AUTOMATED HIRING

IFEOMA AJUNWA*

ABSTRACT

In the past decade, advances in computing processes such as data mining and machine learning have prompted corporations to rely on algorithmic decision-making for business purposes with the presumption that such decisions are efficient and fair. As recent court cases demonstrate, however, the use of such tools in the hiring process presents novel legal challenges. This Article notes the increasing use of automated hiring systems by large corporations and how such technologies might facilitate unlawful employment discrimination, whether due to (inadvertent) disparate impact on protected classes or the technological capability to substitute facially neutral proxies for the demographic details of protected classes. The Article also parses some of the proposed technological solutions to reduce bias in hiring and examines them for the potential for unintended outcomes. The Article argues that technologically-based solutions should be employed only in support of law-driven redress mechanisms that encourage employers to adopt fair hiring practices. The Article makes the policy argument that internal audits of automated hiring platforms should be a mandated business practice that serves the ends of equal opportunity in employment. Furthermore, employers that subject their automated hiring platform to external audits could receive a certification mark that serves to distinguish them in the labor market. Borrowing from Tort law, The Article also argues that an employer’s failure to audit and correct its automated hiring platforms for disparate impact should serve as prima facie evidence of discriminatory intent, leading to the development of the doctrine of discrimination per se. Finally, the Article concludes that ex ante solutions such as the adoption of fairness by design principles for algorithmic hiring systems and the re-thinking of wide employer discretion for hiring criteria represent other viable options to prevent covert employment discrimination via automated hiring platforms.

* Assistant Professor, Cornell University Industrial and Labor Relations (ILR) School. Faculty Associate Member, Cornell Law School. Faculty Associate, Berkman Klein Center at Harvard Law School. Many thanks to Professors Anupam Chander, Julie Cohen, Maggie Gardner, Ruth Okediji, and to the attendees of the Tech Law Colloquium at Cornell University for helpful comments.
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INTRODUCTION

Although Artificial Intelligence (“AI”)\(^1\) has been proposed as the yellow brick road to societal progress,\(^2\) and machine learning algorithms,\(^3\) have automated many work functions previously thought reserved for human judgment,\(^4\) there have been no new regulations to ensure that these new

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\(^3\) 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.” *See, Alan D. Minsk, Patentability of Algorithms: A Review and Critical Analysis of the Current Doctrine, 8 SANTA CLARA HIGH TECH. L.J. 251, 257 (1992). See, also, Gottschalk v. Benson, 409 U.S. 63, 65 (1972). Minsk also references the *Paine, Webber v. Merrill Lynch* 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.” *See, Paine, Webber, Jackson & Curtis Inc v. Merrill Lynch, Pierce, Fenner & Smith, 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, “algorithms are procedure[s] for solving a given type of mathematical problem.” *Diamond v. Diehr*, 450 U.S. 175, 186 (1981). See, Pedro Domingos, *The Master Algorithm: How the Quest for the Ultimate Learning Machine Will Remake our World*, BRILLIANCE AUDIO (2015). (describing how machine learning algorithms work). “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 outcomes the algorithm that turns one into the other. Learning algorithms – known as learners – are algorithms that make other algorithms.”

\(^4\) 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, for example, Erin Winick, Lawyer-Bots Are Shaking up Jobs*, MIT TECHNOLOGY REVIEW (Dec. 12, 2017), https://www.technologyreview.com/s/609556/lawyer-bots-are-shaking-up-jobs/.”

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technological developments will conform to the normative ideal of equal economic opportunity for all, which is the bedrock of our democratic society. The irony also is that automated hiring as a solution for the bias of human managers may in fact merely serve to reproduce bias at scale – that is, due to the volume and velocity of automated hiring, any bias introduced in the system will be magnified and multiplied, greatly dwarfing the bias of any given biased human manager.

The amplification of bias by algorithms is a present danger that must be addressed by both new regulations and a rethinking of legal frameworks. As legal scholars like Professor Julie Cohen have noted, “law for the platform economy is already being written — not via discrete, purposive changes, but rather via the ordinary, uncoordinated but self-interested efforts of information-economy participants and the lawyers and lobbyists they employ.”

This Article represents an attempt at a purposeful and democratic re-writing of the law for the platform economy to conform to one of the widely understood terms of the American social contract – equal opportunity for employment.

Automated hiring represents an ecosystem in which, if left unchecked, a closed loop systems 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 looped back into criteria for job advertisement and selection.

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computerization 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.” Carl Benedikt Frey & Michael A. Osborne, The Future of Employment: How Susceptible are Jobs to Computerisation?, OXFORD MARTIN SCHOOL (Sept. 17, 2013) at: http://www.oxfordmartin.ox.ac.uk/downloads/academic/The_Future_of_Employment.pdf; See also, Eric Siegal, Predictive Analytics: The Power to Predict Who Will Click, Buy, Lie, or Die, WILEY (2013).

Consider that a recent ProPublica investigation revealed that Facebook was allowing advertisers (both for jobs and for housing) to exclude audiences by ethnic group.\(^6\) In what investigators described as “a modern form of Jim Crow,” Facebook had developed a feature it termed “Affinity Groups” – essentially, a method for advertisers to use demographic data to algorithmically target who will receive certain Facebook ads.\(^7\) For example, one page on Facebook Business, titled “How to Reach the Hispanic Audience in the United States,” boasts of the potential for advertisers to reach up to 26.7 million Facebook users of “Hispanic Affinity.”\(^8\) From this specific Affinity Group, 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 audiences.”\(^9\)

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. To demonstrate the implications of the algorithmically targeted ads, ProPublica reporters were able to buy dozens of rental house ads on Facebook that excluded “African

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\(^7\) Id.


\(^10\) Id.
Americans, mothers of high school kids, people interested in wheelchair ramps, Jews, expats from Argentina, and Spanish speakers.”

Following on the heels of this ProPublica investigation, a 2017 class action lawsuit against Facebook contended that Facebook Business tools both “enable and encourage discrimination by excluding African Americans, Latinos, and Asian Americans – but not white Americans from receiving advertisements for relevant opportunities.” In an amended complaint, the 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.” 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 the list to then create a list of Facebook users who are demographically similar to those existing workers. Then, the employer or employment agency uses the new “Lookalike Audience” list created by Facebook as the population to receive its employment ads. 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. However, to date, Facebook still allows advertisers to narrow their target groups by location, age, gender, languages, interests, or other custom preferences. Furthermore, the aforementioned page that allows advertisers to target people of “Hispanic Affinity” is still available on the Facebook website, indicating that Facebook may not have acted very seriously to block advertisers from excluding audiences by race and ethnicity.

Job recruitment algorithms on platforms like Facebook are, however, not the sole problem. Algorithms that quickly sort job applicants based on

16 See Julia Angwin, supra note 6.
17 See About Ad Targeting: Create A New Audience, supra note 8.
18 See U.S. Hispanic Affinity on Facebook, supra note 9.
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. In one class action, the named plaintiff, Kyle Behm, a college student with a near perfect SAT score, who had been diagnosed with bipolar disorder, found himself repeatedly rejected for minimum wage jobs at supermarkets and retail stores which all used a personality test that had been modeled on the “Five Factor Model Test” used to diagnose mental illness. 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. In addition, other test questions, such as the length of commute time, could be seen as covertly discriminating against those from minority neighborhoods that lack a reliable transportation infrastructure.

To be sure, human managers hold biases that are reflected in unfavorable employment decisions for protected classes but as these cases of algorithmic discrimination in job recruitment and hiring highlight, the impact of one biased human manager is quite limited compared to the potential adverse reach of algorithms that could be used to exclude thousands of job applicants from viewing a job advertisement or to sort thousands of resumes. Although recent publications like *Algorithms of Oppression* have detailed the racially-biased impact of algorithms on information delivery on the internet and others like *Automating Inequality* have outlined the misuse of algorithms in criminal justice and public welfare decision-making, the role of algorithms in perpetuating inequality in the labor market has been relatively overlooked. This Article is concerned with parsing the labor market exclusionary effects of algorithmic hiring tools and outlining some potential solutions. I also bring to bear concepts from organizational theory like the idea of automated hiring

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20 Id.

21 See, for example, *Woman Sues Over Personality Test Job Rejection*, ABC NEWS (Oct. 1, 2012) (in which a hearing-impaired woman was rejected from a position as a supermarket cashier because her pre-employment personality test reported that she failed to “listen carefully.”)


25 More than merely the role of algorithms, some scholars have argued that workplaces in the U.S. are essentially allowed to operate as self-contained, self-governing bodies, without much scrutiny or oversight from regulatory bodies in regards to how the workplace is structured and organized. See, Elizabeth Anderson, *Private Government: How Employers Rule Our Lives*, PRINCETON UNIVERSITY PRESS (2015) (making the argument that workplaces have become authoritarian private governments with little protection for the worker from the State).
platforms as a _tertius bifrons_\textsuperscript{26} to propose new legal frameworks that will better address the novel sociological phenomenon of the _algorithmic capture_\textsuperscript{27} of employment.

First, I note that the definition of the term “AI” varies in legal literature and in popular media,\textsuperscript{28} and thus, in this Article, in lieu of “AI,” I employ the more precise terms of “algorithms” and “machine learning algorithms.”\textsuperscript{29} Furthermore, my focus here is on algorithmic work tools that are implicated in automating the hiring process and thus powering economic progress.\textsuperscript{30} Much attention has been paid to advances in AI that seek to mimic human behavioral process; 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.\textsuperscript{31} While such algorithmic technological advances also present us with unprecedented legal challenges,\textsuperscript{32} the use of machine learning algorithms in decision-making hiring processes, represents a particularly sensitive legal issue because of their potential to create or exacerbate economic inequality.

Consider that nearly all Global 500 companies use recruitment and algorithmic hiring tools.\textsuperscript{33} Yet, a recent study conducted by Aaron Smith and Monica Anderson of the Pew Research Center found that most

\begin{footnotesize}
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\item \textsuperscript{26} See, infra, Section IV (A).
\item \textsuperscript{27} See, infra, Section I (A).
\item \textsuperscript{28} See, for example, Woman Sues Over Personality Test Job Rejection, ABC NEWS (Oct. 1, 2012) (in which a hearing-impaired woman was rejected from a position as a supermarket cashier because her pre-employment personality test reported that she failed to “listen carefully.”); Debra Cassens Weiss, Do Job Personality Tests Discriminate? EEOC Probes Lawyer’s Complaint, Filed on Behalf of His Son, ABA JOURNAL (Sept. 30, 2014) at: http://www.abajournal.com/news/article/do_job_personality_tests_discriminate_eec_probes_lawyers_complaint_file
\item \textsuperscript{29} Id.
\item \textsuperscript{30} Erik Brynjolfsson & Andrew McAfee, The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies, W.W. NORTON & COMPANY (2014) (arguing that we akin to how the Industrial Revolution changed the path of human invention, the Artificial Intelligence age will similarly revolutionize work as we know it).
\item \textsuperscript{31} Chris Welch, Google Just Gave a Stunning Demo of Assistant Making an Actual Phone Call, THE VERGE (May 8, 2018), at https://www.theverge.com/2018/5/8/17332070/google-assistant-makes-phone-call-demonstration.
\item \textsuperscript{32} 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, “[A]t the present state of art, artificial intelligence cannot engage in analogical reasoning or legal reasoning.” Symposium, Legal Reasoning and Artificial Intelligence: How Computers “Think” Like Lawyers, 8 U. CHI. L. SCH. ROUNDTABLE 1, 19 (2001). See, Harry Surden, Machine Learning and Law, 89 WASH. L. REV. 87, 88 (2014) (detailing gaps in the law in regards to machine learning algorithms), and Solon Barocas & Andrew Selbst, Big Data’s Disparate Impact, 104 CAL. LAW REVIEW, 104, 3-4 (detailing issues of disparate impact associated with algorithmic decision-making).
\item \textsuperscript{33} Linda Barber, E-recruitment Developments, BRIGHTON INSTITUTE FOR EMPLOYMENT STUDIES (2006).
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Americans underestimate the diffusion of these automated hiring platforms in the workplace. 34 Markedly, the study revealed that “fewer than half of Americans are familiar with the concept of computer programs that can review job applications without human involvement.” 35 In fact, 57% of Americans say that they have heard nothing at all about automated hiring platforms in the past. 36 Only 9% of respondents reported to have heard “a lot” about the technology. 37 However, after learning about this kind of application review system, very few respondents responded enthusiastically about the prospects for the use of such a system in the future. Only three percent of respondents were “very enthusiastic” about the development and use of hiring algorithms. 38 Additionally, results showed that this general lack of enthusiasm is widespread, transcending many demographic categories. 39 Remarkably, 76% of Americans stated that they would not want to apply for jobs that use a computer program to make hiring decisions. 40 The reasons for the response are varied, but most commonly, the individuals expressed the belief that computer systems could not capture everything about an applicant. 41 One 22-year-old woman wrote, “a computer cannot measure the emotional intelligence or intangible assets that many humans have.” 42 Another stated that “I do believe hiring people requires a fair amount of judgment and intuition that is not well automated.” 43 On the other side of this spectrum, 22% of individuals reported that they would want to apply for jobs that use a computer program to make hiring decisions. 44 The most common rationale for this response was the belief that software would be less biased than human reviewers. 45

The apprehensions about algorithm-based hiring decisions that Smith and Anderson’s study captures are indeed supported by facts. In this paper, I approach the problem of automated hiring from several vantages and seek to answer these questions: 1) what legal duty does the employer who uses hiring platforms owe and how might such an employer be held liable for disparate hiring results that disadvantage protected categories? 2) What legal duty does the maker of hiring platforms owe and to whom? 3) What new regulations might help reduce the potential for returning biased results from automated hiring systems? Part I of this Article documents issues of bias and unlawful discrimination associated with hiring algorithms and the

35 Id.
36 Id.
37 Id at 51.
38 Id.
39 Id.
40 Id at 52.
41 Id at 53.
42 Id.
43 Id.
44 Id.
45 Id.
legal implications of the socio-technical phenomenon of assigning blame to the algorithm. Part II details some of the technological approaches aimed at solving bias in algorithms and cautions against techno-solutionism. Part III parses business solutions to the problem of algorithmic bias. Notably, I advocate for self-auditing as sound business practice and for the promulgation of a Fair Employment Mark that would set standards for the use of algorithms in the hiring process. Part IV proposes new legal frameworks for addressing algorithmic discrimination in employment and borrows from tort law to update employment law in the face of algorithmic hiring. Notably, intent to discriminate could be implied from the act of negligence to audit and correct bias in algorithmic hiring systems. Furthermore, consumer protection laws might serve as a spur for ensuring that information collection by algorithmic hiring systems are designed to reduce bias. Part V presents examples of fairness by design for algorithmic hiring systems and calls for some limits to the employer discretion in hiring criteria.

This Article affirms worker diversity as a normative business ideal. While much can be said about the ethical benefits of a diverse workforce, particularly in regards to reducing economic inequality and its attendant negative effects, a diverse workplace is also a business advantage.46 These proposals, rooted in business practice, go beyond merely creating a legal shield to avoid discrimination lawsuits, they could also serve as vehicles to usher in new diverse business talent to achieve the ends of higher creativity, better decision-making, and greater innovation.47

I. THE ALGORITHMIC TURN

Derived from the name of a Persian mathematician, Al-Khwarizmi,48 the word “algorithm” and the mathematical system of problem-solving it stands for has escaped the cloisters of mathematics and has gained prominence in all spheres of social and economic life in the past three decades.49 With advancements in computing technologies, and the

46 Sheen S. Levine, et al., Ethnic Diversity Deflates Price Bubbles, PROCEEDINGS OF THE NATIONAL ACADEMY OF SCIENCES OF THE UNITED STATES OF AMERICA (Dec. 30, 2014) at: http://www.pnas.org/content/111/52/18524 (sociological research showing that diverse teams make better decisions and are more innovative).
49 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
capacity for rapid mining of big data, algorithms now pervade our daily lives and exert influence over many important decisions.\textsuperscript{50}

The \textit{algorithmic turn} is what I term the profusion of algorithmic decision-making in our daily lives, even in the absence of established regulatory or ethical frameworks to guide the deployment of those algorithms.\textsuperscript{51} Consider that an algorithm decides all of the following: the answer to a search one conducts online,\textsuperscript{52} the best romantic prospects provided by a dating website,\textsuperscript{53} what advertisements one sees during a visit to a given website,\textsuperscript{54} one’s creditworthiness,\textsuperscript{55} whether or not one should be considered a suspect for a crime,\textsuperscript{56} and whether or not one is qualified for a job.\textsuperscript{57} The algorithmic turn, as a socio-technical phenomenon in which we turn to machine learning algorithms for efficiency in decision-making does not, in of itself, represent a legal problem; rather it is when the algorithmic turn becomes algorithmic capture that legal issues emerge. I use the term \textit{algorithmic capture} to describe the combined effect of the belief that algorithms are more efficient and fair\textsuperscript{58} and the abdication of human


\textsuperscript{51}See, Neil M. Richards & Jonathan H. King, \textit{Big Data Ethics}, 49 WAKE FOREST LAW REVIEW 393, 393 (2014), noting that “large datasets are being mined for important predictions and often surprising insights.”

\textsuperscript{52}This nomenclature takes, as inspiration, Professor Julie Cohen’s description of the “participatory turn” in which innovative surveillance methods are positioned as exempt from legal and social control and rather held up as evidence of economic progress. \textit{See}, Julie Cohen, \textit{The Surveillance-Innovation Complex: The Irony of the Participatory Turn, The Participatory Condition} (2015), at https://ssrn.com/abstract=2466708.

\textsuperscript{53}See for example, Latanya Sweeney, \textit{Discrimination in Online Ad Delivery}, 56 COMM. OF THE ACM 44 (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.


\textsuperscript{55}Thorin Klosowski, \textit{How Facebook Uses Your Data to Target Ads, Even Offline}, LIFE HACKER (Apr. 11, 2013), at http://lifehacker.com/5994380/how-facebook-uses-your-data-to-target-ads-even-offline, explaining how Facebook uses your likes (in addition to those of your friends) to tailor ads or target your for specific advertisements.

\textsuperscript{56}Frank Pasquale, \textit{The Black Box Society}, supra note 25.

\textsuperscript{57}Andrew G. Ferguson, \textit{Big Data and Predictive Reasonable Suspicion}, 163 U. PA. L. REV. 1137 (2015), 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.

\textsuperscript{58}Claire Miller, \textit{Can an Algorithm hire Better than a Human?}, THE NEW YORK TIMES (June 25, 2015), at: http://www.nytimes.com/2015/06/26/upshot/can-an-algorithm-hire-better-than-a-human.html; Sarah Green Carmichael, \textit{Hiring C-Suite Executives by Algorithm}, HARVARD BUSINESS REVIEW (Apr. 6, 2015), detailing how established headhunting firms like Korn Ferry are incorporating algorithms into their work, too.

\textsuperscript{59}Danah Boyd & Kate Crawford, \textit{Critical Questions for Big Data}, JOURNAL OF INFORMATION, COMMUNICATION & SOCIETY 15 (2012), at:
Accountability for undesirable outcomes as a result of employing machine learning algorithms in a decision-making process. In the following subsections, I discuss the algorithmic capture of employment, detail the ways in which algorithms involved in hiring has been found to return discriminatory results, and raise legal questions for assigning responsibility to machine learning algorithms rather than their human creators.

A. The Algorithmic Capture of Employment

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 his or her 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. 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 20 private employers in the U.S. Fortune 500 list (comprised of mostly retail companies) that survey indicated that nearly all job applications for such retail jobs must be submitted online, where they will be first sorted by an automated hiring platform powered by an algorithm.

The algorithmic capture of the hiring process goes beyond the hourly workforce as white collar and white shoe firms are also increasingly turning to hiring automation. In 2016, the investment firm, Goldman Sachs, announced a key change to its process for hiring summer intern and first year analysts. Candidates will have their resumes scanned - ostensibly by machine learning algorithms, in search of keywords and experiences that have been pre-judged to be “good barometers of a person’s success at Goldman.” Goldman Sachs is also considering the addition of personality tests as part of its hiring program. The world’s largest hedge fund has also

59 See Linda Barber, supra note 33. (noting that nearly all global 500 companies use recruitment and hire screening algorithmic tools).
61 Id.
63 Mary Thompson, Goldman Sachs Is Making a Change to the Way It Hires, CNBC (June 23, 2016) at: https://www.cnbc.com/2016/06/23/goldman-sachs-is-making-a-change-to-the-way-it-hires.html.
64 Id.
65 Id.
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. Although in many respects the algorithmic turn to hiring is purportedly driven by a desire for fairness and efficiency – for example, Goldman Sachs’ hiring changes were prompted by a desire for a more diverse candidate pool, these machine learning algorithms may have the unintended effects of perpetuating structural biases or could have a disparate impact on protected categories.

B. The Fault in the Machine

With the algorithmic capture of employment, algorithms have been shown to return results that are inconsistent with the principles of employment law. Although blame is often placed on faulty algorithms for returning discriminatory results, we must remember that algorithms are created and maintained by humans. In one recent example of algorithmic bias, a study by Carnegie Mellon University found that Google search ads showed more high-paying executive jobs to people believed to be men conducting searches than to searchers believed to be women. While that study revealed that algorithms may not be exempt from the biases that plague society, it, however, revealed little as to the cause of the bias, and further still, nothing as to how to fix it. Generally, most technology companies are secretive about the workings of their algorithms which they consider proprietary; a lack of transparency that is bolstered by intellectual

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67 See Mary Thompson, supra note 63.
68 See Harry Surden, Machine Learning and Law, supra note 32 (detailing gaps in the law in regards to machine learning algorithms), and See, Solon Barocas & Andrew Selbst, Big Data’s Disparate Impact, supra note 32 (detailing issues of disparate impact associated with algorithmic decision-making).
69 The Harvard computer scientist, Professor Latanya Sweeney was one of the first to sound the alarm when she found that Google’s search algorithm showed higher returns for criminal records for names that were associated with African-Americans. See Latanya Sweeney, supra note 50.
In an attempt to avoid regulatory oversight, the use of machine learning algorithms is often accompanied by assertions that the machine learning algorithmic processes are unknowable – as machine learning algorithms (armed with lessons from past results and training data) are constantly creating de novo algorithms for solving the problems that are presented to them. This haplessness in regards to transparency in the workings of machine learning programs, however, presents a problem of pressing legal concern given that algorithms are currently being lauded as the next revolutionary hiring tool with the power to solve the issues of gender and racial bias in the workplace.

Consider also the implications of assigning blame to algorithms, as if the algorithm could be considered as legally liable as a human actor. The anthropomorphizing of algorithms is not only technically imprecise, it represents an end-run around against anti-discrimination employment laws that require human intent.

In the example of Google’s disparate ad delivery for men versus women, there could be several potential explanations. For example, other than deliberate sexism on the part of Google ad developers, it could be that the algorithm used to conduct searches was trained on data that is reflective of the existing structural sexism of the C-suite that is, that more men are employed in higher paying jobs than women. The algorithm did not (and could not) interrogate the reasons why this was so, or if this ought to be so, rather, it concluded that, it is so and proceeded to return results to match that conclusion by showing higher paid jobs to men rather than women.

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74 In this case, I refer to trade secret law. But see, Amanda Levendowski, How Copyright Law Can Fix Artificial Intelligence’s Implicit Bias Problem, WASHINGTON LAW REVIEW, Forthcoming (July 24, 2017) at: https://ssrn.com/abstract=3024938 (making the argument that a type of intellectual property law, copyright law, would actually serve to make AI less biased if the fair use doctrine would allow for algorithms to be exposed to more diverse (but copyrighted) training data).

75 Harry Surden, Machine Learning and Law, supra note 32.

76 Nathan R. Kuncel, et al., In Hiring, Algorithms Beat Instinct, HARVARD BUSINESS REVIEW (May 2014), at: https://hbr.org/2014/05/in-hiring-algorithms-beat-instinct

77 Cathy O’Neil, I’ll stop calling algorithms racist when you stop anthropomorphizing AI, MATHBABE (Apr. 7, 2016), at: https://mathbabe.org/2016/04/07/i’ll-stop-calling-algorithms-racist-when-you-stop-anthropomorphizing-ai/.

78 See for example, Title VII requirements for proof of intent to discriminate under the disparate treatment doctrine. See also, Title VII Legal Manual: Section 4, Proving Discrimination, THE UNITED STATES DEPARTMENT OF JUSTICE, at: https://www.justice.gov/crt/fcs/T6Manual6#PID

79 See, for example, Herminia Ibarra, Hidden Bias Prevents Gender Equality in the C-Suite, FORBES (Oct. 29, 2013) at: https://www.forbes.com/sites/insacid/2013/10/29/hidden-bias-prevents-gender-equality-in-the-c-suite/#73b2af1c59d3; see also, Analissa Merelli, Only 4.2% of Fortune 500 Companies are Run by Women, QUARTZ (Mar. 7, 2017) at: https://qz.com/925821/how-rare-are-female-ceos-only-4-2-of-fortune-500-companies-are-run-by-women/
AUTOMATED HIRING

That first explanation reflects that machine learning algorithms are especially vulnerable to the problem of what I call *societal noise*. Societal noise are factors present in the data used to train algorithms and which are not truly predictive of the desired outcome.⁸⁰ Those factors might be perceived as neutral information or even as related to the outcome being sought, but I argue that those factors are, in actuality, merely reflective of the history of inequity in the United States.⁸¹

A less generous potential explanation for the disparity in ad delivery is that the employers who had purchased the advertisements had specified, in direct contravention of anti-discrimination employment laws, that their ads be shown to men rather than women and Google had complied with this request.⁸² While employment anti-discrimination laws are implicated in this second explanation – Title VII of the Civil Rights Act and EEOC guidelines prohibit sex discrimination in job advertisements – the question remains as to what protections are afforded the job applicant in the face of the first explanation that algorithms are merely reflecting biases gleaned from training data that bear the historical taint of previous biased decisions.

C. Exposing the Mechanical Turk

An important feature of algorithms is that they tend to obscure the role of the human hand in both framing and setting parameters for solving any given problem, with the final result attributed solely to the machine.⁸³ Consider that proponents of automations have always tended to downplay or deny the role of the human mastermind.⁸⁴ As an early example, consider


⁸¹ For other scholars raising similar concerns, see, for example, Anupam Chander, Reviews, *The Racist Algorithm?*, 115 MICH. L. REV. 1023, 1039 (2017); Frank Pasquale, *Bittersweet Mysteries of Machine Learning (A Provocation)*, LONDON SCH. ECON. & POL. SCI.: MEDIA POL’Y PROJECT BLOG (Feb. 5, 2016), at http://blogs.lse.ac.uk/mediapolicyproject/2016/02/05/bittersweet-mysteries-of-machine-learning-a-provocation/.

⁸² I have no evidence that this potential explanation is factual. However, there is evidence that both Google and Facebook allowed their algorithms to direct ads to people who had been categorized as “anti-Semitic.” See, Sapna Maheshwari & Alexandra Stevenson, *Google and Facebook Face Criticism for Ads Targeting Racist Sentiments*, THE NEW YORK TIMES (Sept. 15, 2017) at: https://www.nytimes.com/2017/09/15/business/facebook-advertising-anti-semitism.html

⁸³ Harry Surden, *Machine Learning and the Law*, 1 WASHINGTON LAW REVIEW 89, 115 (2014); Jatinder Singh, et. al., *Responsibility & Machine Learning: Part of a Process*, CENTER FOR COMMERCIAL LAW STUDIES, QUEEN MARY UNIVERSITY OF LONDON (2016) (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.)

⁸⁴ Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 GEORGETOWN LAW JOURNAL 1147, 1207 (2017) (which points out that machine-learning technology is not yet fully understood and that
“The Mechanical Turk” also known as “the chess Turk, " which was a chess-playing machine constructed in the late 18th century. 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. The hidden chess master controlled the machine while the seemingly automated machine beat notable statesmen like Napoleon Bonaparte and Benjamin Franklin at chess. Thus, the Mechanical Turk operated on obfuscation and subterfuge and sought to reserve the glory of the win to the machine.

With the growing allure of artificial intelligence as a venture-capital generating marketing ploy, modern day corporations have been discovered 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.” 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.” While the work on Amazon Turk, and its notoriously low...

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87 Id.
88 See, Frank Pasquale, The Black Box Society, supra note 25 (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, Human Intelligence Through an API, AMAZON at: https://www.mturk.com/
89 “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 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. See, Ellen Huet, The Humans Hiding Behind the Chatbots, BLOOMBERG TECHNOLOGY (April 18, 2016) at: https://www.bloomberg.com/news/articles/2016-04-18/the-humans-hiding-behind-the-chatbots
90 Miranda Katz, Amazon’s Turker Crowd Has Had Enough, WIRED (Aug. 23, 2017) at: https://www.wired.com/story/amazons-turker-crowd-has-had-enough/
91 Sarah O’Connor, My Battle To Prove I Write Better Than An AI Robot Called ‘Emma’, FINANCIAL TIMES (May 4, 2016) at: https://www.ft.com/content/92583120-0ae0-11e6-b0f1-61f222853ff3
pay is no top secret, a Bloomberg expose revealed that several corporations were disingenuously passing off the labor of human workers as that of AI.92

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.93 But while algorithms remove the final decision 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.94 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 -- were also made by humans.95 For example, if a hiring algorithm is trained on a corpus of resumes, a human must still make impactful 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 users of runaway algorithms should not be permitted to disavow their creations, rather the creators, like Dr. Frankenstein, must bear the ultimate liability for any harm wrought by their creations.

92 “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.” See, Ellen Huet, The Humans Hiding Behind the Chatbots, supra note 89.

93 Frank Pasquale, Restoring Transparency to Automated Authority, 9 JOURNAL ON TELECOMMUNICATIONS AND HIGH TECHNOLOGY LAW 235 (2011).

94 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., James, Gareth, et al., An Introduction to Statistical Learning With Applications in R, SPRINGER TEXTS IN STATISTICS 112 (2013).

95 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, PROCEEDINGS OF THE 21th ACM SIGKDD, INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING (2015).
II. EX MACHINA: TECHNOLOGICAL APPROACHES

As legal scholars have called for more transparency\(^96\) and accountability\(^97\) for machine learning algorithms, increasingly, attention has shifted towards technological approaches to combating algorithmic capture in employment. These techno-solutionist approaches fall into two categories: 1) the adjustment of human job search behavior to use technology to “game” machine learning algorithms; and 2) the creation of new algorithms that promise to eliminate human bias. This section examines both approaches and notes their limitations. I conclude with a warning that techno-solutionism will never be sufficient for problems that are, at their root, derived from socio-technical interactions arising from structural bias and societal prejudices.\(^98\)

A. Humans Conform to the Machine

One approach to counteract the biased effects of hiring algorithms is to teach to the test or help applicants beat the system. Thus, humans learn to devise strategies to hurdle routine machine learning errors and other encoded biases. Consider a LinkedIn article, with the straightforward title: *Modifying your Resume to Beat ATS Algorithms*.\(^99\) The author, a recruiting manager counsels job applicants on how to avoid getting axed by the applicant tracking system (ATS). The article provides advice ranging from appropriate file format for resumes, (PDFs are difficult for hiring algorithms to read), to the idea of choosing keywords pulled from the job ad to ensure that an unsophisticated algorithm, that is one lacking the full spectrum of the lexicon for a given field, does not reject the application simply because the algorithm was designed to only recognize a narrow list of words provided for a keyword search.\(^100\)

In a similar vein, there are online communities dedicated to cheating the personality tests that have now become ubiquitous features of automated

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\(^{97}\) Joshua Kroll, et al., *supra* note 73.

\(^{99}\) See, for example, Anupam Chander, *Reviews, The Racist Algorithm?*, *supra* note 81.


\(^{100}\) *Id.*
hiring. Although some question the reliability of personality tests, the tests remain a popular part of automated hiring systems. Some experts estimate that as many as 60 percent of workers are now asked to take workplace assessments. The $500-million-a-year industry has grown by about 10 percent annually in recent years. While many organizations use personality testing for career development, about 22 percent use it to evaluate job candidates, according to the results of a 2014 survey of 344 Society for Human Resource Management members. While some lawsuits have sought to change the use of the tests, most workers have reconciled themselves to encountering the test as part of the hiring process and online “answer keys” have been created to cheat the tests. These “answer keys,” however, represent conformity to the practices of automated hiring practices, rather than a wholesale rejection of the personality tests and their potential to discriminate in insidious ways. That is, efforts to cheat or beat the system merely represent the acquiescence of humans to a regime of algorithmically-derived worker selection that is fundamentally unfair to protected categories of workers such as those with mental disease.

B. Algorithms to the Rescue

Another technological approach is the development of new algorithmic hiring tools that purport to eliminate biases. A recent swell of start-ups —
including HireVue, Gild, Entelo, Textio, Doxa, Jobaline, and GapJumpers etc — are innovating new ways to automate hiring. Their claim is that their hiring algorithms are more effective and efficient than any human manager. Some of these companies also claim that their technological approaches ensure employment decisions that are non-discriminatory. Although these start-ups may very well have the good intention of eliminating human bias in hiring, their techno-solutionist attempts fall short of this goal. Below is a table in which I parse the solutions offered by these start-ups and surface the potential for bias that I believe still remain.

### C. The Perils of Techno-solutionism

The problem with techno-solutionists methods is that they fail to address the bias encoded in the business practices deployed in the hiring process. In fact, they may even serve to replicate the short-comings of human decision-making.

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112. “Jobaline is the leading recruiting solution optimized for hourly jobs.” See Jobaline Official Company Website at: www.jobaline.com

113. “Discover talent the Voice way: employers use our technology to find untapped talent using blind auditions.” See GapJumpers Official Company Website at: https://www.gapjumpers.me. It is important to add that unlike other automated hiring programs, GapJumpers advocates “blind auditions” wherein the candidates are tested for talent without their identity or other identifying characteristics (such as school pedigree) made known to recruiters/hiring managers. Our data repair is a more complete method of doing this as it would remove all “societal noise” from the available data about candidates.


making processes in hiring. For example, although the online websites to beat employment personality tests through “answer keys,” may help a handful of people who would otherwise have been rejected, they also ultimately serve to reify the personality tests as part of the job application process and to calcify the same practice as part of business procedure for employers to screen applicants. In effect, such resistance efforts may merely reflect symptom of, “algorithmic governmentality,” which “anticipates our every move, mapping out in advance an apolitical ideal of behaviour and performance…to which the subject must adapt and conform without reflection.” This suggests a need for solutions that do not unquestioningly privilege technological innovation but which, rather, evoke the spirit of antidiscrimination laws for a reconsideration of algorithmically-driven hiring practices. As other scholars have noted, techno-solutionist approaches to societal problems are foiled by the “garbage in, garbage out” problem. That is, techno-solutionist approaches that fail to take into account structural biases encoded in the algorithm or which fail to question the provenance of training data (and how they might bear the taint of historical inequities) are doomed to replicate the same biased results.

Consider the use of zip codes for resume sorting. While zip codes might be seen as a neutral factor for determining distance to job site, this is a factor that bears societal noise as it correlates closely to race given that housing location bears the vestiges of historical segregation practices. I argue that the responsibility for interrogating whether algorithms are returning truly accurate decisions rather than merely mimicking societal biases ultimately rests on the human architects of algorithms.

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116 Douglas Spencer, Proletarianization Isn’t Working, RADICAL PHILOSOPHY (Feb. 2018) at: https://www.radicalphilosophy.com/reviews/individual-reviews/proletarianisation-isnt-working


118 See, for example, “The G.I. Bill deliberately left the distribution and implementation of federal education and housing benefits to universities, private banks, realtors, and white homeowners’ associations, all of whom discriminated openly and pervasively against blacks.” Juan F. Perea, Doctrines of Delusion: How the History of the G.I. Bill and Other Inconvenient Truths Undermine the Supreme Court’s Affirmative Action Jurisprudence, 75 U. PITT. L. REV. 583 (2014) at, http://lawcommons.luc.edu/cgi/viewcontent.cgi?article=1552&context=facpubs; See, e.g., Angela Onwuachi-Willig & Jacob Willig-Onwuachi, A House Divided: The Invisibility of the Multiracial Family, 44 HARV. C.R.-C.L. L. REV. 231 (noting the still persistent and insidious housing discrimination and segregation in the United States). Consider that the same can be said of credit scores (high scores are enabled by the intergenerational transfer of wealth that had been previously denied generations of African-Americans). Sarah Ludwig, Credit Scores in America Perpetuate Racial Injustice: Here’s How, THE GUARDIAN (Oct. 13, 2015) at: http://www.theguardian.com/commentisfree/2015/oct/13/your-credit-score-is-racist-heres-why
III. *EX FIDA BONA: BUSINESS SOLUTIONS*

This section sets forth three proposals for business practices that would better address the employment discrimination issues presented by automated hiring systems. While some of these proposals involve the use of technology, the primary aim, however, is to institute thoughtful and accountable business practices that seek to minimize the effects of bias in the hiring process. These processes include: 1) self-auditing by business entities, 2) standards-setting for algorithmic hiring via a Fair Automated Hiring Mark (FAHM) certification system, and 3) contractual bias reduction for companies that outsource their hiring to automated hiring platforms.

A. *Internal Auditing as Sound Business Practice*

The tendency towards algorithmic capture is concomitant with the abdication of the responsibility to review outcomes to ensure they are the best possible ones; mandated internal auditing, as a business practice, ensures that companies will diligently review the outcomes of automated hiring. Thus, I propose that large corporations and other entities should be required to implement a business system of regular self-audits of their hiring outcomes to check for disparate impact. This system of mandated self-audits would be similar to the mandated self-audits of financial institutions. In an internal audit activity, self-auditing, or self-assessment, a “department, division, team of consultants, or other practitioner(s) [provide] independent, objective assurance and consulting services designed to add value and improve an organization’s operations.” By evaluating and improving the effectiveness of “governance, risk management and control processes” in a systematic and disciplined way, internal auditing helps an organization reach its objectives.\(^{119}\)

Standards and best practices already exist for conducting an effective internal audit. As an international professional association, the Institute of Internal Auditors (IIA) gives guidance on internal auditing.\(^{120}\) For an internal audit to be considered effective, it should achieve at least one of the ten Core Principles, which includes “Demonstrates competence and due professional care” and “Is insightful, proactive, and future-focused.”\(^{121}\) Also, as listed in the Code of Ethics, internal auditors are expected to uphold the following principles: Integrity, Objectivity, Confidentiality, and

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\(^{120}\) Id.

The quality of the internal audit activity should also be assured through internal and external assessments, which are public reviews and day-to-day measurement, supervision, and review of the activities and assessment by an independent reviewer from outside of the organization, respectively. The independence of these audits has been constantly emphasized by relevant institutions; the 2001 guidelines of the Basel Committee on Banking Supervision, the principal agency establishing international banking standards, and the guidance issued by a subcommittee of the Federal Reserve system underline that bank’s internal audit must be independent from the every-day internal control process and day-to-day functioning of the bank and that it should have access to all bank activities. In support of this, the manuals of the FDIC, OCC, and FFIEC advocate that internal auditors report “solely and directly” to the audit committee, consisting of outside directors, without reporting to their supervisors so that the auditing can avoid management interference.

Self-auditing is also conducted and recommended in different types of industries, such as manufacturing sectors, because it helps the businesses meet the requirements of relevant laws. For instance, an occupational safety and health (OHS) self-audit is an “assessment of workplace hazards, controls, programs, and documents performed by a business owner or employee” done for the company to comply with OSHA regulations. In their article "Self-audit of lockout/tagout in manufacturing workplaces: A Pilot Study," Samuel C. Yamin, et al., discuss the importance of self-audits in manufacturing environments.

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123 Standards for the Professional Practice of Internal Auditing, supra note 119; Matthew Bender, Banks & Thrifts: Govt Enforce & Receivership § 5.04 (2018).
124 Federal banking regulators suggest that the internal audit function be conducted according to professional standards. Id; See Michael E. Murphy, Assuring Responsible Risk Management in Banking: The Corporate Governance Dimension, 36 DEL. J. CORP. L. 121, 136-137 (2011).
127 Id at 137-138.
**pilot study**, Yamin et al. discuss the significance of OHS self-audit in manufacturing companies and suggest ideas to improve inter-rater reliability and accuracy in the process.\(^{130}\) Furthermore, OSHA allows hiring a consultant within the company to perform self-audits when OSHA is not able to do an inspection immediately.\(^{131}\)

In addition, some articles describe self-audit methods related to other aspects of a business. For instance, Kok et al. suggest that self-audit be conducted to enhance corporate social responsibility. In addition to fourteen aspects of social responsibility they define, they list four levels of CSR self-audit instrument, which instruct businesses to examine their performance in relation to ad hoc policy, standard policy, planned policy, and evaluated and reviewed policy.\(^{132}\) Furthermore, an article\(^{133}\) published as part of the journal *Strategic Direction* by the Emerald Publishing gives insights about self-audit for quality improvement, which allows strategic and operational business planning through identification of strengths and prevention of problems. It indicates that self-audit process requires “proper training of self-auditors, allocation of sufficient time to perform the audit, preparation of audit aids, management support, and an adequate follow-up to audit findings.”\(^{134}\)

As it stands, the job applicants who do not make it past the hiring algorithm are typically lost to the ether. Thus, there is no sure way to determine relative percentages of minority job applicants who were hired against the number who applied, and there is still no sure way to confirm best hiring outcomes against the actual pool of qualified applicants. Thus, corporations could set up their hiring systems to ensure that data from failed job applicants are preserved to be later compared against the successful job applicants, with the aim of discovering whether the data evinces disparate impact regarding the population of failed job applicants. This means that there is a role for qualified labor and employment lawyers who are also versed in data science to advice or work in-house with the human resources departments of large corporations and the engineers of hiring algorithms to ensure that the companies are not inadvertently contravening the spirit of Title VII and other civil rights laws that have been promulgated to grant true equal opportunity for employment to all American citizens.

Determining disparate impact in hiring algorithms, is a relatively simple matter of evaluating the outcomes using the EEOC rule.\(^{135}\) This rule mandates that a selection rate for any race, sex, or ethnic group which is less

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\(^{130}\) *Id.*


\(^{133}\) See *Self-Audit for Quality Improvement*, 18 STRATEGIC DIRECTION 5, 17 (2002).

\(^{134}\) *Id.*

\(^{135}\) See Uniform Guidelines on Employee Selection Procedures, BIDDLE CONSULTING GROUP, §4(D) at: [http://uniformguidelines.com/uniformguidelines.html#18](http://uniformguidelines.com/uniformguidelines.html#18)
than four-fifths (or eighty percent) of the rate for the group with the highest rate will generally be regarded by the Federal enforcement agencies as evidence of adverse impact.\textsuperscript{136} One problem is that it is difficult to legally obtain the full outcomes of algorithmic hiring systems, and companies have financial incentives not to disclose their proprietary algorithms.\textsuperscript{137} Through self-audits, companies could protect themselves from disparate impact claims, without any obligation to disclose proprietary information. Also, rather than merely serving as a protectionist tool, self-audits would also serve corporations interested in diversifying their personnel. Business scholars have shown that a workplace with diverse employees is ideal for achieving sought after business goals such as greater innovation.\textsuperscript{138} Thus, the self-audits could provide corporations with a tool to discover their blind spots in regards to preconceived notions of qualification and fit and might even help bring other problems of bias in hiring to the attention of the corporation. For example, the audits could shatter misconceptions as to qualifications by surfacing rejected candidates who nonetheless went on to become stellar employees at other companies. Or, the audits could reveal a rather shallow pool of diverse qualified applicants, pointing either to a negative brand image for the company, work climate problems, or the need to establish a sturdier pipeline to the industry for diverse candidates.

B. Standards Setting: The Fair Automated Hiring Mark (FAHM)

Given the proprietary nature of hiring algorithms, one approach that balances intellectual property protection concerns with the need for greater accountability is a certification system that operates on external third-party audits by an independent certifying entity.\textsuperscript{139} Other legal scholars have proposed certification systems for algorithms. Notably, Andrew Tutt has proposed an “FDA for algorithms,”\textsuperscript{140} in which the federal government

\textsuperscript{136} Id (showing the original language of the EEOC’s “four-fifths rule”).

\textsuperscript{137} For example, Nicole Wong in her role as Google Inc’s Associate General Counsel, has stated that “Google avidly protects every aspect of its search technology from disclosure”. See Nicole Wong, \textit{Response to the DoJ Motion, GOOGLE OFFICIAL BLOG https://googleblog.blogspot.com/2006/02/response-to-doj-motion.html}

\textsuperscript{138} See Katherine Phillips, et al., \textit{supra} note 47 (showing that diverse groups outperform homogenous groups because of both an influx of new ideas and more careful information processing); \textit{See also}, Sheen S. Levine & David Stark, \textit{supra} note 47.

\textsuperscript{139} I take as inspiration for my proposed certification system, Professor Ayres and Gerarda’s framework for corporations to certify discrimination-free workplaces that comply with ENDA. “By signing the licensing agreement with us, an employer gains the right (but not the obligation) to use the mark and in return promises to abide by the word-for-word strictures of ENDA. Displaying the mark signals to knowing consumers and employees that the company manufacturing the product or providing the service has committed itself not to discriminate on the basis of sexual orientation.” Ian Ayres & Jennifer Gerarda Brown, \textit{Marketing Nondiscrimination: Privatizing ENDA with a Certification Mark}, 104 MICHIGAN LAW REVIEW 1639, 1643 (2006).

\textsuperscript{140} See Andrew Tutt, \textit{An FDA for Algorithms}, 69 ADMIN. L. REV. 83 (2017).
would establish an agency to oversee different classes of algorithms to ensure that, much like food and medicine marketed for human consumption, those algorithms would pose no harm to those over whom they exercise decision-making power. I envision a certification system that would take the form of a non-governmental entity, much like say the Leadership in Energy and Environmental Design (LEED) certification system, rather than a governmental agency. LEED was created by the U.S. Green Building Council (USGBC), which in turn was established in 1993 “with a mission to promote sustainability-focused practices in the building industry.” Thus, LEED serves as a “green certification program for building design, construction, operations, and maintenance.” The LEED certification involves a formal certification letter, as well as, plaques and signage for buildings, and an electronic badge that may be displayed on a website.

The process of certification for algorithmic hiring tools would involve periodic audits of the hiring algorithms to check for disparate impact on vulnerable populations. Thus, this would not be a one-time audit, but an ongoing process of periodic audits to ensure that the corporations/organizations will continue to hew to fair automated hiring practices. In return, the corporation or organization would earn the right to use a Fair Automated Hiring Mark (see illustration of the mark below) for its online presence, communication materials, as well as, to display the mark on hiring advertisements to attract a more diverse pool of applicants.

![The Fair Automated Hiring Mark](image)

Figure 1: The Fair Automated Hiring Mark

The decision to propose a non-governmental certification agency, rather than a governmental agency, stems from the recognition of regulatory capture. As history has shown, governmental agencies are vulnerable to

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141 Id.
142 See, About USGBC, The United States Green Building Council Official Website, at: https://new.usgbc.org/about
143 Id.
144 See, Certification, The United States Green Building Council Official Website, at: https://new.usgbc.org/post-certification
145 Daniel Carpenter and David Moss define “regulatory capture” as “the result and process by which regulation, in law or application, is consistently or repeatedly directed away from the public interest and towards the interests of the regulated industry, by the action or intent of the industry itself.” Daniel Carpenter & David A. Moss, Preventing Regulatory Capture: Special Interest Influence and How to Limit It, CAMBRIDGE UNIVERSITY PRESS, 19 (2014).
regulatory capture,\textsuperscript{146} meaning that private influence on the workings of such agencies, as well as, political wind shifts can render such agencies, toothless or ineffectual. Examples of regulatory capture abound in American government, including that of the U.S. Securities and Exchange Commission (SEC)\textsuperscript{147} and that of the Federal Drug Administration Agency (the FDA).\textsuperscript{148} Most recently, an in-depth investigative report by the New Yorker, revealed the staggering extent of the regulatory capture of the FDA by Purdue Pharma, a privately held company established by the Sackler family and which developed the prescription painkiller, OxyContin.\textsuperscript{149} The painkiller, which is almost twice as powerful as morphine, has been at the forefront of the current American opioid crisis, as it was extensively marketed for long-term pain relief, despite medical evidence of its addictive properties.\textsuperscript{150} The FDA, without corroborating evidence from clinical trials, approved a packaged insert for OxyContin which announced that the drug was safer than competing painkillers – the FDA examiner who approved the package insert, Dr. Curtis Wright, was hired at Purdue Pharma soon after he left the FDA.\textsuperscript{151}

A commercial third party certifying entity, with a business reputation to protect, would be much less susceptible to regulatory capture. For one, as the nature of the relationship between the certifying entity and the employer making use of automated hiring systems is voluntary, there is much less of an impetus for regulatory capture in the first place. Thus, the “FAHM” mark, rather than representing a mere rubber stamp, will come to serve as a reputable market signal for employers who are truly interested in creating a more diverse workplace. Of note, also, is that a non-governmental entity would better withstand the sort of vagaries brought about by political wind shifts, as was recently demonstrated by events at Federal Communications Commission (FCC)\textsuperscript{152} and the Federal Trade Commission (FTC) regarding

\textsuperscript{146} See, for example, Stavros Gadinis, The SEC and the Financial Industry; Evidence from Enforcement Against Broker Dealers, 67 BUSINESS LAWYER (May 2012), (highlighting the inherent connection between the public and private enforcement of securities laws); David Freeman Engstrom, Corralling Capture, 36 HARVARD JOURNAL OF LAW AND PUBLIC POLICY 1 (Oct. 2013) (arguing that the structural conditions that facilitate regulatory capture naturally move legislatures and agencies together.)

\textsuperscript{147} Other scholars have detailed a revolving door of SEC employees to and from the financial sector and how this has contributed to regulatory capture of the SEC. Brown, Stewart L., Mutual Funds and the Regulatory Capture of the SEC (Nov. 20, 2016) at https://ssrn.com/abstract=2854312 or http://dx.doi.org/10.2139/ssrn.2854312


\textsuperscript{149} Id.

\textsuperscript{150} Id.

\textsuperscript{151} Id (detailing how OxyContin lobbied for the insert to increase its market share of drug sales).

net neutrality\textsuperscript{153} or the Environmental Protection Agency (EPA) regarding climate change.\textsuperscript{154}

I envision that such a third-party certification entity would be composed of multi-disciplinary teams of auditors comprising both lawyers and software engineers/data scientists who would audit the hiring algorithms employed by corporations and organizations. This would prevent some of the tunnel-vision problems associated with technology that is created without consideration for legal frameworks and larger societal goals. Furthermore, I envision that such a certification system would serve as a feed-back mechanism, and might be able to create better models and best practices for fairer automated hiring systems to be emulated by designers of automated hiring systems.

\textbf{C. Contractual Protections: Representations of Bias Reduction}

In addition to third-party certifications, another business solution to produce fair automated hiring practices is the adoption of contractual language that binds the vendors of automated hiring systems. This proposed solution requires the recognition of employers as consumers of automated hiring systems, and of the right of employers to consumer protection when purchasing or acquiring the license to those products. Such a legal recognition will privilege the protection of employers from the false promises of vendors of automated hiring systems. Professors’ Hanson and Kysar have illustrated the ways that consumer cognitive bias may be exploited for profit.\textsuperscript{155} Currently, algorithmic systems enjoy an aura of impartiality, efficiency, and accuracy.\textsuperscript{156} Vendors of automated hiring systems capitalize on this perception to hawk their products to HR professionals who believe that these algorithmic tools will streamline their

\textsuperscript{156} See, Danah Boyd & Kate Crawford, \textit{supra} note 58.
work while obtaining good results. Consumer protection laws that dictate fairness in advertising and in contractual representations as to the reduction of bias by hiring algorithms may therefore represent a viable vehicle to protecting consumers of automated hiring systems from liability. 157

Professors Neil Richards and Woodrow Hartzog argue that a key factor in the relationship between information providers and information users has failed. 158 They argue that trust is at the core of relationships and that, to create a symbiotic and trusting relationship between both data providers and data users, data users must promise loyalty to data providers. 159 The question then arises as to what should be the legal basis for mandating that parties act in both loyal and trusting ways. In another article, authors Daniel Solove and Woodrow Hartzog look to a more tangible solution for improving privacy laws by comparing the Federal Trade Commission’s (FTC’s) privacy jurisprudence to common law. 160 They argue that the FTC “has risen to act as a kind of data protection authority in the United States,” although it has been largely ignored by the legal academy because its doctrines have not been developed in judicial decisions. 161 However, given the variety of rules that the FTC has set from the ground up, they argue that the next natural steps for improving consumer protection in the United States — such as the development of contractual promises from data users — may be best channeled through the FTC. Thus, perhaps the FTC may yet prove to be a valuable player by exerting its power by setting standards for contractual protections for consumers of algorithmic hiring tools.

IV. EX LEGIS: NEW LEGAL FRAMEWORKS

In this section, I propose the shifting of legal frameworks to address novel legal issues arising from the use of algorithmic hiring tools. A thorny legal issue is who 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? Below, I discuss different approaches for holding liable either the maker of the algorithmic hiring tool, or the employer who uses the algorithmic tool in a way that returns disparate results.

157 See, Infra Section IV (B) for further discussions of consumer law in regards to protecting job applicants.
159 Id.
161 Id. at 676.
A. A Fiduciary Duty to Correct Bias

A pressing legal question is who owes the duty to correct algorithmic bias in automated hiring. Even if it is accepted that employers owe no duties to job applicants, some legal scholars would argue that the makers of hiring platforms do owe a legal duty to job applicants. 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.”162 In the context of employment, the primary question is: How should the law conceptualize the responsibilities of these hiring platforms as fiduciaries in regards to the information they solicit and transmit? 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.”163 Thus, I extend Professor Balkin’s analogy,164 comparing the relationship between platforms and their users to the relationship that patients enjoy with both doctors and nurses.165 In this vein, the role of the online hiring platform might be compared to that of a nurse, who does triage, that is, the nurse reads through records and conducts a preliminary check-up, thereby acquiring medical histories and background information as to medical symptoms before bringing in a doctor. Then, the information is passed to a doctor to conduct a more in-depth review of the patient’s condition, if it is serious. This is similar to the function that an online hiring platform might fulfill before passing on information to a hiring manager. Thus, one might argue that, like an information fiduciary, an online hiring platform “has an obligation to act in the interests of its clients.”166

As other scholars have argued, these platforms, which connect users to one another, “necessarily exercise a great deal of control over how users’ encounters are structured.”167 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.168 Thus,

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164 Jack Balkin, Information Fiduciaries and the First Amendment, supra note 162.
165 Author, Age Discrimination by Platform, BERKELEY JOURNAL OF EMPLOYMENT AND LABOR LAW, 26 (Forthcoming 2019).
166 See Jack Balkin, Information Fiduciaries and the First Amendment, supra note 162, 1207.
167 Karen Levy & Solon Barocas, Designing Against Discrimination in Online Markets, supra note 163.
platforms should not be held completely blameless for the discrimination that occurs – even if their users may be influenced by pre-existing biases.\textsuperscript{169}

I agree that the platforms cannot merely be seen as neutral blameless intermediaries. Rather, the law should recognize platform authoritarianism as a socio-technical phenomenon that has transformed the responsibility and liability of platforms.\textsuperscript{170} Platform authoritarianism is 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.”\textsuperscript{171} Recognizing the fiduciary duty that the purveyors of online platforms owe to their users is the first step towards combating platform authoritarianism and returning to a rule of law for algorithms.

Several scholars have recently called for the extension of fiduciary duties to other areas of law.\textsuperscript{172} Established concepts from organizational theory scholarship also further bolster the argument that hiring platforms are performing a brokerage function and thus should be considered fiduciaries.\textsuperscript{173} 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.\textsuperscript{174} The tertius iungens (“the third who joins”) orientation is derived from the Latin verb “iungo” which means to join, unite or connect. The emphasis of this orientation is on the joining of people. Thus, a tertius iungens broker will operate with a strategic emphasis on creating friendship and collaboration between two parties. This can usually be done by linking disparate parties in one’s social network in order to create outcomes that are mutually beneficial for two or more parties.\textsuperscript{176} In contrast, the tertius gaudens (“the third who enjoys”) orientation emphasizes the strategic separation of

\textsuperscript{169}Id.
\textsuperscript{170}See Author, Age Discrimination by Platform, supra note 165.
\textsuperscript{171}Author, Facebook users aren’t the reason Facebook is in trouble now, WASHINGTON POST (March 23, 2018) at: https://www.washingtonpost.com/news/posteverything/wp/2018/03/23/facebook-users-arent-the-reason-facebook-is-in-trouble-now/?utm_term=.e18a9f63872b; See also, Author, Age Discrimination by Platform, supra note 165.
\textsuperscript{173}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, SOCIAL STRUCTURE AND NETWORK ANALYSIS, 201-218 (1982).
\textsuperscript{174}Georg Simmel, The Triad, FREE PRESS (1950).
\textsuperscript{175}David Obstfeldt, Social Network, the Tertius Iungens Orientation and Involvement in Innovation, 50 ADMINISTRATIVE SCIENCE QUARTERLY 1, 102 (2005).
\textsuperscript{176}Id.
\textsuperscript{177}Id.
parties.\textsuperscript{178} In this sense, a broker would enjoy the benefit of the measured separation between two parties for the broker’s own gain.\textsuperscript{179}

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 broker subsequently recedes in importance, and (4) introduce or facilitate interaction between parties while maintaining an essential coordinative role over time.”\textsuperscript{180} The automated hiring process represents a triad with the automated hiring platform as broker. In this triad, hiring platforms are information fiduciaries who perform an “essential coordinative role over time” by continuously parsing resume received from job applicants before delivering them to employers. Furthermore, following Simmel’s typology of brokers, automated hiring platforms which may 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 teritus bifrons” (that is, “the two-faced third”). This means 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 one of the parties to the triad (that is the employer), while maintaining the appearance of working for both employers and job applicants.

This categorization rings true in light of the class action allegations against Facebook.\textsuperscript{181} Facebook users entrust their information to platforms like Facebook with the expectation that those platforms would use that information in the service of bettering the users’ experience. However, what is alleged in the class action is that Facebook, by creating “affinity groups” and “look-alike audiences” from its users’ information (and when such Facebook-provided features are then used in defiance of the goals of antidiscrimination laws),\textsuperscript{182} has brokered information to employers in a way that benefits both Facebook and the employer, but not necessarily the user. This brokerage of job applicant information, in a manner that is inconsistent with the best interests of the job applicant, violates the fiduciary duty of the hiring platform as an information fiduciary.

\textsuperscript{178} Id.
\textsuperscript{179} Id.
\textsuperscript{180} Id at 104.
\textsuperscript{182} Communications Workers of America v. T-Mobile, Inc., First Amended Class Action Complaint, supra note 10.
B. 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 protecting for unfair algorithmic outcomes. The Federal Credit Reporting Act (FCRA),\(^{183}\) for example, while typically thought to be solely for the distribution of credit reports, may also be helpful in the context of hiring algorithms. Applied from this lens, the FCRA could potentially be leveraged when an employer relies on information from third parties – namely, an application pre-screener or a hiring algorithm software.\(^{184}\)

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 credit-worthiness. 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.\(^{185}\) 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 limit this kind of unfair and opaque credit reporting.

The law also protects consumers from unfair background checks and 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, employment.\(^{186}\) Further, the law goes so far as to protect consumers by providing that creditors or employers must be “obtain a written authorization from any applicant or employee for the procurement of a report, and certify to the consumer reporting agency its compliance with the requirements of the statute such that it will not violate any equal employment opportunity law.”\(^{187}\) 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.\(^{188}\) Now, it also applies to a variety of agencies that collect and sell information that is found outside the workplace to employers for applicant-
reviewing purposes.\textsuperscript{189} With the coverage of many consumer reporting agencies (CRAs) whose sole purpose is employment pre-screening, 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 consumer reporting agency, 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 reports to third parties.”\textsuperscript{190} 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.

Moreover, these companies arguably develop consumer reports, by the legal definition of the term. The FCRA defines “consumer reports” 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.”\textsuperscript{191} Through an analysis of the terms of service of two algorithm-based employment screening companies – Monster Hiring and Newton Software – 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 publically-available websites and may use this information to create a Profile or append it to an existing Profile” on the company’s website.\textsuperscript{192} 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.\textsuperscript{193} For an example of the service costs, the cost to post

\textsuperscript{189} See, for example, \url{https://Checkr.com} (which screens applicants for criminal records, driving records, and also provides employment verifications, international verifications, and drug screenings); \url{www.HireRight.com} (which boasts the industry’s broadest collection of on-demand screening applications); and First Advantage Corporation at \url{www.fadv.com} (which provides criminal and pre-employment background checks, as well as drug-testing and tenant screening services).

\textsuperscript{190} 15 U.S. Code § 1681a(d)(2)(f).

\textsuperscript{191} 15 U.S. Code §1681a(d)(1).

\textsuperscript{192} See \textit{Terms of Use}, \textsc{Monster} (2018) at: \url{http://inside.monster.com/terms-of-use}.

\textsuperscript{193} See \textsc{Monster: Job Board Overview for Employers Plus FAQs and Pricing}, \textsc{BetterTeam} (2018) at: \url{https://www.betterteam.com/monster}.
and promote one job ad on Monster is $425 for a 60-day post longevity.\footnote{Monster: Job Board Overview for Employers Plus FAQs and Pricing, BETTERTEAM (2018) at: \url{https://www.betterteam.com/monster}} That cost includes the distribution of one job ad on Monster’s “job board,” as well as “access to 20 recommended resumes from the Monster database” – from job-seekers selected by Monster, who seem to fit the qualifications an employer lists in the job description.\footnote{Monster: Job Board Overview for Employers Plus FAQs and Pricing, BETTERTEAM (2018) at: \url{https://www.betterteam.com/monster}} 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.”\footnote{Karen Levy & Solon Barocas, Designing Against Discrimination in Online Markets, supra note 163.}

By doing so, it can certainly be said that Monster is “communicating information that bears on a consumer’s character, general reputation, personal characteristics, and mode of living, and are expected to be used as a factor in establishing the consumers’ eligibility for employment purposes.”\footnote{15 U.S. Code §1681a(d)(1).} Most specifically, by retaining the right to add any information it discovers online, it is clear that Monster can take 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 Newton Software. Newton Software is, for all purposes, a background-check access provider, although it also advertises resume-parsing tools and interview-streamlining data reports.\footnote{See ATS Made Simple, NEWTON SOFTWARE HOME PAGE (2018) at \url{https://newtonsoftware.com/features/}} The software platform advertises to employers that it takes in applicant information and “intelligently stores the information into new candidate profiles, so that errors from manually inputting applicant data are a thing of the past.”\footnote{Id.} From these profiles, employers can find employees to “best fit” the requirements of the job descriptions they release.\footnote{Id.} Then, Newton Software gives employers access to background check software provided by third parties, which Newton itself entirely oversees.\footnote{Id.} Given these features, I argue that Newton has enough of a hand in the report-creating process as to have the final reports attributed to itself, making its reports “consumer reports.”

\begin{footnotes}
\item[196] Karen Levy & Solon Barocas, Designing Against Discrimination in Online Markets, supra note 163.
\item[197] 15 U.S. Code §1681a(d)(1).
\item[198] See ATS Made Simple, NEWTON SOFTWARE HOME PAGE (2018) at \url{https://newtonsoftware.com/features/}
\item[199] Id.
\item[200] Id.
\item[201] Background Check Software for Hiring, NEWTON SOFTWARE (2018) at \url{https://newtonsoftware.com/features/integrated-background-checks/}
\end{footnotes}
The information-analyzing services put forth by Newton Software are certainly more hands-on than those of Monster. Newton 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 providing new, standardized profiles on applicants for employers to reference, Newton is certainly changing the nature of the resumes that employees have submitted and is thereby creating its own reports with their information, as well. All of this data, which Newton relays to employers, can and likely will be used to determine the employment eligibility of many job applicants. Therefore, under the language of the FCRA, it seems that the reports put forth by Newton certainly qualify as “consumer reports,” since Newton takes applicants’ personal information and compiles it to send to employers for job eligibility screening.

Further, the Federal Trade Commission (FTC), the body that oversees the FCRA, has recently held that that “just saying you’re not a consumer reporting agency is not enough.”202 The case, which took place in 2013, dealt with Filiquarian Publishing, an application for purchase on iTunes which advertised that it could make “quick criminal background checks for convictions” in specific states.203 The application had access to hundreds of thousands of criminal records and could help employers discover if any of the convictions could be attributed to their applicants.204 However, Filiquarian 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.205 The FTC took issue with this, finding that Filiquarian provided the exact same information as CRAs, but simply said “don’t use this information for employment purposes,” which is not a reasonable excuse from FCRA compliance.206 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.” It is simple to see how this logic could be applied to sites like Monster and Newton, given the fact that they provide such similar screening services.

If these companies were to be considered consumer reporting agencies under the FCRA down the road, Monster, Newton, 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 maximum possible accuracy of their files, which cause individuals to be denied” employment

203 Id.
204 Id.
205 Id.
206 Id.
opportunities. In one case, *Thompson v. San Antonio Retail Merchants Association* (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 Fair Credit Reporting Act, 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.

One potential response to the classification of hiring algorithms as CRAs can be extrapolated from Professor Ryan Calo’s article, *Open Robotics.* 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. 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 given that those developers hold the power to create features that may enable employment discrimination and also exercise considerable control over how applicant’s 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 could result in a new defense for employers who use such services, giving them less liability for using discriminatory hire screening tools that they do not create themselves.

### C. Discrimination Per Se

In the absence of overt discriminatory action as alleged in the class action against Facebook and others, holding corporations responsible for

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207 *Thompson v. San Antonio Retail Merchants Asso.*, 682, F.2d 509 (1982). See also, *Spokeo 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.)

208 *Thompson v. San Antonio Retail Merchants Asso.*, supra note 207.


210 *Id* at 106.
the algorithmic bias of the automated hiring platforms they use represents a challenging legal problem because of the difficulty of establishing intent. Antidiscrimination laws, such as Title VII,\textsuperscript{211} require intent for liability to attach.\textsuperscript{212} The question arises then whether the liability of corporations could be mitigated by a lack of intent to discriminate or even a lack of awareness that an algorithm is producing biased results. For example, one researcher, Jatinder Singh, has argued that the line of responsibility for problems created by machine learning algorithm is blurred.\textsuperscript{213} More specifically, if a machine learning algorithm can operate without being specifically programmed, by creating a model from available data – should the responsibility for problems created by that algorithm lie with its creator, the entity who chose the training data, or with the algorithm itself, assuming the technology is essentially “thinking” on its own? This, Singh argues, is a question that has yet to be succinctly answered by any current legal framework. I argue here that the well-established tort principle of 	extit{negligence per se} should be the model for creating new legal framework to answer the question of intent when it comes to discriminatory results obtained by machine learning hiring algorithms.

One seminal 	extit{negligence per se} case involved a Minnesota drug-store clerk who sold a deadly poison to a customer, at the customer’s request.\textsuperscript{214} At the time of the sale, the clerk did not label the substance as a “poison,” which was required by a state statute for the sales of such substances.\textsuperscript{215} Later, the customer who had purchased the substance ingested the chemical, which caused her death.\textsuperscript{216} Given these facts, should the clerk have been held legally liable for his actions, which indirectly caused the customer’s death? This case, 	extit{Osborne v. McMasters}, became one of the earliest cases in the United States to analyze the illegal concept of 	extit{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.\textsuperscript{217} In explanation, the court detailed that it was “well-settled that where a statute or municipal ordinance imposes upon a person a specific duty for the protection or benefit of others, that if he neglects to perform that duty he is liable to those for whose protection or benefit it was

\begin{footnotes}
\item[212] Proving clear intent is necessary when attempting to make a disparate treatment case under Title VII. However, under the disparate impact of clause of action codified in Title VII, the intent is implied from an established pattern. See, U.S. Civil Rights Act of 1964 §7, 42 U.S.C. §2000e-2(1)(A) (1964).
\item[214] Osborne v. McMasters, 40 MINN. 103 (1889).
\item[215] Id.
\item[216] Id.
\item[217] Id at 1.
\end{footnotes}
imposed for any injuries of the character which the statute or ordinance was designed to prevent.”

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. For example, in Mikula v. Tailors, an Ohio business invitee was taken to the emergency room after falling snow-covered parking lot at the place of business to which she was invited. 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 snow fall from that day. After careful consideration, the jury determined that “a deep hole in a parking lot, which is filled or covered 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 show 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.”

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 his or her 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. 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. The court in Miller found that Allan Christian, the landlord, was liable for the damage of 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.

Often, “failure to correct” claims also entail a consideration of whether the plaintiff knew of the problem, as it is presumed that a defendant with knowledge of an existing problem would be reasonable enough so as to avoid injury by the issue altogether. In one case, Walker v. RLI Enterprises, a tenant in an apartment building sued her landlord, after she stepped out

218 Id.
219 See, for example, Williams v. Calhoun, 175 GA. APP. 332 (1985) (in which the defendant’s failure to stop at a stop sign constituted negligence per se); Lombard v. Colo. Outdoor Educ. Cir., Inc., 187 P.3D 565 (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, 108 Wn.2D 220 (1987) (in which a cocktail lounge was found negligent per se for serving alcohol to a minor).
220 Id at 16.
221 Id at 1.
223 Id at 1.
the back door of the building and slipped on a sheet of ice. She suffered serious injuries to her ankle. In her suit, the tenant asserted that the landlord was negligent in maintaining the property, because she had given them notice of a leaky water faucet by the back door of her apartment. This negligence, the court determined, was negligence per se, because the landlord had an obligation to maintain the premises under Ohio law.

At trial, however, the landlord argued that “a landlord is only liable where he has ‘superior knowledge of the defect that led to the injury.’” By this, the landlord meant that the tenant had alerted him of the problem, showing that she clearly knew that it could be dangerous. He then pointed out that she had taken no further action to avoid the leaky faucet, and could thus be responsible for her own injury. 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.

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.

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, if self-audits or external audits of hiring algorithms become mandated by law, I argue that for an employer who willfully neglects to audit and correct its automated hiring systems, a prima facie intent to discriminate could be implied given rise to what I term, discrimination per se. This argument becomes persuasive when you consider 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 that only the corporation could have “superior knowledge” of any problems of disparate impact.

D. A Defense to Discrimination by Algorithm

Even when hiring algorithms have been found to have a disparate impact on protected categories, employers may still be able to escape liability by providing defenses available under the disparate impact framework of Title VII. In the following subsections, I focus on two defenses in particular which could represent hardy defenses to claims of

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226 Id.
227 Id.
228 Walker v. RLI Enters., supra note 225.
230 Walker v. RLI Enters., supra note 225.
232 Walker v. RLI Enters., supra note 225.
hiring discrimination as part of an automated hiring system: 1) non-race/non-protected category criteria; and 2) business necessity.

1. Non-Race/Non-Protected Category Criteria

The assertion of a non-race based criteria was the defense given in *McKinzy v. Union Pacific Railroad* in 2010, when a job applicant, McKinzy, sued Union Pacific, a prospective employer, on the basis of racial discrimination by algorithm.233 McKinzy’s trial showed that a “prescreener” had reviewed his application materials and rejected him for his sporadic work record and large gaps in his employment history.234 When McKinzy claimed that he had been screened out because of his race, Union Pacific’s defense put forth evidence that McKinzy was not qualified for the open position, and showed that it had applied non-race-based criteria to make its determination.235 After reviewing such evidence, the court ruled in Union Pacific’s favor. Thus, the ability to put forth another pretext for applicant rejection proved to be a strong defense. The availability of a neutral criteria defense to disparate impact results could prove to be a stumbling block when attempting to address discrimination resulting from the use of machine learning algorithms. This is despite the fact that some hiring criteria, while neutral on their face, may nonetheless be tied to protected variables such as race or age. Consider this example, a business trains its hiring algorithm to prefer applicants from certain zip codes; although zip codes seem neutral, the history of housing segregation in the U.S. mean that zip codes are highly correlated with race. Thus, once the algorithm learns that there is not a high probability that certain races may be present in the privileged zip code, it may start to exclude those races altogether. Or consider that an employer may train its algorithms to pick applicants that have certifications in certain programs, well, if those programs are new programs, then possessing those certifications may be highly correlated with more recent graduates, thereby negatively impacting older workers. Thus, a nefarious employer could very well use neutral variables as proxies for legally-protected categories as an end-run to discriminate against minority groups via automated hiring.

2. The Business Necessity Defense

Some employers accused of algorithmic discrimination may also be able to put forth the business necessity defense. First articulated in *Griggs v. Duke Power Co.*, the Supreme Court held that Title VII prohibits not only overt discrimination, but also disparate impact, or practices which may seem to be facially neutral, but have an otherwise discriminatory effect in

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234 *Id.*
235 *Id.*
operation.\textsuperscript{236} In doing so, the court also held that an employer must be able to show that its job application requirements are directly related to an applicant’s successful performance of the job for which they would be used.\textsuperscript{237} The disparate impact theory of action for discrimination, however, allows for a “business necessity” defense, if an employer can show that a test is consistent with business necessity.\textsuperscript{238} With reference to cases of algorithmic discrimination, this defense might apply if the employer can show that the data that an algorithm relies upon is a “business necessity” or, in other words, “statistically correlated” with job success.\textsuperscript{239} In light of the potential for corporations to use this defense as both shield and sword, Professor Kim argues that entities “who use data mining models should bear the burden of demonstrating the accuracy and representativeness of the data used to construct the models, rather than requiring complainants to identify the flaws giving rise to biased outcomes.”\textsuperscript{240} However, as this is currently not the legal standard that employers must meet in discrimination cases, it is likely that business necessity claims will continue be a viable defense to discriminatory automated hiring results.

\section{Ex Ante: Fairness By Design for Hiring Systems}

Despite the promising potential for litigation-driven solutions to algorithmic bias in hiring, I argue that \textit{ex ante} solutions remain the best option. One common retort to addressing bias in algorithms is that machine learning algorithms, which are constantly changing, are ungovernable.\textsuperscript{241} These machine learning algorithms which have the capacity to derive new models as they learn from large data sets are constantly reevaluating the variable inputs to calculations. Some researchers have argued that humans could feasibly lose their agency over algorithms given their extensive potential for calculations and the amount of data they use.\textsuperscript{242} To limit this reduction in choice-making power, some have exhorted that humans need to set “checks” on algorithms, ensuring that they can inspect both the data that enters the calculation system, and the results that exit.\textsuperscript{243} By doing so, humans might reduce the chance that algorithms grow to be unintelligible over time. For example, IBM’s Watson algorithm allows periodic inspections by presenting researchers with the documents it uses to form the basis for its decisions.\textsuperscript{244} Although allowing its researchers to see its inputs

\begin{footnotesize}
\begin{enumerate}
\item Id.
\item Pauline Kim, \textit{Data-Driven Discrimination at Work}, 58 WILLIAM & MARY LAW REVIEW 857, 908 (2017).
\item Id.
\item Id at 867.
\item See, Joshua Kroll, et al., \textit{ supra} note 73.
\item Id.
\item Id.
\end{enumerate}
\end{footnotesize}
might not entirely mitigate the problem of an algorithm learning too much and developing on its own, it certainly can aid in the development of more understandable future use, as well as the issue of answering where the liability for an algorithm’s mistakes lies. In the following sub-sections, I note some suggestions for programming in fairness to hiring algorithms and also in the collection of information by those same algorithms.

A. Designing Fairness in Hiring Algorithms

Programmers can reduce discriminatory effects of hiring algorithms by complying with key standards of legal fairness in determining design features such that the algorithms will avoid a disparate impact for protected classes and comply with the principles of laws such as the Civil Rights Act of 1964 or the Age Discrimination in Employment Act of 1967 (ADEA). Mark MacCarthy in *Standards of Fairness for Disparate Impact Assessment of Big Data Algorithms* explains conditions for algorithms to be certified as fair. Algorithms are fair when they meet one of the following: Fairness Through Blindness (algorithms do not contain or use variables that refer directly to a protected status), Group Fairness (algorithms treat groups equally), Statistical Parity (algorithms equalize positive acceptance rates across protected groups), Equal Group Error Rates (the rate at which algorithms return false positives and false negatives is the same for all protected groups), Individual Fairness (algorithms return the same outcome regardless of an individual’s group membership), Predictive Parity (algorithms equalize positive predictive value across groups), and Similarity Measures (algorithms classify individuals the same when they have similar characteristics relevant to performing a particular task).

These conditions cannot all be satisfied at once. For example, there are disputes about statistical concepts of fairness, especially between group fairness and individual fairness, because some believe that antidiscrimination laws aim at practices that disadvantage certain groups, while others think these laws target arbitrary misclassification of individuals. Those that support group fairness measure, such as statistical parity and

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246 Id.

247 Id at 91.


equal group error rates, try to reduce the subordination of disadvantaged groups even by allowing for some sacrifice of equal accuracy. For instance, King and Mrkonich describe that fair selection algorithms “[rate] members of the majority and protected groups equally” and refer to the Uniform Guidelines on Employee Selection Procedures to define “unfairness” as a condition where “members of one race, sex, or ethnic group characteristically obtain lower scores on a selection procedure than members of another group, and the differences in scores are not reflected in differences in a measure of job performance.”

However, those who advocate individual fairness aim to promote equal accuracy in classification. To them, algorithms are considered fair “when they make equally accurate predictions about individuals, regardless of group membership.” Also, they require that “enforcing similar probabilities of outcomes for two individuals [be] less than any differences between them” and that “any two individuals who are similar with respect to a particular task [be] classified similarly.” As notions of fairness diverge, organizations must choose which standard to adopt by considering the context of use as well as normative and legal standards.

Legal scholars have called for greater transparency for hiring algorithms, with the belief that “greater disclosure of how [algorithms] operate” will help avoid unfairness. Professor Frank Pasquale, the author of The Black Box Society suggests that a solution to the problem of algorithmic discrimination is transparency; he does so by using the metaphor of “black box” and proposes that algorithms should not operate as black boxes but should be open up for examination. However, many argue that this call for transparency is not sufficient for algorithms to be completely fair in regard to legal standards. This is because transparency alone does not fully explain why a particular decision was made or how fairly the system operates. Kroll et al. in Accountable Algorithms suggest technical strategies that would help overcome hidden biases in the algorithms. For instance, they suggest incorporating randomness to maximize the gain of learning from experience; if the hiring algorithms are random such that they hire some candidates who are not predicted to do

253 See Cynthia Dwork et al., Fairness Through Awareness, supra note 249, at 1.
255 See Danielle Keats Citron & Frank Pasquale, supra note 96.
257 See Anupam Chander, The Racist Algorithm?, supra note 81; Frank Pasquale, Bittersweet Mysteries of Machine Learning (A Provocation), supra note 81.
258 See Kroll et al., supra note 73.
well, the validity of the initial assumptions can be tested and the accuracy and fairness of the whole system will benefit over time.\textsuperscript{260}

### B. Algorithmic Affirmative Action

I contend that arguments over standards of fairness and other approaches to algorithmic accountability tend to neglect the role of data in perpetuating discrimination and thus, that an affirmative correction of training data or evaluation data is one potential approach to curbing discrimination. As other scholars have noted, data is never neutral, rather, all data is marked by inequities as a result of historical discrimination.\textsuperscript{261} Thus, one true \textit{ex ante} attempt to prevent algorithms from returning biased results is “algorithmic affirmative action,” which focuses on transparency and the correction of the data the algorithms use rather than in the design of algorithms.\textsuperscript{262} For example, one company excluded addresses from being considered by its hiring algorithm out of concern that neighborhoods in the U.S. reflect homogenous racial compositions due to historical racial segregation.\textsuperscript{263} Furthermore, programmers can program algorithms to focus on job performance qualities of applicants, such as “social intelligence, goal-orientation fluency, implicit learning, task-switching ability, and conscientiousness,”\textsuperscript{264} rather than demographic characteristics. Savage and Bales demonstrate this by showing that these algorithms, which only identify individual personal qualities, can reduce discrimination in evaluating job applicants.\textsuperscript{265} Thus, for example, according to some researchers, administering algorithm-based video games in the initial hiring process will not only decrease disparate treatment and disparate impact discrimination, because they test for individual skill sets, but they might also reduce unconscious biases in evaluation of job candidates.\textsuperscript{266}

Even with these suggested strategies, there is no guarantee that algorithms will not return biased results. Thus, programmers should be educated as to the limitation of algorithmic decision-making, and should be able to examine and review whether datasets are missing information from particular populations or would cause any unintended impact, and ensure

\textsuperscript{260} See Kroll, et al., \textit{supra} note 73.

\textsuperscript{261} See Mike Ananny & Kate Crawford, \textit{Seeing Without Knowing: Limitations of the Transparency Ideal and Its Application to Algorithmic Accountability,} NEW MEDIA & SOCIETY (2016); Anupam Chander, \textit{The Racist Algorithm?}, \textit{supra} note 81.

\textsuperscript{262} See Anupam Chander, \textit{The Racist Algorithm?}, \textit{supra} note 81.

\textsuperscript{263} \textit{Id.}


\textsuperscript{265} \textit{Id} at 224-226.

\textsuperscript{266} \textit{Id.}
validation procedures so that the algorithms are truly predictive. Moreover, at times, a third party or independent certifier may be appropriate to review the fairness of hiring algorithms as part of auditing. Lastly, it is advisable that multiple programmers with different backgrounds, perspectives, and biases create the algorithms and that the algorithms have two parts working in tandem, for instance, one incorporating disparate impact framework and the other changing the data set to remove any discriminatory effects found, to minimize the discriminatory effects and enhance fairness of algorithms.

C. Re-Thinking Wide Employer Discretion

Another ex ante approach to algorithmic discrimination in hiring requires a re-thinking of the employment relationship. As evidence by at-will employment wherein employees can be hired and fired based on a vast list of criteria determined by the employee, American law has historically given much deference to employers when it comes to the employment bargain. Thus, it is no secret that employers exercise a great deal of latitude in choosing which job applicants they hire. Typically, employers scan resumes, interview candidates, and have applicants complete tests to assess their candidacy. It is also not unusual for an employer to Google-search a job applicant. The availability of online information, coupled with an employer’s nearly unlimited discretion in criteria employed in selecting candidates, can oftentimes be costly for job applicants. For example, as some statistics show, nearly 1 in 10 young job hunters is rejected because of an employer’s assessment of his or her social media

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268 See Anupam Chander, The Racist Algorithm?, supra note 81.
274 R. Edward Freeman, et. al., Facebook(a), Darden Case No. UVA-E-0318 (2009).
accounts.\textsuperscript{275} Why do employers have so much leniency with regard to their candidate-selection and the information they can use to make such selections? Furthermore, should employers have such open discretion? With regard to the first question, it seems that employers have a great deal of discretion for two reasons: the growing need to sort out candidates and the existence of at-will employment.

The nature of the hiring relationship can be explained succinctly by the following quote: “the typical matching of a worker to a position does not reflect the outcome of workers picking from among several job offers. Rather, it is the result of an employer picking from among several job applicants.”\textsuperscript{276} This quote details a fact that many of us still know to be true today: 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 27 jobs before they attain one interview.\textsuperscript{277} Of course, since only 17\% of interviews actually result in employment, it is likely that these applicants apply to far more than 27 jobs throughout their entire job search.\textsuperscript{278} In one extreme case, in fact, 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.\textsuperscript{279}

On the employer’s side of this surge in applications, an average of 59 people applies for each open position.\textsuperscript{280} From this pool of applicants, then, the employer is required to cut out a large number of candidates in order to find candidates that they would like to interview – and, ultimately hire. Due to the large pool of applicants, though, an average only 12\% of applicants will be interviewed for any open position.\textsuperscript{281} This indicates that employers must use the information available to them to cut down a large number of applicants before they can make substantial progress in finding the “most talented candidates.” The sheer necessity of this culling of possible job applicants has left some scholars in support of employers’ total discretion in the hiring process.\textsuperscript{282}

\begin{footnotes}
\item[275] Erik Sherman, \textit{1 in 10 Young Job Hungers Rejected Because of Their Social Media}, AOL FINANCE (2013) at: https://www.aol.com/2013/06/04/applicants-rejected-social-media-on-device-research/
\item[280] Martha White, \textit{Here’s How Long It Really Takes to Get a Job}, supra note 278.
\item[281] Id.
\end{footnotes}
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. Cultural fit is defined as “the likelihood that job candidates will be able to conform and adapt to the core values and collective behaviors that make up an organization.” While scholars largely agree about the need for resumes and descriptions of past experiences, many are at odds about the idea of an employer’s determination of an applicant’s cultural fit.

In many regards, the determination of a candidate’s cultural fit seems subjective. Some articles report that assessing cultural fit “comes down to an employer’s gut feeling.” Others have reported that a candidate might be a good fit if “they work well with others” – which seems to be something that is difficult to predict without ever seeing a candidate work with other people. 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. Others have shown that interviewers are not even significantly adept at assessing applicants’ personal characteristics from interviews.

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. Furthermore, a study of 38 interviewers who were in the process of making hiring decisions found that interviewers can actually assess cultural fit “with a significant level of accuracy” and that this factor is often “the best predictor of employment.” 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 that the said

284 Margaret Rouse, What is Cultural Fit?, SEARCHCIO (2014) at: https://searchcio.techtarget.com/definition/Cultural-fit
285 See, 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 HARVARD JOURNAL OF LAW AND GENDER 175, (2010) (arguing that cultural fit within the finance industry is imperfect, as bias has been historically ingrained.)
286 Robert Half, How to Know If a Candidate Will Match Your Company Culture, ROBERT HALF TECHNOLOGY (2017).
287 Jeff Pruitt, Many Factors Go into Making the Right Hire: Here’s How to Make Sure Your Candidate Is Right for Your Company’s Culture, INC. BUSINESS (2017).
factor would likely help in the hiring process, so long as an employer could make his or her determination accurately.

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, non-discriminatory reason can be prescribed.”292 Thus, I argue against wide employer discretion to deploy variables that indicate “cultural fit” as part of algorithmic hiring. Rather, the law should mandate that the criteria used in algorithmic hiring have some probative value for determining fitness to perform required job duties.

CONCLUSION

Proponents of algorithms 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 an oracle. Consider the ur-Oracle, the Oracle of Delphi.293 The Oracle, a figure known in Greek mythology, spoke veraciously but in truth that was wrapped in layers, spun in riddle, and with many strands of interpretation.294 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, a great empire would surely fall.”295 Of course, this advice was highly vulnerable to misinterpretation, and the King’s own empire later fell to the Persians.296 The same is true of algorithms. Although these computerized mathematical processes possess utility for organizations in the automation of hiring processes, we must continue to interrogate them to ensure that the answers obtained and how those answers are interpreted represent the whole truth and is in furtherance of the shared American goal of a just and equal society.

295 Id.
296 Id.
### Table 1: An Evaluation of Extant Hiring Algorithms

<table>
<thead>
<tr>
<th>Automated Hiring Platform/Software Program</th>
<th>Year created</th>
<th>Companies using them</th>
<th>Some features</th>
</tr>
</thead>
</table>
| ADP Workforce Now                         | 2009         | -More than 20,000 clients by 2011 | - Presents candidate data in proprietary dashboard  
  -“Benchmarking” insights used to determine compensation etc.; bills data as “decision-quality” |
| ApplicantPro                              | 2007         | -Goodwill           | -Automated screening  
  -JC Resorts  
  -New York State Psychiatric Institute | -Integrated behavioral assessments  
  -Integrated background checks  
  -Automates tracking of compliance data |
| Arya (LeoForce)                           | 2013         | ???                 | -Purports to be “unbiased” on company website  
  -Mimics searches of company’s most successful recruiters  
  -Automated sourcing  
  -Predicts whether candidates are likely to move jobs  
  -Data includes things like “growth in the companies they have worked for” |
| Ascentis                                  | ~2007?       | -Bel Brands USA     | -Advertises itself as defense to discrimination lawsuits and seeks to automate EEO/OFCPP compliance  
  -BevMo!  
  -Calibre  
  -Cancún Resort Las Vegas  
  -Ghiradelli  
  -Level 3 Communications  
  -LaForce  
  -Proficio Bank  
  -Voxellab  
  -Visit Philadelphia | -Social media integration  
  -Can track demographic trends in applicant sourcing |
| AssessFirst                               | 2003         | -Air France         | -Predicts recruiting success with psychometrics  
  -Burger King  
  -Olympus  
  -Ingenico Group  
  -AXA  
  -BNP Paribas  
  -SMCP | -Can pre-select candidates  
  -Algorithm compares job profile to candidate profiles to source applicants |
<table>
<thead>
<tr>
<th>App Name</th>
<th>Year</th>
<th>Companies</th>
<th>Features</th>
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| BALANCEtrak (Berkshire Associates) | 2010 | - Sodexo  
- FCS Financial  
- 84 Lumber  
- Baltimore City Community College  
- Atlas Copco  
- Spangler Candy  
- Admiral Beverage Company  
- AgChoice Farm Credit | - Screening and scoring features  
- Tracks jobseeker activity  
- Background check integration |
| BirdDogHR                | 2010 | - Utz  
- CF Evans Construction  
- Iowa DOT  
- Martin Marietta Materials  
- Optima Tax Relief  
- Surgical Specialties Corporation | - Automated screening and scoring  
- Integrated drug testing and background check results |
| Breezy HR                | 2014 | - Shipt  
- Linium  
- Microsoft  
- Personnel  
- Docebo  
- Appcues  
- Telus  
- Piksel  
- Zapier  
- Freshii  
- Johnson & Johnson  
- SweetIQ  
- Dodge Data & Analytics  
- Knock  
- T-Mobile | - Pre-recorded applicant video interviews  
- Standardized guides for interviewing and scoring  
- Quantify (and therefore “justify”) subjective evaluations  
- Sources candidates based on where recruiters previously sourced  
- Generates EEO/OFCCP compliance report, which could be problematic |
| Bullhorn                 | 1999 | - Vet2Tech  
- The Chatham Group  
- Perma-Seal  
- BVS Trans Tech  
- Ecotech  
- EXILANT Technologies  
- Medsys Group  
- Adams Consulting Group  
- Apex Systems  
- ALKU  
- HCS Healthcare  
- Allen Recruiting | - Predictive intelligence suggests who to contact, when to contact them, and how to take action  
- Captures info from the Web to source candidates  
- Encourages “running your business by the numbers” |
<table>
<thead>
<tr>
<th>Company</th>
<th>Year</th>
<th>Features</th>
</tr>
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<tbody>
<tr>
<td>ClearCompany</td>
<td>2004</td>
<td>- Borden&lt;br&gt;- MetaBank&lt;br&gt;- Goodwill&lt;br&gt;- Jackson Hospital&lt;br&gt;- Arizona Supreme Court&lt;br&gt;- Sandhills Community College&lt;br&gt;- PSCU Financial Services&lt;br&gt;- Philips&lt;br&gt;- Edible Arrangements&lt;br&gt;- Applied Technical Systems&lt;br&gt;- Predictive performance data and quality of hire reports&lt;br&gt;- Pre-recorded video interviewing&lt;br&gt;- Enables text messaging with candidates, then attaches those conversations to profile&lt;br&gt;- Automates background and reference checks; can make authorizations less explicit&lt;br&gt;- Passive candidate sourcing&lt;br&gt;- Gives current employees referral tools&lt;br&gt;- Lets users organize applicants by any metric&lt;br&gt;- Comes with automatic “interview guides” to suggest what should be asked&lt;br&gt;- One-click background check</td>
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<td>CleverStaff</td>
<td>2014</td>
<td>- Kama Games&lt;br&gt;- Conscencia&lt;br&gt;- Verta Media&lt;br&gt;- Svitla Systems&lt;br&gt;- Avon&lt;br&gt;- RSM&lt;br&gt;- Suggests “appropriate” candidates&lt;br&gt;- Résumé parsing</td>
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<td>Comeet</td>
<td>2012</td>
<td>- Gartner&lt;br&gt;- Gett&lt;br&gt;- Fiverr&lt;br&gt;- Sodastream&lt;br&gt;- SironSource&lt;br&gt;- AppsFlyer&lt;br&gt;- Zoom&lt;br&gt;- Chegg&lt;br&gt;- Matomy Media Group&lt;br&gt;- Playbuzz&lt;br&gt;- Playtika&lt;br&gt;- Redislabs&lt;br&gt;- Assessment analytics&lt;br&gt;- App guides interviewers&lt;br&gt;- Sourcing includes social media profiles</td>
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<tr>
<td>COMPAS for Staffing</td>
<td>2008</td>
<td>- TEEMA&lt;br&gt;- Cyprus&lt;br&gt;- Talener&lt;br&gt;- David Aplin Group&lt;br&gt;- Assessments&lt;br&gt;- Recruiting intelligence analytics&lt;br&gt;- Social integration&lt;br&gt;- Automated sourcing</td>
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<tr>
<td>Crelate Talent</td>
<td>2012</td>
<td>???&lt;br&gt;- Detailed candidate profiles&lt;br&gt;- Candidate analytics in reports&lt;br&gt;- Generates EEO/OFCCP compliance report, which could be problematic&lt;br&gt;- Prescreening questions</td>
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<td>Entelo</td>
<td>2010</td>
<td>- Predicts best candidates using hundreds of variables</td>
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<td>- Candidate social media automatically available</td>
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<td></td>
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<td>- Predicts whether currently employed candidates are likely to move</td>
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<td>- While it allows users to sort candidates from underrepresented groups to the top, that also implies a user could sort those candidates out</td>
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<td>Exelare</td>
<td>1999</td>
<td>- Résumé harvesting</td>
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<td>- Color-codes candidates to rank them</td>
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<td>- Records all communication with candidates, from text to VOIP, for everyone in company to use</td>
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<td>Firefish</td>
<td>2010</td>
<td>- AI &quot;stack ranks&quot; candidates and sends personalized messages</td>
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<td>- Auto-scores screening, allowing people with no technical knowledge to evaluate performance on technical tasks</td>
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<td>- One-way video interviewing</td>
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<td>- Tracks if candidates opened emails</td>
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<td>Glider</td>
<td>2015</td>
<td>- Tavant Technologies</td>
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<td>- Student Loan Hero</td>
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<td>- Molecular Connections</td>
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<td>- Darkmatter</td>
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<td>Company</td>
<td>Year</td>
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</tbody>
</table>
| Greenhouse       | 2012 | - Airbnb  
- Evernote  
- Pinterest  
- Red Ventures  
- Twilio  
- Vimeo  
- SurveyMonkey  
- DocuSign  
- Golden State Warriors  
- Lyft  
- J.D. Power | - Attempts to standardize interviews with Interview Kits  
- Tracks to generate insights on candidates  
- “Data-driven hiring”  
- Compares company hiring metrics to industry standards, reinforcing status quo |
| HireCentric (ExactHire) | 2007 | - Kreig Devault  
- Endeavor Robotics  
- Navy Army Community Credit Union  
- Wabash Valley Power  
- Bluestone Properties  
- Central Restaurant Products | - Social media integration  
- Screening and scoring  
- Integrated background checks  
- Touts compliance |
<table>
<thead>
<tr>
<th>HireVue</th>
<th>2004</th>
</tr>
</thead>
<tbody>
<tr>
<td>Singapore Airlines</td>
<td>-Predictive people analytics</td>
</tr>
<tr>
<td>TJX</td>
<td>-Uses “video intelligence” to make automated assessments based off video interviews (verbal response, intonation, nonverbal communication, and other data) and predict skills, fit, and performance</td>
</tr>
<tr>
<td>Honeywell</td>
<td>-Micro-facial analysis for traits such as veracity and trustworthiness</td>
</tr>
<tr>
<td>Intel</td>
<td>-Acquired MindX (psychometric games) to further develop assessment capabilities</td>
</tr>
<tr>
<td>Mount Sinai</td>
<td>-Structured interviews</td>
</tr>
<tr>
<td>IBM</td>
<td></td>
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<tr>
<td>Vodafone</td>
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<tr>
<td>Urban Outfitters</td>
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<tr>
<td>Under Armour</td>
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<tr>
<td>Hilton</td>
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<tr>
<td>Unilever</td>
<td></td>
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<tr>
<td>Rackspace</td>
<td></td>
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<tr>
<td>Atlanta Public Schools</td>
<td></td>
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<tr>
<td>Carnival</td>
<td></td>
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<tr>
<td>Boston Red Sox</td>
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<tr>
<td>Ocean Spray</td>
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<tr>
<td>Shipt</td>
<td></td>
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<tr>
<td>Mercedes-Benz</td>
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<td>Maxis</td>
<td></td>
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<tr>
<td>Tiffany &amp; Co</td>
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<td>GEICO</td>
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<td>Blackbaud</td>
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<td>Dunkin Brands</td>
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<td>Cathay Pacific</td>
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<td>Children’s Healthcare of Atlanta</td>
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<td>Oracle</td>
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<td>HBO</td>
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<td>Dow Jones</td>
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<tr>
<td>Adventist Health System</td>
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<tr>
<td>Thurgood Marshall College Fund</td>
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<td>Power Design</td>
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<td>Sequoia</td>
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<tr>
<td>TMX Finance</td>
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<tr>
<td>Stance</td>
<td></td>
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<tr>
<td>Murphy Oil Corporation</td>
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<tr>
<td>CDW</td>
<td></td>
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<tr>
<td>Healthsouth</td>
<td></td>
</tr>
<tr>
<td>BASF</td>
<td></td>
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<tr>
<td>Brigham Young University</td>
<td></td>
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<tr>
<td>CARFAX</td>
<td></td>
</tr>
<tr>
<td>Church &amp; Dwight Co., Inc.</td>
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</tr>
<tr>
<td>Ciber</td>
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<td>ConocoPhillips</td>
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<td>Devon</td>
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<tr>
<td>Discovery Communications</td>
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<tr>
<td>FranklinCovey</td>
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<tr>
<td>Harland Clarke</td>
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<tr>
<td>New Belgium</td>
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<tr>
<td>Overstock</td>
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<tr>
<td>Company</td>
<td>Year</td>
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<td>iCIMS</td>
<td>1999</td>
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<td></td>
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</tr>
<tr>
<td>JazzHR</td>
<td>2016</td>
</tr>
<tr>
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<tr>
<td>JobDiva</td>
<td>2003</td>
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<tr>
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</tr>
<tr>
<td>Company</td>
<td>Year</td>
</tr>
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<td>---------</td>
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</tr>
</tbody>
</table>
| Jobjet  | 2016 | - Cisco  
- Amazon  
- Korn Ferry  
- Synechron  
- Zoom  
- Parsons  
- AMN Healthcare  
- Kaiser Permanente  | - Finds personal emails and mobile phone numbers for candidates, even if they didn’t apply with them  
- Also finds professional history, even if not disclosed  
- Uses “Big Data” to source and qualify candidates  
- Brands on speed—“20x faster” |
| JobScore| 2006 | - Dialpad  
- Bleacher Report  
- Parc  
- Gracenote  
- Edmunds  
- Hearst  
- Sesame Workshop  | - ROI analytics on applicant sources  
- Employee referral integration  
- Social media integration  
- Automated compliance  
- Standardized interviewing/templates  
- Turns résumés into weighted scores  
- Sorts interviewed candidates by “thumbs up/down” rankings  
- Claims to reduce hiring risk with data that originates with a ranked list of what the company finds important |
| Jobsoid | 2013 | - Shift Technology  
- Destinations of the World  
- The Fern Hotels & Resorts  
- VIB  
- PBS Worldwide BVBA  
- Voglis Co. Ltd.  
- English Lakes Hotels, Resorts and Venues  
- BIHZEB  
- Waman Hari Pethe Jewelers  
- Axtrum Solutions  
- Keley Consulting  | - Social integration  
- Sourcing with “advanced intelligence”  
- Interview scoring  
- Video screening |
| Jobvite | 2006 | - Weight Watchers  
- JCPenney  
- LinkedIn  
- Blizzard Entertainment  
- Education First  
- Havas Group  
- Universal Music Group  
- Partners in Health  
- Seneca  
- Trek  
- Wayfair  | - Referral emphasis  
- Filters out candidates  
- Emphasizes time and costs saved  
- One-way video for recorded assessments |
<table>
<thead>
<tr>
<th>Company</th>
<th>Year</th>
<th>Features</th>
</tr>
</thead>
</table>
| Lever        | 2012 | - Automated sourcing  
|              |      | - Assessments built-in  
|              |      | - Predictions and recommendations  
|              |      | - Encourages fast decisions as “data-driven”  
|              |      | - Features to automate nurturing top talent  
| LinkedIn Talent Insights | 2017 | - Predicts candidate interest in company/industry, how candidates will work with current employees, and who would relocate  
|              |      | - Tracks LinkedIn user searches, connections, follows, publications, and likes to generate data for recruiters  
|              |      | - Uses factors like candidate city or school in reports on how to find talent  
| Loxo         | 2012 | - Finds personal contact info on candidates  
|              |      | - Automates sourcing  
| Mya          | 2017 | - Automates sourcing, screening, and scheduling  
|              |      | - Sends data from “conversations” directly to ATS  
|              |      | - Machine learning means her interactions are based on past candidates  
|              |      | - Can only interact with candidates who apply online; thus, candidates who apply in-person cannot be hired  
| Newton       | 2009 | - Built-in EEO/OFCCP compliance could raise concerns  

- Quora  
- Reddit  
- Lyft  
- Hot Topic  
- KPMG  
- Wieden + Kennedy  
- Netflix  
- Success Academy Charter Schools  
- Eventbrite  
- Soylent  
- Affirm  
- Lowe’s  
- Shopify  
- Kickstarter  
- UCSF Health  
- Nestlé  
- Amazon  
- Dropbox  
- Siemens  
- Valor Partners  
- Ingenium  
- Contract Recruiter  
- Robinson Resource Group  
- The Carolan Group  
- Indigo Partners  
- Dental Team Finder  
- Adecco Group  

- Built-in EEO/OFCCP compliance could raise concerns
<table>
<thead>
<tr>
<th>Company</th>
<th>Year</th>
<th>Clients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oleeo</td>
<td>2018</td>
<td>- Bank of America</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Morgan Stanley</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- NBCUniversal</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- WPP</td>
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<td></td>
<td></td>
<td>- Marks &amp; Spencer</td>
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<tr>
<td></td>
<td></td>
<td>- UK Civil Service</td>
</tr>
<tr>
<td></td>
<td>(1995 as WCN)</td>
<td>- Claims to eliminate bias by automating every step</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Prescriptive hiring recommendations</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Clients can apply via social profiles</td>
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<tr>
<td></td>
<td></td>
<td>- Sorting in/out based on skills</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Auto-scoring of applicants</td>
</tr>
<tr>
<td>Olivia (Paradox)</td>
<td>2017</td>
<td>- CVS Health</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Staples</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Sprint</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Delta Air Lines</td>
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<tr>
<td></td>
<td></td>
<td>- DXC Technology</td>
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<tr>
<td></td>
<td></td>
<td>- Alorica</td>
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<td></td>
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<td>- Pilot Flying J</td>
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<tr>
<td></td>
<td></td>
<td>- Assistive intelligence recruiting assistant that “talks” to interested candidates and creates data on them</td>
</tr>
<tr>
<td>Oracle Taleo</td>
<td>2012</td>
<td>- Western Union</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Hitachi Consulting</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Hill International</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- NMDP                                     - Machine learning means her interactions are based on past candidates</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Chubb                                                                         - Social media and referral sourcing</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Chicago Public Schools</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- JPMorgan Chase</td>
</tr>
<tr>
<td></td>
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<td>- Wegmans</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Honda</td>
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<tr>
<td></td>
<td></td>
<td>(Taleo existed before, but acquired by Oracle then)</td>
</tr>
<tr>
<td>PeopleFluent</td>
<td>1997</td>
<td>- Altair</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- American Cancer Society</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Aon</td>
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<td></td>
<td></td>
<td>- Avaya</td>
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<tr>
<td></td>
<td></td>
<td>- Blue Cross Blue Shield</td>
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<tr>
<td></td>
<td></td>
<td>- Citrix</td>
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<tr>
<td></td>
<td></td>
<td>- Family Dollar</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Hertz</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- McDonald’s</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Nationwide</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Integrates recruiting software with other talent management platforms (learning, compensation, collaboration, etc.)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Vendor Management</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Software gives control over contingent/contract labor</td>
</tr>
<tr>
<td>QJumpers</td>
<td>2006</td>
<td>- Toyota</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Avis/Budget</td>
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<tr>
<td></td>
<td></td>
<td>- Briscoe Group</td>
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<tr>
<td></td>
<td></td>
<td>- Bupa</td>
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<tr>
<td></td>
<td></td>
<td>- Calder Stewart</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Skyline</td>
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<tr>
<td></td>
<td></td>
<td>- New Zealand Avocado</td>
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<tr>
<td></td>
<td></td>
<td>- Marra Building</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Soltuions</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Elms Hotel</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Automatically ranks candidates</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Will soon automate searching for top talent</td>
</tr>
<tr>
<td>Company</td>
<td>Year</td>
<td>Features</td>
</tr>
<tr>
<td>--------------</td>
<td>-------</td>
<td>-------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Recruitee</td>
<td>2015</td>
<td>- Greenpeace - Vice - Taco Bell - Hotjar - Hudson’s Bay - Sky - Zomato - QWILR - Scotch &amp; Soda - Lacoste - Growth Tribe - Arcadia</td>
</tr>
<tr>
<td>Recruiterbox</td>
<td>2009</td>
<td>- Wolfram - The Onion - Makita - Swift Capital - Olark</td>
</tr>
<tr>
<td>Recruiterflow</td>
<td>2017</td>
<td>- FusionCharts - Ixigo - Canvas Search Group - Khosla Labs - ParallelDots - E2X</td>
</tr>
<tr>
<td>SmartRecruiters</td>
<td>2010</td>
<td>- Optimizely - Colliers International - Berkshire Healthcare - Associa - Atlassian - Foster Farms - FishNet Security - Smaato - Equinox</td>
</tr>
<tr>
<td>Company</td>
<td>Year</td>
<td>Features</td>
</tr>
<tr>
<td>------------------</td>
<td>------</td>
<td>---------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Talenthire (CEIPAL)</td>
<td>2013</td>
<td>Social media integration, vendor management integration for contingent labor, target sourcing</td>
</tr>
<tr>
<td>Teamtailor</td>
<td>2012</td>
<td>Social media integration, screening questions for applicants, sortable by candidate answers, roi-driven analytics, discourage innovative recruiting</td>
</tr>
<tr>
<td>TextRecruit</td>
<td>2014</td>
<td>Artificial intelligence texting/online messaging chatbot performs “sentiment analysis” to determine candidate satisfaction during conversations (also does this for current employees), integrates with ats</td>
</tr>
<tr>
<td>VidCruiter</td>
<td>2009</td>
<td>Automates interviewing with one-way video using predetermined questions, automatically ranks candidates based on pre-recorded interviews, website advertises that it “protect[s]” from discrimination lawsuits by using structured interviews, partnered with checkr (background check app) to give immediate background check reports right in the recruitment platform, specifically promotes ability to see what candidates look like before interviewing, gamification of skills testing (“engag[ing],” “interesting”)</td>
</tr>
<tr>
<td>Whozwho</td>
<td>2017</td>
<td>Attempts to use behavioral science to determine cultural fit, ranks on personality, in addition to assessments of skills, experience, and education</td>
</tr>
</tbody>
</table>
### Table 2: Strategies for Beating Automated Hiring Platforms

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>“Key Word” Usage</td>
<td>Look at employer’s job description and try to</td>
<td>Trudy Steinfeld, <em>Decoding the Job Search</em></td>
</tr>
</tbody>
</table>
|自動化洽談 | 包括在你的简历中的许多精确的流行词。避免使用同义词 – 使用精确的语言。 | How to Beat the ATS, Forbes (May 2016).  
Trudy Steinfeld, Decoding the Job Search: How to Beat the ATS, Forbes (May 2016). |
|---|---|---|
|Avoid Over-Complication | 这些系统很容易被过于复杂的内容（包括花哨的字体、颜色和图形）所迷惑，因此，它们不会选择包含这些元素的简历。 | Trudy Steinfeld, Decoding the Job Search: How to Beat the ATS, Forbes (May 2016).  
Trudy Steinfeld, Decoding the Job Search: How to Beat the ATS, Forbes (May 2016). |
|Follow-Up | 人们被排除在AHPs之外，以至于招聘者可能不知道哪些候选人是真正感兴趣的，而哪些只是“丢弃”他们的简历。如果你是真正感兴趣的，其中一种最好的方法是通过LinkedIn或其他网站与招聘者跟进。 | See How to Beat Automated Resume Screening, Workopolis (June 2017).  
See How to Beat Automated Resume Screening, Workopolis (June 2017). |
|Relevant Keywords | 关键词在与相关文本相关的段落中被算法更高度评价，因此如果你可以在与你成就相关的部分增加这些关键词，你就应该这样做。 |  
See How to Beat Automated Resume Screening, Workopolis (June 2017). |
|Use Free Screening Tools | 求职者可以查看他们的简历是否通过使用免费的网站如jobscan.com进行扫描。 | How to Beat Automated Resume Screening, Workopolis (June 2017).  
How to Beat Automated Resume Screening, Workopolis (June 2017). |

---

297 Trudy Steinfeld, Decoding the Job Search: How to Beat the ATS, FORBES (May 2016) at: [https://www.forbes.com/sites/trudysteinfeld/2016/05/31/decoding-the-job-search-how-to-beat-the-ats-applicant-tracking-system/-3afa49b46d84](https://www.forbes.com/sites/trudysteinfeld/2016/05/31/decoding-the-job-search-how-to-beat-the-ats-applicant-tracking-system/-3afa49b46d84)
298 Id.
299 Id.
301 Id.
302 Mark Slack & Erik Bowitz, Beat the Robots: How to Get Your Resume Past the System & Into Human Hands, THE MUSE (2018) at:
<table>
<thead>
<tr>
<th>Topic</th>
<th>Advice</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avoid Spelling Mistakes</td>
<td>Many AHPs will terminate your application immediately if you have spelling mistakes, because they will not understand what you’re trying to say.</td>
<td>Mark Slack and Erik Bowitz, <em>Beat the Robots: How to Get Your Resume Past the System &amp; Into Human Hands</em>, The Muse (2018). 303</td>
</tr>
<tr>
<td>Avoid Headers and Footers</td>
<td>Headers and footers will “jam” algorithms, meaning that the algorithm will not be able to process your resume further. Avoid these!</td>
<td>Peter Cappelli, <em>How to Get a Job? Beat the Machines</em>, Time (June 2012). 304</td>
</tr>
<tr>
<td>Submit Resume in Text Format</td>
<td>While many people opt to send their resumes in PDF format, this leaves the parser open to making more errors. Typically, the easiest format for the scanner to read is in Text Format.</td>
<td>Peter Cappelli, <em>How to Get a Job? Beat the Machines</em>, Time (June 2012). 305</td>
</tr>
<tr>
<td>Include Postal Address</td>
<td>Most scanners will automatically screen out your resume if it does not include a postal address. Just remember – don’t include this information in a header or footer, as it will not be screened!</td>
<td>Pamela Skillings, <em>How to Get the Applicant Tracking System to Pick Your Resume</em>, Big Interview (</td>
</tr>
<tr>
<td>Pay Attention to Font</td>
<td>Avoid serif fonts (such as Times New Roman), because some screeners reject resumes with these fonts. You can find a list of sans-serif fonts: <a href="https://en.wikipedia.org/wiki/List_of_sans_serif_typefaces">here</a>.</td>
<td>Melanie Pinola, <em>Format Your Resume So It Gets Past Applicant Screening Software</em>, LifeHacker (Feb. 2013). 307</td>
</tr>
</tbody>
</table>
| Stick to “Orthodox” Sections            | Name your sections “Work Experience” and “Education”, instead of “Career Achievements” or “Training”, because AHPs are trained to search for | See *Is Your Resume Ready for Automated*

[303] Id.

[304] Id.

[305] Id.


| Apply Early | Some AHPs charge employers by the applicant, so it’s cheaper for companies to review the first 50 applicants than to review every applicant who applies. Thus, late applicants are sometimes discarded without even being screened. | See *Is Your Resume Ready for Automated Screening? Resume Hacking* (Jan. 2016). |
| Be Average on Personality Tests | “Score somewhere between the 40th and 60th percentiles” and “try to answer as if you were like everyone else is supposed to be.” Basically, try to answer questions in the most average way as possible. | William H. Whyte, *The Organization Man*, Sixth Printing (1956), 405. |
| When Asked for Word Associations… | “When asked for word associations or comments about the world, give the most conventional, run-of-the-mill, pedestrian answer possible.” | William H. Whyte, *The Organization Man*, Sixth Printing (1956), 405. |
| Incline to Conservatism | When asked about your values on personality tests, read closely through all questions to look for patterns. In some tests, the “right” or “most conservative” answers will be located in the same multiple-choice position for each question. | William H. Whyte, *The Organization Man*, Sixth Printing (1956), 408. |

---


309 *Id.*


311 *Id.*

312 *Id* at 408.
<table>
<thead>
<tr>
<th>When it Comes to Hypothetical Judgment Questions, Don’t Reflect</th>
<th>Many personality tests include hypothetical situations that are followed by questions about how the respondent would act if faced with that scenario. Research has shown that it is best not to reflect on the question before answering, and that respondents should answer as quickly as they can to avoid giving off the sense that they are confused about what steps they would take.</th>
<th>William H. Whyte, <em>The Organization Man</em>, Sixth Printing (1956), 409.(^{313})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Add Buzz Words in White Ink</td>
<td>To “trick” the algorithm into sorting you through, some applicants have suggested including more buzz words throughout their resumes, but in white ink so that they are not visible to the human eye. Thus, their application will be automatically screened into the “yes” pile without having to awkwardly force buzz words into their documents.</td>
<td>Osas Obaiza, <em>Hack Your Resume to Fool Keyword-Hunting Robots &amp; Land Yourself More Interviews (The Evil Way)</em>, Wonder How To (May 2013).(^{314})</td>
</tr>
</tbody>
</table>

\(^{313}\) Id at 409.