrimination, employers exercise a great deal of latitude in choosing which job applicants they hire and fire.¹⁹⁸ This is especially true of at-will jurisdictions, where employees can be hired and fired based on a vast list of criteria determined by the employer.¹⁹⁹ In her article, *Discrimination at Will: Job Security Protections and Equal Employment Opportunity in Conflict*,²⁰⁰ Professor Julie Suk notes that employment discrimination scholars have argued that “employment at will seriously undermines the effectiveness of employment discrimination law in bringing about race and gender equality in the workplace.”²⁰¹ Other legal scholars have articulated exactly why this is the case as they note that the job protections present in antidiscrimination law might dissuade employers from hiring job applicants from protected groups. In her book, *Working Together*,²⁰² Professor Estlund argues that employers have perverse disincentives to hire racial minorities when Title VII operates in the context of employment at will²⁰³ because of the risk of incurring expenses in a Title VII suit. As Professors Ian Ayres and Peter Siegelman put it, “protection against discriminatory firing acts as a kind of tax on hiring those to whom it is extended.”²⁰⁴ Furthermore, employment at-will as a norm “affects the burdens of production and proof under the *McDonnell Douglas* framework when individual Title VII cases are litigated, often to the detriment of plaintiffs.”²⁰⁵

¹⁹⁸ Clyde W. Summers, *Employment at Will in the United States: The Divine Right of Employers*, 3 U. PA. J. LAB. & EMP. L. 65 (2000).

¹⁹⁹ “The rule of employment at will allows either the employer or the employee to terminate the employment relationship at any time for good reason, bad reason, or no reason.” Julie C. Suk, *Discrimination at Will: Job Security Protections and Equal Employment Opportunity in Conflict*, 60 STAN. L. REV. 73, 78 (2007). At-will employment is the law in every U.S. state except for Montana. See *At-Will Employment—Overview*, NAT’L CONF. ST. LEGISLATURES (Apr. 15, 2008), <http://www.ncsl.org/research/labor-and-employment/at-will-employment-overview.aspx> [https://perma.cc/Y47U-64EN].

²⁰⁰ Suk, *supra* note 199.

²⁰¹ *Id.* at 81.

²⁰² CYNTHIA ESTLUND, *WORKING TOGETHER: HOW WORKPLACE BONDS STRENGTHEN A DIVERSE DEMOCRACY* (2003).

²⁰³ Suk, *supra* note 199, at 83; see ESTLUND, *supra* note 202, at 152.

²⁰⁴ Ian Ayres & Peter Siegelman, *The Q-Word as Red Herring: Why Disparate Impact Liability Does Not Induce Hiring Quotas*, 74 TEX. L. REV. 1487, 1489 (1996).

²⁰⁵ Suk, *supra* note 199, at 81.

The Supreme Court's 1993 decision in *St. Mary's Honor Center v. Hicks* illustrates the detriments of the employment-at-will standard to employment discrimination plaintiffs.²⁰⁶ The plaintiff, Hicks, a black correctional officer, experienced repeated and severe disciplinary actions at the hands of a new supervisor.²⁰⁷ Hicks was eventually fired.²⁰⁸ Hicks then filed a Title VII case and presented a prima facie case under the standards of *McDonnell Douglas Corp. v. Green*.²⁰⁹ Although the district court found that the defendant offered false nondiscriminatory reasons for the firing, the district court nonetheless found for the defendant because the plaintiff had not proven that the employer's actions were "racially rather than personally motivated."²¹⁰

Amidst the legal backdrop of employer discretion and deference, the use of algorithmic hiring systems can exacerbate, rather than ameliorate, issues of bias, particularly given the well documented technological capability for those types of hiring systems to substitute facially neutral variables as proxies for protected demographic characteristics such as race and gender.²¹¹ The nature of the hiring relationship can be explained succinctly by the following quote: "typically the matching of a worker to a position does not reflect the outcome of the worker picking from among several job offers. Rather, it is the result of an employer picking from among several applicants."²¹² Employers choose candidates and not the other way around. Today, with the growing expanse of online job applications, job seekers apply to an average of twenty-seven jobs before they attain one interview.²¹³ Of course, since only seventeen percent of interviews actually result in an offer of employment, it is likely that these

²⁰⁶ *St. Mary's Honor Ctr. v. Hicks*, 509 U.S. 502, 508 (1993).

²⁰⁷ *Id.* at 505.

²⁰⁸ *Id.*

²⁰⁹ *Id.* at 505–06. Under *McDonnell Douglas Corp. v. Green*, 411 U.S. 792 (1973), a plaintiff could establish a prima facie case without direct evidence by proving (1) that he was a member of a protected group, (2) that he was qualified for the job, (3) he applied for the job and was rejected, and (4) the job continued to remain open. *Id.* at 802.

²¹⁰ *St. Mary's Honor Ctr.*, 509 U.S. at 508

²¹¹ Barocas & Selbst, *supra* note 3, at 692–93.

²¹² John M. Barron, John Bishop & William C. Dunkelberg, *Employer Search: The Interviewing and Hiring of New Employees*, 67 REV. ECON. & STAT. 43, 43 (1985).

²¹³ Matthew Nitch Smith, *You Now Have to Apply for 27 Jobs Just to Get 1 Interview*, BUS. INSIDER (May 16, 2016, 5:51 AM), <http://www.businessinsider.com/job-seekers-have-to-apply-for-27-jobs-for-every-interview-survey-finds> [<https://perma.cc/X34D-HBRH>].

applicants apply to far more than twenty-seven jobs throughout their entire job search.²¹⁴ In one extreme case, an applicant even built his own algorithm to apply to thousands of jobs at once, in an attempt to “beat” being sorted out by automated hiring platforms.²¹⁵

On the employer’s side of this surge in applications, on average, fifty-nine people apply for each open position.²¹⁶ From this pool of applicants, then, the employer is required to eliminate a large number of candidates in order to find candidates to interview—and ultimately hire. Due to the large pool of applicants, though, an average of only twelve percent of applicants will be interviewed for any open position.²¹⁷ This indicates that employers must use the information available to them to eliminate a large number of applicants before they can make substantial progress in finding the most talented candidates. The sheer necessity for this culling of possible job applicants has left some scholars in support of the employers’ total discretion in the hiring process.²¹⁸ Yet, it is undeniable that granting such near-total discretion opens the door for human bias to be introduced into the employment decision-making process. The subsequent use of algorithmic systems only allows said bias to become entrenched and more difficult to detect.

B. *The Problem of “Cultural Fit”*

Given the wide discretion that employers enjoy, an insidious manner in which bias may infiltrate the employment decision-making process is through the discernment of “cultural fit,” as, in many ways, the variables employed to algorithmically cull resumes are approximations of “cultural fit.” The problem is that some of those variables may be inherently at odds with Title VII, while allowing employers to avoid hiring protected classes of applicants, “as long as some credible

²¹⁴ Martha C. White, *Here’s How Long It Really Takes to Get a Job*, MONEY (Oct. 22, 2015), <http://time.com/money/4053899/how-long-it-takes-to-get-hired> [<https://perma.cc/L5J2-WMEN>].

²¹⁵ Robert Coombs, *I Built a Bot to Apply to Thousands of Jobs at Once—Here’s What I Learned*, FAST CO. (Mar. 23, 2017), <https://www.fastcompany.com/3069166/i-built-a-bot-to-apply-to-thousands-of-jobs-at-once-heres-what-i-learned> [<https://perma.cc/Q47L-8KQC>].

²¹⁶ White, *supra* note 214.

²¹⁷ *Id.*

²¹⁸ See, e.g., Peter Cappelli, *Career Jobs Are Dead*, 42 CAL. MGMT. REV. 146 (1999).

nondiscriminatory reason . . . can be presented.”²¹⁹ This issue is exacerbated by machine learning algorithms that may not treat “cultural fit” as the amorphous concept that it is but rather as a strict rule, thus creating the genre of scenarios I detailed before wherein a hiring algorithm or algorithms might deduce that only men named “Jared” and who play lacrosse are “fit” for the job.²²⁰

To achieve culling, employers study a number of qualities about candidates—from their resumes, to their past employment experiences, and their “cultural fit” within the perspective company.²²¹ Cultural fit is defined as “the likelihood that a job candidate will be able to conform and adapt to the core values and collective behaviors that make up an organization.”²²² For example, “60% of recruiters rate culture fit of highest importance when making a hiring decision.”²²³ This shows that recruiters considered cultural fit as more significant than cover letters (26%), prestige of college (21%), and GPA (19%). Cultural fit of a candidate is topped only by previous job experience (67%).²²⁴ When judging whether a candidate is a cultural fit, eighty-three percent of recruiters consider communication style most important.

While scholars largely agree about the need for resumes and descriptions of past experiences, many are at odds with the idea of an employer’s determination of an applicant’s cultural fit.²²⁵ In many regards, the determination of a candidate’s cultural fit is subjective. Some articles report that assessing cultural fit comes down to an employer’s

²¹⁹ Suk, *supra* note 199, at 73.

²²⁰ See Gershgorn, *supra* note 92.

²²¹ See Laura Morgan Roberts & Darryl D. Roberts, *Testing the Limits of Antidiscrimination Law: The Business, Legal, and Ethical Ramifications of Cultural Profiling at Work*, 14 DUKE J. GENDER L. & POL’Y 369 (2007).

²²² Margaret Rouse, *What Is Cultural Fit?*, TECHTARGET: SEARCHCIO, <https://searchcio.techtarget.com/definition/Cultural-fit> [<https://perma.cc/T3UH-CQAZ>] (last updated Sept. 2014).

²²³ JOBVITE, JOBVITE RECRUITER NATION REPORT 2016: THE ANNUAL RECRUITING SURVEY (2016), <https://www.jobvite.com/wp-content/uploads/2016/09/RecruiterNation2016.pdf> [<https://perma.cc/KSC4-PV3Q>].

²²⁴ See *id.*

²²⁵ See, e.g., Christine Sgarlata Chung, *From Lily Bart to the Boom-Boom Room: How Wall Street’s Social and Cultural Response to Women Has Shaped Securities Regulation*, 33 HARV. J.L. & GENDER 175 (2010) (arguing that cultural fit within the finance industry is imperfect, as bias has been historically ingrained).

“gut feeling.”²²⁶ Others have reported that a candidate might be a good fit if “[t]hey work well with others”—which seems to be something that is difficult to predict without ever seeing a candidate work with other people.²²⁷ To this end, some researchers have promoted the idea that corporate culture can be learned, indeed, because nearly every company that hires a new employee has a period of “socialization” or social training.²²⁸ Others have shown that interviewers are not even significantly adept at assessing applicants’ personal characteristics from interviews.²²⁹

On the other hand, researchers have argued that assessing cultural fit is important because “employee alignment to company culture influences worker satisfaction, engagement and retention,” which can ultimately help the corporation to succeed.²³⁰ Furthermore, a study of thirty-eight interviewers who were in the process of making hiring decisions found that interviewers can actually assess cultural fit “with significant degrees of accuracy” and that this factor is often “the best predictor[] of hiring recommendations.”²³¹ Given both arguments, it is clear that there can be both positive and negative implications of trying to assess a candidate’s cultural fit—but cultural fit can only be a useful criterion for hiring so long as an employer could make an accurate determination of such fit.

The problem there is that, as employment law scholars such as Professor Natasha Martin have noted, “workplace decision-makers may gain awareness of the lack of cultural fit only after some time has

²²⁶ Lauren Brown, ‘Gut Feeling’ Still the Most Common Deciding Factor in Hiring, Survey Shows, PEOPLE MGMT. (July 11, 2018), <https://www.peoplemanagement.co.uk/news/articles/gut-feeling-most-common-deciding-factor-in-hiring-survey-shows> [<https://perma.cc/DZV4-SYEC>].

²²⁷ Jeff Pruitt, 3 Ways to Know if an Employee Is a Culture Fit, INC. (Aug. 12, 2016), <https://www.inc.com/jeff-pruitt/3-ways-to-know-if-an-employee-is-a-culture-fit.html> [<https://perma.cc/9BEC-JCBH>].

²²⁸ Richard Pascale, *The Paradox of “Corporate Culture”: Reconciling Ourselves to Socialization*, 27 CAL. MGMT. REV. 26 (1985).

²²⁹ Richard D. Arvey & James E. Campion, *The Employment Interview: A Summary and Review of Recent Research*, 35 PERSONNEL PSYCHOL. 281 (1982).

²³⁰ Lauren Dixon, *The Pros and Cons of Hiring for ‘Cultural Fit,’* CHIEF LEARNING OFFICER: TALENT ECON. (Dec. 6, 2017), <https://www.chieflearningofficer.com/2017/12/06/pros-cons-hiring-cultural-fit> [<https://perma.cc/NWW2-8TQE>].

²³¹ Daniel M. Cable & Timothy A. Judge, *Interviewers’ Perceptions of Person-Organization Fit and Organizational Selection Decisions*, 82 J. APPLIED PSYCHOL. 546, 558 (1997).

passed.”²³² This means that even if an individual is hired, it is likely that the decision-maker’s view of the worker changes over time with greater exposure.²³³ Professor Martin notes that “[t]his social construction of identity bears on selection of individuals when organizations make decisions based on cultural fit. By aligning employees with environmental factors, employers focus less on the candidate’s skill set, and more on the intangibles that make uncovering discriminatory motive more difficult.”²³⁴ For instance, cultural fit qualifications, such as “relish change,” “possess passion for exceptional quality,” “confront risks,” or “think creatively,” have an “amorphous quality because they are generalized and undefined with respect to any particular job task or role.”²³⁵ Therefore, the ultimate decisions can rest merely on gut feelings like “I just like that candidate” or “he just feels right.”²³⁶ Even though choosing an individual based on seemingly aligned values may look like a good business decision, the problem with cultural fit in the selection process lies in the “imperceptibility of such characteristics, and the conscious and unconscious layering of meaning on such abstract terms by the decision-maker.”²³⁷ Professor Martin cites to Professor Charles Lawrence’s law review article,²³⁸ in which he observes that “where an ‘employer perceives the white candidate as “more articulate,” “more collegial,” “more thoughtful,” or “more charismatic[,]” [h]e is unaware of the learned stereotype that influenced his decision.”²³⁹

In sum, the problem with cultural fit is about the “perception of who belongs.”²⁴⁰ Employers try to select candidates who match their “culturally consistent selection criteria,” and in the fast-paced workplace, an employer has to make decisions with incomplete information about each candidate and hire an individual who seems to be a “good fit based

²³² Natasha T. Martin, *Immunity for Hire: How the Same-Actor Doctrine Sustains Discrimination in the Contemporary Workplace*, 40 CONN. L. REV. 1117, 1156 (2008).

²³³ *See id.*

²³⁴ *Id.* at 1158.

²³⁵ *Id.*

²³⁶ *Id.*

²³⁷ *Id.* at 1159.

²³⁸ *Id.* (alteration in original) (citing Charles R. Lawrence III, *The Id, the Ego, and Equal Protection: Reckoning with Unconscious Racism*, 39 STAN. L. REV. 317 (1987)).

²³⁹ *Id.*; Lawrence, *supra* note 238, at 343.

²⁴⁰ Martin, *supra* note 232, at 1159.

on paper credentials and limited staged interview interaction.”²⁴¹ Later, the same employee “might be deemed unfit in cultural terms . . . because he failed to attune to the organization’s culture.”²⁴² In this situation, “[p]eople of color and other workplace minorities are often encouraged to assimilate, mask their true identity or ethnic salience, for example, to adapt to an organization’s culture.”²⁴³ Citing to the work of Professors Devon Carbado and Mitu Gulati,²⁴⁴ Martin explains that “[a]s long as the worker’s difference is innocuous and unobtrusive, then the worker benefits from efforts to belong” and “once the employee fails to sufficiently cover, he may be deemed inconsistent with the organization and no longer befitting of inclusion.”²⁴⁵ Professors Carbado and Gulati have also argued that the “extra” identity work that women and minorities are forced to do to conform to workplace perceptions of “cultural fit” is a form of employment discrimination.²⁴⁶

Courts, however, have consistently sided with defendants in contestations of cultural fit as a criterion for hiring and firing. One notorious case is *Natay v. Murray School District*,²⁴⁷ in which the courts sided with the employer when deciding the cultural fit of an employee. The plaintiff, hired by the school district as a provisional teacher, was the only Native American in the group of forty-seven recently hired provisional teachers and on the school faculty.²⁴⁸ Plaintiff described her treatment at the school as discriminatory from the start; the principal snubbed her at the first staff meeting, disciplined her but not another teacher, and came late to her scheduled evaluations. In addition, the principal told Natay at one point that she was “geographically, racially, culturally, and socially out of place” at the school, and her contract was not renewed after unfavorable evaluations.²⁴⁹ The school district superintendent also decided that the plaintiff was “not an excellent

²⁴¹ *Id.*

²⁴² *Id.*

²⁴³ *Id.*

²⁴⁴ See Devon W. Carbado & Mitu Gulati, *Working Identity*, 85 CORNELL L. REV. 1259, 1262 (2000); Devon W. Carbado, *Racial Naturalization*, 57 AM. Q. 633, 655 (2005).

²⁴⁵ Martin, *supra* note 232, at 1160.

²⁴⁶ See Carbado & Gulati, *supra* note 244, at 1262.

²⁴⁷ *Natay v. Murray Sch. Dist.*, 119 F. App’x 259 (10th Cir. 2005).

²⁴⁸ See *id.* at 260.

²⁴⁹ See *id.*

teacher and not someone [he] would want Murray School District to hire on a long-term basis.”²⁵⁰ Natay had an informal conference with the superintendent, but her arguments did not change the decision. Of the district’s provisional teachers hired for that school year, only Natay’s contract was not renewed, and on her last day of work, the principal made another racially derogatory comment to her.²⁵¹ Natay brought a discriminatory discharge claim in federal district court, and the court entered summary judgment in favor of the employer. She appealed.

In the Tenth Circuit, the court reviewed the district court’s grant of summary judgment, using the same standards, as well as the evidence and reasonable inferences drawn from the evidence. It stated that although the plaintiff proved that the principal showed discriminatory actions, she lacked evidence showing that the superintendent, the ultimate decision-maker, had a discriminatory reason not to renew her contract.²⁵² Based on the “cat’s paw” doctrine, she did not prove that the “manager who discharged the plaintiff merely acted as a rubber stamp, or the ‘cat’s paw,’ for a subordinate employee’s prejudice,”²⁵³ regardless of the manager’s discriminatory intent. Also, the court used the *McDonnell Douglas* burden-shifting framework. The court decided that the plaintiff satisfied the prima facie case and succeeded in shifting the burden to the school district. Although the plaintiff claimed that the superintendent’s investigation of her performance was inadequate because he never sat in her classroom to observe her, the court stood on the side of the superintendent, whose affidavit detailed other steps in his investigation and decision to not renew the contract due to her ineffectiveness. Thus, the court concluded that the plaintiff’s showing did not reasonably give rise to an inference that the employer’s reasons were pretextual and affirmed the decision of the district court.²⁵⁴

²⁵⁰ *Id.* at 261.

²⁵¹ *See id.*

²⁵² *See id.*

²⁵³ *Id.* at 262.

²⁵⁴ *Id.*

C. *Re-Thinking Employer Discretion*

Given that deference to an employer's determination of cultural fit may not bode well for members of protected groups, as an *ex ante* approach to curbing algorithmic discrimination in hiring, I argue for a rethinking of employer discretion, particularly regarding variables meant to indicate "cultural fit" as part of algorithmic hiring. I propose that the law should mandate that the criteria used in algorithmic hiring must have some probative value for determining fitness to perform required job duties. This proposal is supported by new studies that show that "cultural fitness" is not always necessary for long-term success at a firm. One such study conducted by business professors at Stanford and Berkeley found that the capacity to change and flexibility—that is, high "enculturability"—were more important than pre-existing cultural fit in regard to long-term success.²⁵⁵ According to the authors of the study:

Our results suggest that firms should place less emphasis on screen for cultural fit, . . . [a]s other work has shown, matching on cultural fit often favors applicants from particular socioeconomic backgrounds, leading to a reduction in workplace diversity. Instead, our work points to the value of screening on enculturability.²⁵⁶

The study concludes with three enculturability questions that employers might pose to potential candidates during the hiring process: "1. To what extent do candidates seek out diverse cultural environments? 2. How rapidly do they adjust to these new environments? 3. How do they balance adapting to the new culture while staying true to themselves?"²⁵⁷

As a result of such new studies, more companies are moving away from "cultural fit" as a factor for hiring. For example, in a bid to create a more inclusive hiring process, Facebook outlawed the term "culture fit"

²⁵⁵ Amir Goldberg, Sameer B. Srivastava, V. Govind Manian, William Monroe & Christopher Potts, *Fitting In or Standing Out? The Tradeoffs of Structural and Cultural Embeddedness*, 81 AM. SOC. REV. 1190 (2016).

²⁵⁶ Rich Lyons, *Lose Those Cultural Fit Tests: Instead Screen New Hires for 'Enculturability'*, FORBES (June 7, 2017, 10:00 AM), <https://www.forbes.com/sites/richlyons/2017/06/07/lose-those-cultural-fit-tests-instead-screen-new-hires-for-enculturability/#450b9e6b63a8> [https://perma.cc/5EYT-KF36].

²⁵⁷ *Id.*

as interview feedback, “requiring interviewers to provide specific feedback that supported their position.”²⁵⁸ Facebook also took steps to “proactively identify unconscious bias” in their interview process and “developed a ‘managing unconscious bias’ training program.”²⁵⁹

Other companies now embrace “hiring for values fit” as a method to decrease unconscious bias in interviewing. For example, Atlassian, an Australia-based company, redesigned its interview process: “values fit interviewers are carefully selected and given training on topics like structured interviewing and unconscious bias.”²⁶⁰ The interview is structured with a set of behavioral questions to assess whether a candidate would thrive in an environment with their company values.²⁶¹ As one of Atlassian’s chief officers explains: “Focusing on ‘values fit’ ensures we hire people who share our sense of purpose and guiding principles, while actively looking for those with diverse viewpoints, backgrounds, and skill sets. We’re trying to build a healthy and balanced culture, not a cult.”²⁶² This approach has borne positive results for Atlassian. In 2015, ten percent of their technical workforce identified as female. In 2016, seventeen percent of recent hires were women, and women held fourteen percent of all technical roles. Similarly, in 2015, their U.S.-based team had twenty-three percent of employees identifying as people of color. In 2016, people of color comprised thirty-two percent of their new hires.²⁶³

IV. *EX LEGIS*: NEW LEGAL FRAMEWORKS

In this Part, I discuss potential new legal frameworks that could address bias in automated hiring platforms. An open legal issue is who

²⁵⁸ Lars Schmidt, *The End of Culture Fit*, FORBES (Mar. 21, 2017, 7:50 AM), <https://www.forbes.com/sites/larsschmidt/2017/03/21/the-end-of-culture-fit/#70fbb72638a> [<https://perma.cc/N7H3-SNZS>].

²⁵⁹ *Id.*; Sheryl Sandberg, *Managing Unconscious Bias*, FACEBOOK: NEWSROOM (July 28, 2015), <https://newsroom.fb.com/news/2015/07/managing-unconscious-bias> [<https://perma.cc/A2KG-H5AZ>].

²⁶⁰ Schmidt, *supra* note 258.

²⁶¹ *Id.* A description of Atlassian’s company values is available here: *Company Values*, ATLISSIAN, <https://www.atlassian.com/company/values> [<https://perma.cc/WS37-QL4Q>].

²⁶² Schmidt, *supra* note 258.

²⁶³ *Id.* Atlassian diversity hire figures are public available here: *Building Equitable, Balanced Teams and a Sense of Belonging*, ATLISSIAN, <https://www.atlassian.com/belonging> [<https://perma.cc/3949-T3ZN>].

should bear the legal liability for when an automated hiring algorithm is returning biased results. Is it the business firm that is using the algorithms for its hiring process? Or is it the maker of the algorithmic hiring platform? In this Part, I approach the issue of liability from different vantages: A) from the position of holding accountable the maker of the algorithmic hiring system; B) from the position of holding the employer accountable; and C) from the position of holding liable both the maker of the algorithmic system and, potentially, also the employer.

A. *Improving on the Fiduciary Duty Concept*

Even if it is accepted that employers owe no duties to job applicants, some legal scholars would argue that the makers of hiring platforms should owe a legal duty to job applicants.²⁶⁴ Professor Jack Balkin characterizes information fiduciaries as entities “who, because of their relationship with another, [assume] special duties with respect to the information they obtain in the course of the relationship.”²⁶⁵ According

²⁶⁴ See, e.g., Ford, *supra* note 30 (arguing that employment law imposes a duty of care on employers to avoid decisions that undermine social equality).

²⁶⁵ Jack M. Balkin, *Information Fiduciaries and the First Amendment*, 49 U.C. DAVIS L. REV. 1183 (2016) [hereinafter Balkin, *Information Fiduciaries and the First Amendment*]; The phrase “information fiduciaries” was first coined by Professor Kenneth Laudon. See Kenneth C. Laudon, *Markets and Privacy*, ICIS 1993 PROC. 65, 70–71 (1993) (proposing a “National Information Market” within which “information fiduciaries . . . would accept deposits of information from depositors and seek to maximize the return on sales of that information in national markets or elsewhere in return for a fee”). Professor Jack Balkin popularized the term in several writings. See Jack M. Balkin, *Information Fiduciaries in the Digital Age*, BALKINIZATION (Mar. 5, 2014), <https://balkin.blogspot.com/2014/03/information-fiduciaries-in-digital-age.html> [<https://perma.cc/AL58-WWLT>]; Jack M. Balkin, *Free Speech in the Algorithmic Society: Big Data, Private Governance, and New School Speech Regulation*, 51 U.C. DAVIS L. REV. 1149, 1160–63 (2018); Jack M. Balkin, *Free Speech Is a Triangle*, 118 COLUM. L. REV. 2011, 2047–55 (2018); JACK M. BALKIN, HOOVER INST., *FIXING SOCIAL MEDIA’S GRAND BARGAIN* 11–15 (2018), https://www.hoover.org/sites/default/files/research/docs/balkin_webreadypdf.pdf [<https://perma.cc/RN22-4D86>]. Professor Jonathan Zittrain has also made important theoretical contributions to the concept of information fiduciaries. See Jack M. Balkin & Jonathan Zittrain, *A Grand Bargain to Make Tech Companies Trustworthy*, ATLANTIC (Oct. 3, 2016), <https://www.theatlantic.com/technology/archive/2016/10/information-fiduciary/502346> [<https://perma.cc/P436-G96Z>]; Jonathan Zittrain, *Facebook Could Decide an Election Without Anyone Ever Finding Out*, NEW REPUBLIC (June 1, 2014), <https://newrepublic.com/article/117878/information-fiduciary-solution-facebook-digital-gerrymandering> [<https://perma.cc/935C-QGWN>]; Jonathan Zittrain, *How to Exercise the Power You Didn’t Ask For*, HARV. BUS. REV. (Sept.

to Professor Balkin, the relationship between the consumer and job applicant is analogous to that between a doctor and patient.²⁶⁶ Thus, an information fiduciaries “have special duties to act in ways that do not harm the interests of the people whose information they collect, analyze, use, sell, and distribute.”²⁶⁷ In the context of employment, the primary question is: How should the law conceptualize the responsibilities of these hiring platforms in regard to the information they solicit and transmit?

I depart from Professor Balkin’s analogy,²⁶⁸ to offer a more critical view of the relationship between job seekers and the automated hiring platform as brokering intermediary. My theorizing responds directly to trenchant critiques of the information fiduciary idea. Notably, Professors Lina Khan and David Pozen have expressed doubts in their essay, *A Skeptical View of Information Fiduciaries*,²⁶⁹ as to “whether the concept of information fiduciaries is an adequate or apt response to the problems of information asymmetry and abuse” of platforms and whether such a theory ignores “fundamental problems associated with market dominance and with business models that demand pervasive surveillance.”²⁷⁰ The authors also conclude that the information-fiduciary framework “invites an enervating complacency about issues of structural power and a premature abandonment of more robust visions of public regulation.”²⁷¹

My aim in this Article is not to adjudicate whether the concept of information fiduciaries can *comprehensively* offer the solution to problems associated with online platforms.²⁷² I do, however, find the

19, 2018), <https://hbr.org/2018/09/how-to-exercise-the-power-you-didnt-ask-for> [<https://perma.cc/K3TV-KMLP>]; Jonathan Zittrain, *Mark Zuckerberg Can Still Fix This Mess*, N.Y. TIMES (Apr. 7, 2018), <https://www.nytimes.com/2018/04/07/opinion/sunday/zuckerberg-facebook-privacy-congress.html> [<https://perma.cc/AVM9-AETF>].

²⁶⁶ Balkin, *Information Fiduciaries and the First Amendment*, *supra* note 265, at 1205–09.

²⁶⁷ *Id.* at 1209.

²⁶⁸ *Id.* at 1205–09.

²⁶⁹ Lina M. Khan & David E. Pozen, *A Skeptical View of Information Fiduciaries*, 133 HARV. L. REV. 497 (2019).

²⁷⁰ *See id.* at 501.

²⁷¹ *See id.* at 502.

²⁷² *Cf.* James Grimmelman, *When All You Have Is a Fiduciary*, LAW & POL. ECON. (May 30, 2019), <https://lpeblog.org/2019/05/30/when-all-you-have-is-a-fiduciary> [<https://perma.cc/753R-CVLD>] (suggesting that while fiduciary principles are ill-suited to problems of self-dealing, content moderation, and market concentration on online platforms, the “best version” of U.S. information

concept useful in discussing problems associated with one particular type of online platform, and that is the automated hiring platform. And as the rest of my Article demonstrates, I consider the idea of the information fiduciary as an important building block towards other theorization regarding online platforms, and also as one of several potential checks to the currently unbridled power of automated hiring platforms to serve exclusionary ends. I believe that there could be a multiplicity of approaches to the governance of online platforms for the betterment of society. For example, while hitherto I have tended to focus on governmental action as the appropriate governance mechanism for algorithmic bias, other legal scholars, like Professor Sonia Katyal, have called for private accountability measures.²⁷³ No one scholar can claim the cure-all solution to the problem of algorithmic bias, but rather than reject proposed solutions outright as nostrum, we should acknowledge that we are all blind men grasping at the elephant and that our collective intellectual attempts may yet reveal a full view of the problem at hand. As such, several legal scholars have recently called for the extension of fiduciary duties to other areas of law.²⁷⁴ And some legal scholars have also argued against the expansion of fiduciary duties.²⁷⁵ I argue that established concepts from organizational theory scholarship further bolster the argument that hiring platforms are performing a brokerage function and thus should be considered fiduciaries.²⁷⁶

privacy law “would cash out fiduciary principles in specifying when and how platforms can use and share user data”).

²⁷³ Katyal, *supra* note 16 (calling for a variety of tools to tackle algorithmic accountability such as codes of conduct, impact statements, and whistleblower protection).

²⁷⁴ See D. Theodore Rave, *Politicians as Fiduciaries*, 126 HARV. L. REV. 671 (2013); see also D. Theodore Rave, *Fiduciary Voters?*, 66 DUKE L.J. 331 (2016); cf. Seth Davis, *The False Promise of Fiduciary Government*, 89 NOTRE DAME L. REV. 1145 (2014).

²⁷⁵ See James Grimmelman, *Speech Engines*, 98 MINN. L. REV. 868, 904 (2014) (“[W]e are undergoing something of an academic fiduciary renaissance, with scholars arguing for treating legislators, judges, jurors, and even friends as fiduciaries.” (internal footnotes omitted)); Daniel Yeager, *Fiduciary-isms: A Study of Academic Influence on the Expansion of the Law*, 65 DRAKE L. REV. 179, 184 (2017) (arguing that “academic writing, deploying a sense of *fiduciary* so open as to be empty, has influenced courts to designate” more entities as fiduciaries).

²⁷⁶ I take as authority the definition of brokerage set forth by Marsden: Brokerage is understood as a mechanism by which “actors facilitate transactions between other actors lacking access to or trust in one another” See Peter V. Marsden, *Brokerage Behavior in Restricted Exchange Networks*, in SOCIAL STRUCTURE AND NETWORK ANALYSIS 201–02 (Peter V. Marsden & Nan Lin eds., 1982).

My theorizing then works to clarify both the power and information asymmetry relationships present in the triad of job applicant, hiring platform, and employer. For example, with platform authoritarianism, I make clear the unequal power relationship between the job applicant and the platform, which allows the platform to dictate in what manner the job applicant may make use of the platform thus belying the caretaking imagery conjured by a doctor-patient analogy. With the *tertius bifrons* concept, I reveal the duplicitous relationship between the hiring platform and the job applicant, which then supports the argument for greater employment discrimination liability for the platform.

1. Platform Authoritarianism

As Professor Olivier Sylvain has noted, platforms “shape the form and substance of their users’ content.”²⁷⁷ Furthermore, platforms also shape relationships as they connect users to one another while also enjoying “a great deal of control over how users’ encounters are structured.”²⁷⁸ In evaluating certain design policy choices that these companies make, such as the methods through which they facilitate the amount of information users can learn about one another and how they are to do so, one argument is that online platforms can make choices that exacerbate the discrimination in our current society.²⁷⁹ Thus, makers of platforms cannot be blameless for the discrimination that occurs on them—even if their users may be influenced by pre-existing biases.²⁸⁰ Thus, I theorize “platform authoritarianism” as a sociotechnical phenomenon that has transformed the responsibility and liability of platforms.²⁸¹

²⁷⁷ Sylvain, *Discriminatory Designs on User Data*, *supra* note 150.

²⁷⁸ Karen Levy & Solon Barocas, *Designing Against Discrimination in Online Markets*, 32 BERKELEY TECH. L.J. 1183, 1183 (2017).

²⁷⁹ *Id.*

²⁸⁰ *Id.*

²⁸¹ Ifeoma Ajunwa, *Facebook Users Aren't the Reason Facebook Is in Trouble Now*, WASH. POST (Mar. 23, 2018, 11:12 AM), <https://www.washingtonpost.com/news/posteverything/wp/2018/03/23/facebook-users-arent-the-reason-facebook-is-in-trouble-now> [https://perma.cc/8GXH-UYFQ]. Professor Shoshana Zuboff was one of the first to detail how platforms could be deployed in the surveillance and managerial control of employees. See SHOSHANA ZUBOFF, *IN THE AGE OF THE SMART MACHINE: THE FUTURE OF WORK AND POWER* (1988); see also SHOSHANA ZUBOFF, *THE*

Platform authoritarianism is what I term our present social position vis-à-vis platforms, wherein creators of platforms demand that we engage with those platforms solely “on their dictated terms, without regard for established laws and business ethics.”²⁸² Some scholars have noted that many online platforms can control “who is matched with whom for various forms of exchange, what information users have about one another during their interactions, and how indicators of reliability and reputation are made salient.”²⁸³ This means that for example, job applicants on hiring platforms must acquiesce to data demands from the platforms; they are also not in control of how their candidacy is presented, but rather must relinquish all control to the platform as *quid pro quo* for accessing job opportunity. Rejecting platform authoritarianism in favor of a duty of care that the purveyors of online platforms owe to their users is the first step towards returning to a rule of law for algorithms.

2. The *Tertius Bifrons*

While exercising authoritative control over the content and structure of their users’ interactions, hiring platforms also hide their true relationship to job applicants and this deception can lull applicants into a false sense of trust. According to the sociologist Georg Simmel, brokers, as part of a triad, perform the function of brokering information between two separate groups, acting as either *tertius iungens* or *tertius gaudens*.²⁸⁴ The *tertius iungens* (“the third who joins”) orientation is derived from the Latin verb “iungere,” which means to join, unite, or connect.²⁸⁵ The emphasis of this orientation is on the joining of two parties. Thus, a *tertius iungens* broker will operate with a strategic emphasis on creating friendship and collaboration between two parties.²⁸⁶ For example, linking

AGE OF SURVEILLANCE CAPITALISM: THE FIGHT FOR A HUMAN FUTURE AT THE NEW FRONTIER OF POWER (2019).

²⁸² Ajunwa, *supra* note 281.

²⁸³ Levy & Barocas, *supra* note 278, at 1183.

²⁸⁴ SIMMEL, *supra* note 33.

²⁸⁵ David Obstfeld, *Social Networks, the Tertius Iungens Orientation, and Involvement in Innovation*, 50 ADMIN. SCI. Q. 100, 102 (2005).

²⁸⁶ *Id.*

disparate parties in one's social network in order to create outcomes that are mutually beneficial for two or more parties.²⁸⁷ In contrast, the *tertius gaudens* ("the third who enjoys") orientation emphasizes the strategic separation of parties.²⁸⁸ In this sense, a broker would enjoy the benefit of the continued separation between two parties for the broker's own gain.²⁸⁹

Going beyond the two categories of brokerage, organizational theory scholars have noted that brokers may engage in four different brokering strategies. Brokers may:

- (1) coordinate action or information between distant parties who have no immediate prospect for direct introduction or connection,
- (2) actively maintain and exploit the separation between parties,
- (3) introduce or facilitate preexisting ties between parties such that the coordinative role of the *tertius iungens* subsequently recedes in importance (brief *iungens*), and
- (4) introduce or facilitate interaction between parties while maintaining an essential coordinative role over time.²⁹⁰

The automated hiring process comprises a triad, with the automated hiring platform as the broker negotiating between the applicant and the employer. I argue that, in this triad, hiring platforms are brokers who perform an "essential coordinative role over time"²⁹¹ by continuously parsing resumes received from job applicants before delivering them to employers. Furthermore, I propose that automated hiring platforms, which can be customized at the request of the employer (but not that of the applicant) belong to a new category of brokers that I term "the *tertius bifrons*" (that is, "the two-faced third"). With the introduction of this new term, I am arguing that automated hiring platforms represent a type of broker which works both in its own interest (to maintain its coordinative role) and in the interest of one of the parties to the triad (the employer),

²⁸⁷ *Id.*

²⁸⁸ *Id.*

²⁸⁹ *Id.*

²⁹⁰ *Id.* at 104.

²⁹¹ David Obstfeld, *Social Networks, the Tertius Iungens Orientation, and Involvement in Innovation*, 50 ADMIN. SCI. Q. 100, 104 (2005).

while maintaining the appearance of working for both parties (employer and job applicant).

This categorization rings true in light of the class action allegations against Facebook.²⁹² Facebook users entrust their information to platforms like Facebook with the expectation that those platforms would use that information to better the users' experience. However, what has been alleged is that Facebook, by creating "affinity groups" and "lookalike audiences" from its users' information (and especially when such Facebook-provided features are deployed in defiance of antidiscrimination laws),²⁹³ has brokered information to employers in a way that benefits both Facebook and the employer, but not necessarily the user. I concur with the legal theory then that this brokerage of job applicant information, in a manner that is inconsistent with the best interests of the job applicant, violates a fiduciary duty held by the hiring platform as an information fiduciary.

B. *Discrimination Per Se*

As holding corporations responsible for the algorithmic bias of the automated hiring platforms they use represents a challenging legal problem because of the difficulty of discovering proof and establishing intent, I propose a new burden-shifting theory of liability, *discrimination per se*.²⁹⁴ *Discrimination per se* would allow for a third cause of action

²⁹² See First Amended Class and Collective Action Complaint, *supra* note 158, at 21.

²⁹³ See *id.*

²⁹⁴ Although my proposed doctrine borrows from tort theory, it is important to note that the National Labor Relations Act characterizes some employer actions as per se violations. 29 U.S.C. § 158 (2018). The statute defines per se violations of the bargaining obligation as conduct that violates subsection 8(a)(5) without need for further inquiry, including unilateral changes involving mandatory subjects of bargaining, even when such changes are made in a context that otherwise indicates good faith bargaining, and even where the changes are partially made in an effort to comply with governmental requirements. Other per se violations include: An employer bypassing the union and bargaining directly with employees; insistence to impasse upon permissive subjects of bargaining; and refusing to execute a written agreement embodying the terms of a negotiated contract. See Timothy M. McConville, *Employer Policies May Be Per Se Violations of the National Labor Relations Act (NLRA)*, NAT'L L. REV. (July 12, 2013), <https://www.natlawreview.com/article/employer-policies-may-be-se-violations-national-labor-relations-act-nlra> [<https://perma.cc/8LFL-G568>].

under Title VII.²⁹⁵ The purpose is to aid plaintiffs who cannot show proof of disparate treatment or who would have difficulty obtaining the means to show the statistical proof of disparate impact. Title VII requires intent for liability to attach, or in the absence of intent, a clear demonstration of disparate impact with no excuse of business necessity for the disparity.²⁹⁶ When bringing disparate impact claims, plaintiffs are likely to face three interrelated obstacles: “(1) compiling the requisite statistics to show that the policy has a disparate impact . . . (2) identifying a specific policy or practice that caused the adverse employment decision, and (3) rebutting the employer’s defense that the policy is justified by a business necessity.”²⁹⁷ Also notable, “courts are inconsistent in addressing the requirement of compiling appropriate statistics to show that a policy has a disparate impact.”²⁹⁸ Second, courts often fail to find a “particular employment practice” that caused the disparity because they cannot distinguish actual job tasks from the default norms.²⁹⁹ Many times, courts use the phrase “particular employment practice” to narrow the applicability of disparate impact liability.³⁰⁰

In their essay, *Incomprehensible Discrimination*, Professors James Grimmelman and Daniel Westreich, make the case that when a plaintiff has met the burden of showing disparate impact, “the defendant’s burden to show a business necessity requires it to show not just that its model’s

²⁹⁵ Title VII of the Civil Rights Act protects the job applicant against discrimination on the basis of sex, race, color, national origin, and religion. See Civil Rights Act of 1964 § 7, 42 U.S.C. § 2000e-2 (2018). Plaintiffs must establish that “a respondent uses a particular employment practice that causes a disparate impact on the basis of [a protected characteristic] and the respondent fails to demonstrate that the challenged practice is job related for the position in question and consistent with business necessity.” 42 U.S.C. § 2000e-2(k)(1)(A)(i).

²⁹⁶ Proving clear intent is necessary when attempting to make a disparate treatment case under Title VII. However, under the disparate impact cause of action codified in Title VII, the intent is implied from an established pattern. See 42 U.S.C. § 2000e-2(k)(1)(A).

²⁹⁷ Nicole Buonocore Porter, *Synergistic Solutions: An Integrated Approach to Solving the Caregiver Conundrum for “Real” Workers*, 39 STETSON L. REV. 777, 808 (2010) (internal footnotes omitted).

²⁹⁸ *Id.*; see, e.g., Charles A. Sullivan, *Disparate Impact: Looking Past the Desert Palace Mirage*, 47 WM. & MARY L. REV. 911, 989 (2005).

²⁹⁹ See Porter, *supra* note 297, at 809.

³⁰⁰ *Id.*

scores are not just *correlated* with job performance but *explain* it.”³⁰¹ This heightened burden acknowledges the information asymmetry that exists between the employer and the employee in the context of automated hiring. My proposed doctrine of *discrimination per se* while concurring that there is a duty of care owed by the employer, seeks to further rectify both the information asymmetry and power imbalance present in automated hiring situations by entirely shifting the burden of proof from plaintiff to defendant.

Per my proposal, a plaintiff can assert that a hiring practice (for example, the use of proxy variables resulting in or *with the potential to result in* adverse impact to protected categories) is so egregious as to amount to *discrimination per se*, and this would shift the burden of proof from the plaintiff to the defendant (employer) to show that its practice is non-discriminatory. I do not set forth a specific rule or standard for how to determine discrimination *per se*, rather, I think this is a question of law that, like other types of American legal doctrines, should be generated through case law. Note also that the *discrimination per se* doctrine does not dictate an automatic win for the plaintiff, rather it merely reverses the American legal tradition of deference to employers and allows that an employment discrimination plaintiff will at least get a day in court. Note also that it still remains relatively easy for employers to establish business necessity for their practices and therefore defeat any plaintiffs’ disparate impact claims.³⁰²

Discrimination per se is an answer to the question of whether the liability of corporations could be mitigated by a lack of intent to

³⁰¹ Grimmelmann & Westreich, *supra* note 12, at 170; *see also* Margot E. Kaminski, *Binary Governance: Lessons from the GDPR’s Approach to Algorithmic Accountability*, 92 S. CAL. L. REV. 1529 (2019) (identifying three categories of concerns in regulating algorithmic decision-making: dignitary, justificatory, and instrumental); Andrew D. Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085, 1118–26 (2018) (reviewing the rationales behind calls for explanations of algorithmic decision-making). *But see* Lilian Edwards & Michael Veale, *Slave to the Algorithm? Why a “Right to an Explanation” Is Probably Not the Remedy You Are Looking For*, 16 DUKE L. & TECH. REV. 18, 44 (2017) (arguing that a right to an explanation in the EU General Data Protection Regulation (GDPR) is unlikely to present a complete remedy to algorithmic harms).

³⁰² *See* Porter, *supra* note 297, at 810. It is important to note here that even after a defendant has been able to show business necessity, a plaintiff may nevertheless be able to prevail by showing that there could be an “alternative employment practice” that meets that “business necessity.” 42 U.S.C. § 2000e-2(k)(1)(A), (C) (2018); *see also* Jones v. City of Boston, 845 F.3d 28 (1st Cir. 2016).

discriminate or even a lack of awareness that an algorithm is producing biased results.³⁰³ For example, one researcher, Jatinder Singh, has argued that the line of responsibility for problems created by machine learning algorithms is blurred.³⁰⁴ More specifically, if a machine learning algorithm can operate without being specifically programmed, by de novo creating a model from available data, should the blame for any resulting disparate impact lie with the creator of the algorithm, with the entity who chose the training data, or with the algorithm itself—with the last option presuming that the technology is essentially “thinking” on its own? This, Singh argues, is a question that has yet to be addressed by any current legal framework.³⁰⁵

In one attempt to surmount this problem, Professor Stephanie Bornstein, in the article *Reckless Discrimination*,³⁰⁶ theorizes a recklessness model of discrimination under Title VII, arguing that an employer should be liable for acts done in reckless negligence, which are consequences of implicit bias and stereotyping in employment decisions.³⁰⁷ In doing so, Professor Bornstein argues that recent technological advancements have “allowed some employers to easily and dramatically reduce the biasing effects of subjectivity from their hiring decisions by, for example, using algorithms instead of people to screen applicants.”³⁰⁸

Bornstein explains how employers have made efforts to remove implicit bias from hiring; they have developed “blind interviews over online instant messaging software, application-screening algorithms, pre-commitment to set assessment standards, and more.”³⁰⁹ The author notes that “[t]he ability to prevent and correct for bias and stereotyping in the workplace is more affordable and accessible than ever before.”³¹⁰ She insists that given the development of technological tools, such as predictive algorithms, which employers can utilize to reduce bias in

³⁰³ Professor Charles Sullivan has also grappled with these questions. See Sullivan, *supra* note 12, at 398.

³⁰⁴ Singh et al., *supra* note 177.

³⁰⁵ *Id.*

³⁰⁶ Bornstein, *Reckless Discrimination*, *supra* note 12.

³⁰⁷ *Id.* at 1056.

³⁰⁸ *Id.*

³⁰⁹ *Id.* at 1058.

³¹⁰ *Id.*

decision-making, an employer that knows about the risks of implicit bias, has evidence that such bias may infect its decision-making, and fails to try to prevent it should be liable for discriminatory intent and reckless action.³¹¹

Building on Professor Bornstein's line of argumentation, I propose here that the well-established tort principle of *negligence per se* should be the model for creating a new legal framework to answer the question of intent when it comes to discriminatory results obtained by automated hiring platforms. While another legal scholar, Professor Girardeau Spann, has also borrowed from tort doctrine to argue that the invidiousness of racial discrimination in the United States and the undeniable concomitant racial disparities dictate the strict liability standard of *res ipsa loquitur* for racial discrimination claims,³¹² and I believe that in some instances such a standard might be warranted, I argue that a *discrimination per se* standard that is modeled on the *negligence per se* standard is more generally applicable (that is, it would apply to various cases of employment discrimination, not just racially-motivated discrimination) and also serves to institute more feasible self-regulation practices. The concept of *discrimination per se* is also in line with Professor Ford's argument that employment discrimination law imposes a duty of care on the employer to ensure that its employment practices are not unlawfully discriminatory.³¹³ Note that, as I explain in another article in progress, *Automated Employment Discrimination*, the *discrimination per se* doctrine should work hand in hand with an "auditing imperative" imposed on the employer.³¹⁴ This takes into consideration the practical problems associated with proving disparate impact in an algorithmic hiring scenario and would allow a plaintiff to have some headway in making the case.

The proto *negligence per se* case involved a Minnesota drug store clerk who sold a deadly poison to a customer at the customer's request.³¹⁵ At the time of the sale, the clerk did not label the substance as a "poison,"

³¹¹ *Id.* at 1110.

³¹² See Girardeau A. Spann, *Race Ipsa Loquitur*, 2018 MICH. ST. L. REV. 1025 (2018).

³¹³ See, e.g., Ford, *supra* note 30 (arguing that employment law imposes a duty of care on employers to avoid decisions that undermine social equality).

³¹⁴ I discuss the "auditing imperative" in a forthcoming article. Ajunwa, *supra* note 91.

³¹⁵ *Osborne v. McMasters*, 41 N.W. 543 (Minn. 1889).

which was required by a state statute for the sales of such substances.³¹⁶ Later, the customer who had purchased the substance ingested the chemical, which caused her death.³¹⁷ Given these facts, should the clerk have been held legally liable for his actions, which indirectly caused the customer's death? This case, *Osborne v. McMasters*, became one of the earliest cases in the United States to analyze the illegal concept of *negligence per se*. Given the facts of the case, the court first found that there could be no "serious doubt of defendant's liability"—as he had known of his duty to label the bottle as poison.³¹⁸ In explanation, the court detailed that it was

well settled . . . that where a statute or municipal ordinance imposes upon any person a specific duty for the protection or benefit of others, if he neglects to perform that duty he is liable to those for whose protection or benefit it was imposed for any injuries of the character which the statute or ordinance was designed to prevent. . . .³¹⁹

Since the time of *Osborne*, the doctrine of *negligence per se* has become commonly used for violations of laws such as traffic laws, building codes, blood alcohol content limits, and various federal laws.³²⁰ For example, in *Mikula v. Tailors*, an Ohio business invitee was taken to the emergency room after falling down in a snow-covered parking lot at the place of business to which she was invited.³²¹ Witnesses report to have seen her fall after stepping into a hole in the parking lot that was about seven inches deep and had been covered by the snowfall from that day. After careful consideration, the jury determined that:

³¹⁶ *Id.*

³¹⁷ *Id.*

³¹⁸ *Id.* at 543.

³¹⁹ *Id.*

³²⁰ See, e.g., *Williams v. Calhoun*, 333 S.E.2d 408 (Ga. Ct. App. 1985) (in which the defendant's failure to stop at a stop sign constituted negligence per se); *Lombard v. Colo. Outdoor Educ. Ctr., Inc.*, 187 P.3d 565 (Colo. 2008) (in which an outdoor education teacher fell off of a ladder that was in violation of building code restrictions, establishing negligence per se on the part of the landowner); *Purchase v. Meyer*, 737 P.2d 661 (Wash. 1987) (in which a cocktail lounge was found negligent per se for serving alcohol to a minor).

³²¹ *Mikula v. Tailors*, 263 N.E.2d 316 (Ohio 1970).

[a] deep hole in a parking lot which is filled or covered, or both, by a natural accumulation of snow constitutes a condition, the existence of which the owner of the premises is bound, in the exercise of reasonable care, to know. He is also bound to know that a natural accumulation of snow which fills or covers the hole is a condition substantially more dangerous than that normally associated with snow. . . . Under such circumstances, the owner's failure to correct the condition constitutes actionable negligence.³²²

Moreover, failure to correct an issue can also lend itself to *negligence per se* claims if the accused individual is found to have violated a statute by their failure to respond to a problem. For example, in *Miller v. Christian*, a landlord was found negligent *per se*, after being placed on notice from a tenant that the building's sewage system had recurring problems.³²³ Failure to "fix[] the immediate problem within a reasonable amount of time" resulted in a backup of the sewage system, which caused the tenant's apartment to flood, ruining much of her personal property.³²⁴ The court in *Miller* found that Allan Christian, the landlord, was liable for the damage to the tenant's property because he had a legal duty to maintain the apartment's sewage system in addition to being legally obligated to keep the premises fit for habitation.³²⁵

Often, "failure to correct" claims entail a consideration of whether the plaintiff knew of the problem, as it is presumed that a plaintiff with knowledge of an existing problem would be reasonable enough to avoid injury by the issue altogether. In one case, *Walker v. RLI Enterprises, Inc.*, a tenant in an apartment building sued her landlord after she stepped out the back door of the building and slipped on a sheet of ice.³²⁶ She suffered serious injuries to her ankle.³²⁷ In her suit, the tenant asserted that the landlord was negligent in maintaining the property, because she had given him notice of a leaky water faucet by the back door of her

³²² *Id.* at 322–23.

³²³ *Miller v. Christian*, 958 F.2d 1234 (3d Cir. 1992).

³²⁴ *Id.* at 1234.

³²⁵ V.I. CODE ANN. tit. 29, § 333(b)(1) (2019).

³²⁶ *Walker v. RLI Enters., Inc.*, No. 89325, 2007 WL 4442725, at *1 (Ohio Ct. App. 2007).

³²⁷ *Id.*

apartment.³²⁸ This negligence, the court determined, was *negligence per se* because the landlord had an obligation to maintain the premises under Ohio law.³²⁹

At trial, however, the landlord argued that “a landlord is only liable where the landlord has ‘superior knowledge’ of the defect that led to the injury.”³³⁰ By this, the landlord meant that as the tenant had alerted him of the problem, the tenant then clearly knew as much about the dangerous conditions as he did. He also noted that she had taken no further action to avoid the leaky faucet and could thus be responsible for her own injury.³³¹ However, the court found this argument unconvincing, holding that such an argument only applies in the context of natural accumulations of ice and snow, because most people have experienced such conditions and know that they should take precautions.³³² Site-specific problems, though, are the responsibility of the landlord to correct, as he likely has a “superior knowledge” of the issues on the property than his tenants or site visitors.³³³

In the case of automated hiring systems, employers have an obligation not to unlawfully discriminate against applicants, as proscribed by Title VII of the Civil Rights Act and other federal antidiscrimination laws. Furthermore, as I propose in a separate paper, if self-audits or external audits of hiring algorithms become mandated by law,³³⁴ then it follows that when an employer willfully neglects to audit and correct its automated hiring systems for unlawful bias, a *prima facie* intent to discriminate could be implied, pursuant to the proposed doctrine of *discrimination per se*. This argument becomes persuasive when one considers that some corporations make use of bespoke internal hiring algorithms, such that no one, except the corporation, has access to the hiring algorithm and its results—meaning then that only the corporation could have “superior knowledge” of any problems of bias.

³²⁸ *Id.*

³²⁹ *Id.* at *2.

³³⁰ *Id.* at *5.

³³¹ *Id.*

³³² *Id.*

³³³ *Id.*

³³⁴ I discuss the proposal for mandated self and external audits of hiring algorithms in another article, *Automated Employment Discrimination*. Ajunwa, *supra* note 91.

There are two important arguments against the introduction of the *discrimination per se* doctrine: (1) the difficulty of establishing a standard for when the doctrine might apply; (2) it imposes too large a burden on the employer. Regarding the first, I agree that it will take some work on the parts of the courts to establish clear precedents for when the doctrine could apply. But this is true for any new legal doctrine. In fact, even established legal doctrines still face contestation as to when they should or should not apply.³³⁵ Consider that in the context of automated hiring, the two legal doctrines currently available to the plaintiff on which to build a case are disparate treatment or disparate impact. The fact is that there are very few cases of disparate treatment because employers are now much too sophisticated to leave the kind of “smoking gun” evidence required. For disparate impact, the problem is that there is wide discrepancy in determining what statistics are enough to show a pattern of disparate impact.³³⁶

Regarding the burden on employers, the fact remains that automated hiring is a cost-saving measure. Employers save significant amounts of money and time by using automated hiring platforms. However, automated hiring platforms should not save employers from their duty not to discriminate. Just like an employer holds a responsibility to supervise its human workers for activities that might contravene the law, so, too, remains an obligation to audit automated hiring systems for bias. This burden is neither heavier than when the intermediary is human, nor does it disappear merely because the intermediary is a set of algorithms. The doctrine of *discrimination per se* is meant to prevent employers from shirking their responsibility.

³³⁵ See Laura T. Kessler, *The Attachment Gap: Employment Discrimination Law, Women's Cultural Caregiving, and the Limits of Economic and Liberal Legal Theory*, 34 U. MICH. J.L. REFORM 371, 415–16 (2001) (noting that because men are not usually primary caregivers, women have a difficult time finding comparisons to prove a disparate impact); Michael Selmi, *Was the Disparate Impact Theory a Mistake?*, 53 UCLA L. REV. 701, 769 (2006) (stating that establishing a statistically significant impact might be difficult unless the affected population is sufficiently large and diverse).

³³⁶ William R. Corbett, *Fixing Employment Discrimination Law*, 62 SMU L. REV. 81, 113 (2009) (noting that courts are inconsistent in applying the disparate impact doctrine).

C. Consumer Protection for Job Applicants

Another method for ensuring the accountability of hiring algorithms is to view the job applicant as a consumer and, thus, as deserving consumer protection for unfair algorithmic outcomes. This approach could potentially allow for both the maker of the platform and the employer to be held liable. The Fair Credit Reporting Act (FCRA),³³⁷ while typically thought to solely govern the distribution of credit reports, could potentially be leveraged when an employer relies on information from third parties—namely, an application prescreener or a hiring algorithm software.³³⁸ Note that while the FCRA would not be able to directly hold the employer accountable for any discriminatory use of the data, the point of my proposal here is that the procedural aspects of the FCRA may also enable the job applicant to discover if the employer had access to discriminatory information or even to establish a pattern of discriminatory information furnished to the employer for protected groups, thus perhaps assisting in a disparate impact cause of action.

First, some brief details about the language and intentions of the FCRA. The FCRA, passed in 1970, was initially intended to protect consumers who were being “scanned” for creditworthiness. The language set forth by the FCRA was applied primarily to the “Big Three” credit reporting agencies—Equifax, Experian, and TransUnion—all of which would draw up reports about consumers, using their personal information to determine their credit eligibility.³³⁹ They would then submit these reports to banks and employers, showing the “risk” of the current individual in terms of lending or employment. As such, the FCRA was passed to prevent unfair or opaque credit reporting.³⁴⁰

The law also protects consumers from unfair background checks and unauthorized collections of their private information, ensuring that consumers are alerted to any information that may adversely affect their abilities to obtain either credit or, more recently enforced,

³³⁷ See 15 U.S.C. § 1681a (2018).

³³⁸ Pauline T. Kim & Erika Hanson, *People Analytics and the Regulation of Information Under the Fair Credit Reporting Act*, 61 ST. LOUIS U. L.J. 17 (2016).

³³⁹ *Id.* at 26.

³⁴⁰ See 15 U.S.C. § 1681a.

employment.³⁴¹ Moreover, the law also protects consumers by providing that creditors or employers must disclose “in writing to the consumer who is the subject of the communication, not later than 5 business days after receiving any request from the consumer for such disclosure, the nature and substance of all information in the consumer’s file at the time of the request”³⁴² Through such provisions, the FCRA gives consumers more control over how their personal information is reported by consumer reporting agencies and used by both banks and employers.

However, since the time of its passage, the FCRA has expanded its bounds such that it no longer only applies to the “Big Three” credit reporting agencies.³⁴³ Now, it also applies to a variety of agencies that collect and sell information that is found outside the workplace and that might be pertinent for applicant-reviewing purposes.³⁴⁴ With the coverage of many consumer reporting agencies (CRAs) whose sole purpose is employment prescreening, a question has arisen regarding the point at which a screening service should be considered a CRA by the FCRA. In essence, how big of a role does a reporting agency have to play in the information collection and reporting process in order to face such substantial government regulation?

The language of the FCRA plainly defines the characteristics of entities that can be considered CRAs, as well as the content of reports that can be considered “consumer reports” under the law. A CRA, by definition, is any “person which, for monetary fees, dues, or on a cooperative nonprofit basis, regularly engages in whole or in part in the practice of assembling or evaluating consumer credit information or other information on consumers for the purpose of furnishing consumer

³⁴¹ *Id.* § 1681k(a).

³⁴² *Id.* § 1681a(o)(5)(C)(i).

³⁴³ See CONSUMER FIN. PROT. BUREAU, LIST OF CONSUMER REPORTING COMPANIES (2020), https://files.consumerfinance.gov/f/201604_cfpb_list-of-consumer-reporting-companies.pdf [<https://perma.cc/Y8LW-9JFS>].

³⁴⁴ See, e.g., CHECKR, <https://Checkr.com> [<https://perma.cc/9ECB-2RVN>] (which screens applicants for criminal records, driving records, and also provides employment verifications, international verifications, and drug screenings); HIRERIGHT, <https://www.hireright.com> [<https://perma.cc/6RC7-QJP8>] (which boasts the industry’s broadest collection of on-demand screening applications); FIRST ADVANTAGE, <https://www.fadv.com> [<https://perma.cc/S3YC-ADFW>] (which provides criminal and pre-employment background checks, as well as drug-testing and tenant screening services).

reports to third parties.”³⁴⁵ Application screening software companies could be considered CRAs, as they regularly process and evaluate “other information on consumers” for the purpose of providing reports to employers.

Furthermore, these companies arguably develop “consumer reports,” judging by the legal definition of that term. The FCRA defines “consumer report[s]” as

any written, oral, or other communication of any information by a consumer reporting agency bearing on a consumer’s credit worthiness, credit standing, credit capacity, character, general reputation, personal characteristics, or mode of living which is used or expected to be used . . . as a factor in establishing the consumer’s eligibility for . . . credit or insurance . . . or . . . employment purposes.³⁴⁶

Through an analysis of the terms of service of two algorithm-based employment screening companies—Monster Hiring and Paycor—it becomes clear that the reports that these kinds of corporations create could certainly qualify as consumer reports, where the “consumers” are job applicants.

Monster, a networking platform intended to connect job seekers to available employers, states in its terms of service that it retains the ability to “collect information about [consumers] from publicly-available websites and may use this information to create a Profile or append it to an existing Profile” on the company’s website.³⁴⁷ This information—in addition to any information users choose to add—is then arranged in a profile format on Monster’s website, where employers can pay to post job listings and view applicant resumes.³⁴⁸ For an example of the service costs, the cost to post and promote one job ad on Monster is \$399 for a sixty-day post longevity.³⁴⁹ That cost includes the distribution of one job ad on Monster’s “job board” as well as “[a]ccess to 20 recommended resumes

³⁴⁵ 15 U.S.C. § 1681a(f).

³⁴⁶ *Id.* § 1681a(d)(1)(A)–(B).

³⁴⁷ See *Terms of Use*, MONSTER, <http://inside.monster.com/terms-of-use> [<https://perma.cc/9XHR-3VPA>].

³⁴⁸ See *Monster: Job Board Overview for Employers plus FAQs and Pricing*, BETTERTEAM, <https://www.betterteam.com/monster> [<https://perma.cc/EYV7-62EY>].

³⁴⁹ *Id.*

from the Monster resume database”—from job-seekers selected by Monster, per the qualifications an employer lists in the job description.³⁵⁰ Effectively, the process of arranging profiles in its own structured form, the ability to add information the company finds online, and the practice of recommending “suitable” applicants after an employer pays for a job post all seem to show that Monster exercises reasonable control over the information it releases.³⁵¹ Thus, it could certainly be argued that Monster is creating a report that has

bearing on a consumer’s credit worthiness, credit standing, credit capacity, character, general reputation, personal characteristics, or mode of living which is used or expected to be used or collected in whole or in part for the purpose of serving as a factor in establishing the consumer’s eligibility for . . . employment purposes.³⁵²

Most specifically, by retaining the right to add any information it discovers online, it is clear that Monster takes an active role in distributing information related to an applicant’s job prospects, making its reports qualify as “consumer reports” under the definition of the FCRA.

Another instance in which the FCRA might be applied to algorithm hiring platforms is in the case of platforms in which “consumers”—or job applicants—have even less control over the information that is collected and reported, such as the case of Paycor. Paycor is, for all purposes, a background check access provider, although it also advertises resume-parsing tools and interview-streamlining data reports.³⁵³ The software platform advertises to employers that it takes in applicant information and “intelligently stores that information into the correct fields of the candidate profile, which means errors from manually inputting data are

³⁵⁰ *Id.*

³⁵¹ Levy & Barocas, *supra* note 278.

³⁵² 15 U.S.C. § 1681a(d)(1) (2018).

³⁵³ See *Recruiting Software & Applicant Tracking System*, PAYCOR, <https://www.paycor.com/recruiting-software> [<https://perma.cc/K9UF-YUSV>]. Paycor recently acquired Newton. See *Announcement: Newton Is Now Paycor Recruiting*, PAYCOR, <https://www.paycor.com/newton-software> [<https://perma.cc/LF3U-R4ZK>].

a thing of the past.”³⁵⁴ From these profiles, employers can find employees to fit the requirements of the job descriptions they release.³⁵⁵ Then, Paycor gives employers access to background check software provided by third parties, which Paycor itself entirely oversees.³⁵⁶ Given these features, I argue that Paycor has enough of a hand in the report-creating process as to have the final reports attributed to itself, making its reports “consumer reports.”

The information-analyzing services put forth by Paycor are certainly more hands-on than those of Monster. Paycor acquires sensitive information from third-party background checkers, after overviewing the background screening process, and then relays a report about the screening to its clients. Further, by parsing resumes and creating new, standardized profiles on applicants for employers to reference, Paycor is certainly changing the nature of the resumes that prospective employees have submitted and is thereby creating its own reports with added information. All of this data, which Paycor relays to employers, can, and likely will, be used to determine employment eligibility. Therefore, under the language of the FCRA, the reports put forth by Paycor qualify as “consumer reports.”

Furthermore, the Federal Trade Commission (FTC), the body that oversees the FCRA, has recently held that “[j]ust saying you’re not a consumer reporting agency isn’t enough.”³⁵⁷ The case, which took place in 2013, dealt with an application available for purchase on iTunes, Filiquarian Publishing, which advertised that it could make “quick criminal background check[s] for convictions’ in specific states.”³⁵⁸ The application had access to “hundreds of thousands of criminal records” and could help employers discover if any of the convictions could be

³⁵⁴ See *Paycor Recruiting: Find Quality Candidates and Fill Open Positions Fast*, PAYCOR (Oct. 4, 2019), <https://www.paycor.com/resource-center/recruitment-tools> [<https://perma.cc/3MS9-TVDK>].

³⁵⁵ See *id.*

³⁵⁶ *Recruiting Software & Applicant Tracking System*, *supra* note 353.

³⁵⁷ Tony Rodriguez & Jessica Lyon, *Background Screening Reports and the FCRA: Just Saying You’re Not a Consumer Reporting Agency Isn’t Enough*, FED. TRADE COMMISSION (Jan. 10, 2013, 2:00 PM), <https://www.ftc.gov/news-events/blogs/business-blog/2013/01/background-screening-reports-fcra-just-saying-youre-not> [<https://perma.cc/9YEN-QXKH>].

³⁵⁸ *Id.*

attributed to their applicants.³⁵⁹ However, Fiquarian also reported in a disclaimer on its site that it was not a consumer reporting agency because its background screening reports were not to be considered screening products for insurance, employment, loans, or credit applications.³⁶⁰ The FTC took issue with this, finding that Fiquarian provided the exact same information as CRAs, but simply said they didn't use the information for employment purposes, which is not a reasonable excuse from FCRA compliance.³⁶¹ Ultimately, the FTC's statement was the following: "Companies offering background screening products for employment or other FCRA purposes . . . have to stay in line with the law."³⁶² This mandate should be applied to sites like Monster and Paycor, given that they provide similar screening services.

If these companies were to be considered consumer reporting agencies under the FCRA down the road, Monster, Paycor, and other similar reporting services that find their own information to conduct screening checks might also leave themselves open to FCRA claims for failing to "follow reasonable procedures to assure the maximum possible accuracy of [their] files," which causes individuals to be denied employment opportunities.³⁶³ In one case, *Thompson v. San Antonio Retail Merchants Ass'n* (SARMA), the Fifth Circuit found that SARMA had erred in its creation of a profile for Thompson, automatically "capturing" the incorrect social security number for his profile and erroneously reporting the bad credit history of another man by the same common name. The court ultimately held that under the FCRA, such an oversight by a credit reporting agency as the one presented in *Thompson* was enough to show negligence on the part of the agency.³⁶⁴

One potential rebuttal to the classification of hiring algorithms as CRAs can be extrapolated from Professor M. Ryan Calo's article, *Open*

³⁵⁹ *Id.*

³⁶⁰ *Id.*

³⁶¹ *Id.*

³⁶² *Id.*

³⁶³ *Thompson v. San Antonio Retail Merchs. Ass'n*, 682 F.2d 509, 512 (5th Cir. 1982); *see also* *Spokeo, Inc. v. Robins*, 136 S. Ct. 1540, 1546 (2016) (in which a "people search engine" provided incorrect personal information about a consumer to employers and the Supreme Court ruled that this established concrete injury to the consumer, by damaging his employment prospects).

³⁶⁴ *Thompson*, 682 F.2d 509.

Robotics.³⁶⁵ With reference to the robotics community, Professor Calo argues that just as firearms manufacturers are ultimately not responsible for what end users do with their products, manufacturers of open robotics platforms should not be held responsible either.³⁶⁶ When applied to the regulation of hiring algorithms that develop reports about prospective employees, one could make a similar argument, holding that hiring algorithms and their developers are not ultimately responsible for the negative impacts that employers use them to create. Instead, the consumers—in this case, employers—who use such platforms may be responsible for the decisions that they make once they purchase the hiring tools.

However, hiring platform developers differ significantly from firearm manufacturers or open robotics platforms, given that those developers hold the power to create features that may enable employment discrimination and also given that automated hiring platforms exercise considerable control over how applicants' job applications may be captured, analyzed, and presented to employers. These differences bolster the argument for classifying entities that screen applicants' information to create hiring reports as CRAs under the law. In doing so, job applicants, as consumers, could gain some insight as to how they are evaluated, and society could regain some measure of checks over the information that is used to "screen" candidates as part of the automated hiring trend. Furthermore, the classification of hiring platforms as CRAs would assist the information gathering of a would-be employment discrimination plaintiff in the bid to discover whether information denoting protected class membership has been made available to an employer.

CONCLUSION

Proponents of algorithmic decision-making have favorably likened its workings to that of an oracle. For those adherents, the algorithm is all-knowing and will infallibly provide the answers the intrepid inquirer seeks. This represents a simplistic understanding of the opaque nature of

³⁶⁵ M. Ryan Calo, *Open Robotics*, 70 MD. L. REV. 571 (2011).

³⁶⁶ *Id.* at 576, 604–05.

an oracle. Consider the ur-Oracle, the Oracle of Delphi.³⁶⁷ The Oracle, a figure known in Greek mythology, spoke veraciously, but in truth that was spun in riddle and with many strands of interpretation.³⁶⁸ In the most famous tale of the Oracle, the King of Lydia—who faced a war against the Persians—asked for the Oracle’s advice. However, the King failed to fully interrogate the Oracle and did so at his own peril, departing with a seemingly simple answer that “if [he] went to war then a great empire would surely fall.”³⁶⁹ Of course, this advice was highly vulnerable to misinterpretation, and the King’s own empire later fell to the Persians.³⁷⁰ Similarly, algorithms deployed in the decision-making process are vulnerable to misinterpretation and misuse. Although automated hiring platforms offer efficiency to the hiring process, we must continue to interrogate their results to ensure they are working in furtherance of the shared goal of an equal opportunity society.

³⁶⁷ See WILLIAM J. BROAD, *THE ORACLE: ANCIENT DELPHI AND THE SCIENCE BEHIND ITS LOST SECRETS* (2006).

³⁶⁸ See Mark Cartwright, *Delphi*, ANCIENT HIST. ENCYCLOPEDIA (Feb. 22, 2013), <https://www.ancient.eu/delphi> [<https://perma.cc/GS3E-MRTV>].

³⁶⁹ See *id.*

³⁷⁰ See *id.*