

**AN AUDITING IMPERATIVE FOR AUTOMATED HIRING
SYSTEMS**

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I. INTRODUCTION

Imagine this scenario: A woman seeking a retail job is informed that the job can only be applied for online. The position is a salesclerk for a retail company with store hours from 9:00 AM to 9:00 PM. She is interested in the morning and afternoon hours, as she has children who are in school until 3:00 PM. When completing the application, she reaches a screen where she is prompted to register her hours of availability. She enters 9:00 AM to 3:00 PM, Monday through Friday. However, when she hits the button to advance to the next screen, she receives an error message indicating that she has not completed the current section. She refreshes her screen, she restarts her computer, and still the same error message remains. Finally, in frustration, she abandons the application. Compare the above to this second scenario: A fifty-three-year-old man is applying for a job that requires a college degree. But when he attempts to complete the application online, he finds that the drop-down menu offers only college graduation dates that go back to the year 2000. The automated hiring platform will, in effect, exclude many applicants who are older than forty years old. If the man also chooses to forgo the application like the woman in the previous scenario, the automated hiring system may not retain any record of the two failed attempts to complete the job application.¹

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The vignettes above reflect the real-life experiences of job applicants who must now contend with automated hiring systems in their bid for employment.² These stories illustrate the potential for automated hiring systems to discreetly and disproportionately cull the applications of job seekers who are from legally protected classes.³ Given that legal scholars have identified a “bias in, bias out” problem for automated decision-making,⁴ Automated hiring as a socio-technical trend challenges the American bedrock ideal of equal opportunity in employment,⁵ as such automated practices may not only be deployed to exclude certain categories of workers but may also be used to justify the inclusion of other classes as more “fit” for the job.⁶ This is a cause for the legal concern that algorithms may be used to manipulate the labor market in ways that negate equal employment opportunity.⁷ This concern is further exacerbated given that nearly all Fortune 500 companies now use algorithmic recruitment and hiring tools.⁸ Algorithmic hiring has also saturated the low-wage retail market, with the top twenty Fortune 500 companies, which are mostly retail and commerce companies that boast large numbers of employees, almost exclusively hiring through online platforms.⁹

1. See generally CATHY O’NEIL, *WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY* (2016).

2. Patricia G. Barnes, *Behind the Scenes, Discrimination by Job Search Engines*, AGE DISCRIMINATION EMP. (Mar. 29, 2017), <https://www.agediscriminationinemployment.com/behind-the-scenes-discrimination-by-job-search-engines/> [https://perma.cc/YRY3-JZSV]; Ifeoma Ajunwa & Daniel Greene, *Platforms at Work: Data Intermediaries in the Organization of the Workplace*, in *WORK AND LABOR IN THE DIGITAL AGE* (2019) (discussing the encountered difficulty of completing an online application when applying with constrained hours of availability).

3. Title VII of the Civil Rights Act of 1964 guarantees equal opportunity in employment irrespective of race, gender, and other protected characteristics. 42 U.S.C. §§ 2000e–2000e-17.

4. See Sandra G. Mayson, *Bias In, Bias Out*, 128 YALE L.J. 2218, 2224 (2019) (arguing that the problem of disparate impact in predictive risk algorithms lies not in the algorithmic system but in the nature of prediction itself); Sonia Katyal, *Private Accountability in the Age of Artificial Intelligence*, 66 UCLA L. REV. 54, 58 (2019) (noting the bias that exists within artificial intelligence (“AI”) systems and arguing for private mechanisms to govern AI systems); Andrew Tutt, *An FDA for Algorithms*, 69 ADMIN. L. REV. 83, 87 (2017) (“This new family of algorithms hold enormous promise, but also poses new and unusual dangers.”).

5. Ajunwa & Greene, *supra* note 2; see also Pauline Kim, *Data-Driven Discrimination at Work*, 58 WM. & MARY L. REV. 857, 860 (2017) [hereinafter *Data-Driven Discrimination at Work*].

6. See Ifeoma Ajunwa, *The Paradox of Automation as Anti-Bias Intervention*, 41 CARDOZO L. REV. 1671, 1671 (2020).

7. See Ryan Calo, *Digital Market Manipulation*, 82 GEO. WASH. L. REV. 995, 996, 999 (2014); Julie E. Cohen, *Law for the Platform Economy*, 51 U.C. DAVIS L. REV. 133, 165 (2017); Tal Z. Zarsky, *Privacy and Manipulation in the Digital Age*, 20 THEORETICAL INQUIRIES L. 157, 158, 160–61 (2019); Daniel Susser, Beate Roessler & Helen Nissenbaum, *Online Manipulation: Hidden Influences in a Digital World*, 4 GEO. L. TECH. REV. 1, 2, 10 (2019); Pauline Kim, *Manipulating Opportunity*, 106 VA. L. REV. 867, 869 (2020).

8. LINDA BARBER, INST. FOR EMP. STUD., *E-RECRUITMENT DEVELOPMENTS* 3 (2006).

9. Ajunwa & Greene, *supra* note 2, at 71–72.

Although it is undeniable that there could be tangible economic benefits of adopting automated decision-making,¹⁰ the received wisdom of the objectivity of automated decision-making, coupled with an unquestioning acceptance of the results of algorithmic decision-making,¹¹ have allowed hiring systems to proliferate without adequate legal oversight. As Professor Margot Kaminski notes, addressing algorithmic decision-making concerns requires both individual and systemic approaches.¹² Currently, the algorithmic decisions made in the private sector are largely unregulated, and Kaminski argues for a collaborative approach to governance that could satisfy both individual and collective concerns:

Collaborative governance is a middle ground, a third way, that aims to harness the benefits of self-regulation without its pitfalls. The government stays significantly involved as a backdrop threat to nudge private sector involvement, as a forum for convening and empowering conflicting voices, as an arbiter or certifier in the name of the public interest, and as a hammer that can come down to enforce compliance.¹³

Thus, the goal of this Article is neither to argue against or for the use of automated decision-making in employment, nor is it to examine whether automated hiring systems are better than humans at making hiring decisions. For antidiscrimination law, the efficacy of any particular hiring system is a secondary concern to ensuring that any such system does not unlawfully discriminate against protected categories.¹⁴ Therefore, my aim is to suggest collaborative regulatory regimes for automated hiring systems that will ensure that any benefits of automated hiring are not negated by (un)intended outcomes, such as unlawful discrimination on the basis of protected characteristics.

Furthermore, this Article owes a debt to Professor Katherine Strandburg, who notes that explainability has important normative and practical implications for system design.¹⁵ Specifically, Strandburg notes that inscrutable decision tools disrupt the explanatory flows among the multiple actors responsible for determining goals, selecting

10. See *infra* Section II.A.

11. See Ajunwa, *supra* note 6, at 1684–85.

12. See Margot E. Kaminski, *Binary Governance: Lessons from the GDPR's Approach to Algorithmic Accountability*, 92 S. CALIF. L. REV. 1529, 1533 (2019).

13. *Id.* at 1561.

14. As Professor Charles Sullivan notes: “[T]he antidiscrimination statutes don’t really care whether any particular selection device actually improves productivity so long as it does not discriminate.” Charles Sullivan, *Employing AI*, 63 VILL. L. REV. 395, 398 (2018).

15. Katherine Strandburg, *Rulemaking and Inscrutable Automated Decision Tools*, 119 COLUM. L. REV. 1851, 1867–72 (2019).

decision criteria, and applying those criteria.¹⁶ Thus, seeking the explainability of automated decisions is not just for the benefit of the decision subjects, but really for the benefit of all interested in the outcomes.¹⁷

In a similar vein, Talia Gillis and Josh Simons have argued against focusing on accountability of individual actors.¹⁸ Rather, they note that “[t]he focus on individual, technical explanations . . . [is] driven by an uncritical bent towards transparency.”¹⁹ Instead, they advocate that “[i]nstitutions should justify their choices about the design and integration of machine learning models not to individuals, but to empowered regulators or other forms of public oversight bodies.”²⁰

Furthermore, Professor Pauline Kim makes the case that the law does allow for the revision of algorithmic systems to address bias.²¹ Thus, she argues that the law permits using auditing to detect and correct for discriminatory bias.²² Kim argues that auditing should be an important strategy for examining whether the outcomes of automated hiring systems comport with equal opportunity in employment guidelines.²³

The insights of these legal scholars and others²⁴ form the foundation for my contribution in this Article, in which I posit an auditing imperative for automated hiring systems. Building on Professor Kim’s essay, I argue not just that the law allows for the audits, but that the spirit of antidiscrimination law *requires* it. That is, I follow the footsteps of legal scholars like Professors Richard Thompson

16. *See id.* at 1851.

17. *See id.* at 1857–58; *see also* Deirdre K. Mulligan, Daniel N. Kluttz & Nitin Kohli, *Shaping Our Tools: Contestability as a Means to Promote Responsible Algorithmic Decision Making in the Professions*, in *AFTER THE DIGITAL TORNADO* (Kevin Werbach ed., 2020).

18. *See* Talia Gillis & Josh Simons, *Explanation < Justification: GDPR and the Perils of Privacy*, 2 J.L. & INNOVATION 71 (2019).

19. *Id.* at 76.

20. *Id.* at 81.

21. Pauline Kim, *Auditing Algorithms for Discrimination*, 166 U. PA. L. REV. ONLINE 189, 191 (2017) [hereinafter *Auditing Algorithms*] (responding to Joshua A. Kroll, Joanna Huey, Solon Barocas, Edward W. Felten, Joel R. Reidenberg, David G. Robinson & Harlan Yu, *Accountable Algorithms*, 165 U. PA. L. REV. 633, 636 (2017)).

22. *See id.* at 197–99.

23. *See id.* at 202.

24. *See* Bryan Casey, Ashkon Farhangi & Roland Vogl, *Rethinking Explainable Machines: The GDPR’s “Right to Explanation” Debate and the Rise of Algorithmic Audits in Enterprise*, 34 BERKELEY TECH. L.J. 143, 153–68 (2019). Other scholars have thought about audits in the GDPR context, but I bring the idea of audits to the American employment and labor law context.

Ford,²⁵ James Grimmelmann,²⁶ Robert Post,²⁷ David Benjamin Oppenheimer,²⁸ and Noah Zatz,²⁹ to argue that employment antidiscrimination law imposes an affirmative duty of care on employers to ensure that they are avoiding practices that would constrain equal opportunity in employment. Thus, I argue, that when employers choose to use algorithmic systems, fulfilling their duty of care entails regular audits of those systems. In turn, audits necessitate the record-keeping and data retention mandates that I also propose in this Article.

I note here that automated hiring systems exist in a plethora of forms, with each iteration presenting distinct legal issues. This is because each form of automated hiring does not offer the same level of automation. Ranging from the least automated (which allows for the most human intervention) to the most automated (which allows for the least human intervention), there are: applicant tracking systems (“ATS”), which employ algorithms that parse resumes for keywords;³⁰ machine learning algorithms that could be trained on selecting resumes and deployed to rank them in hundreds or thousands;³¹ and video screening systems, such as HireVue, which provide automated assessments based on facial analysis and vocal indications.³² To offer a full portrait of the proliferation of automated hiring platforms and associated legal issues, the Appendix offers a survey of extant automated hiring systems in which I detail a sampling of the companies currently using those systems, as well as their potentially problematic features. This Article does not delve into the specific legal issues associated with each iteration of automated hiring system; rather, it

25. See Richard Thompson Ford, *Rethinking Rights after the Second Reconstruction*, 132 YALE L.J. 2942 (2014) [hereinafter *Rethinking Rights*]; see also Richard Thompson Ford, *Bias in the Air: Rethinking Employment Discrimination Law*, 66 STAN. L. REV. 1381 (2014) [hereinafter *Bias in the Air*].

26. See James Grimmelmann & Daniel Westreich, *Incomprehensible Discrimination*, 7 CALIF. L. REV. 164, 171–74 (2017).

27. See Robert Post, *1998–99 Brennan Center Symposium Lecture: Prejudicial Appearances: The Logic of American Antidiscrimination Law*, 88 CALIF. L. REV. 1, 36 (2000).

28. See David Benjamin Oppenheimer, *Negligent Discrimination*, 141 U. PA. L. REV. 899 (1993) [hereinafter *Negligent Discrimination*].

29. See Noah D. Zatz, *Managing the Macaw: Third-Party Harassers, Accommodation, and the Disaggregation of Discriminatory Intent*, 109 COLUM. L. REV. 1357, 1359 (2009) [hereinafter *Managing the Macaw*].

30. See, e.g., CLEVERSTAFF, <https://cleverstaff.net> [https://perma.cc/2KBM-5VQH].

31. Jeffrey Dastin, *Amazon Scraps Secret AI Recruiting Tool that Showed Bias Against Women*, REUTERS (Oct. 9, 2018, 10:12 PM), <https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G> [https://perma.cc/6SA7-R35L] (“[A]mazon’s computer models were trained to vet applicants by observing patterns in resumes submitted to the company over a 10-year period. Most came from men, a reflection of male dominance across the tech industry.”).

32. See HIREVUE, <http://hirevue.com> [https://perma.cc/QLH3-QXQM].

recognizes that all job applications share several common legal problems regardless of which iteration of automated hiring system applies, and that the greatest obstacle is meeting the standard of proof for employment discrimination.

But first, consider the growing trend towards automated video interview assessment as perhaps the most extreme of automated hiring systems. According to one article, one of the leaders in the automated video interview market, HireVue, “uses AI to analyze word choice, tone, and facial movement of job applicants who do video interviews.”³³ For some candidates, such video assessments recall an approach³⁴ to hiring that is reminiscent of Frederik Winslow Taylor’s time series experiments on factory workers.³⁵ Relating his experience with HireVue, one candidate whose answers were interrupted by a timer noted: “You just see yourself and a stopwatch ticking down.”³⁶ But the destabilizing effect of timed responses is not the greatest problem associated with automated video interviewing. As researchers have noted, many of these systems are trained on white male faces and voices, which poses a problem for any applicants who diverge from that norm.³⁷ Thus, applicants who are white women, non-binary persons, or racial minorities may have their facial expressions or tone of voice mischaracterized by automated video interviewing platforms.³⁸

Other important concerns raised by critics of automated video interviewing systems are: the collection of the applicant’s personal data, the “black box” nature of how such information is used,³⁹ and a

33. Richard Feloni, *I Tried the Software That Uses AI to Scan Job Applicants for Companies Like Goldman Sachs and Unilever Before Meeting Them — and It’s Not as Creepy as It Sounds*, BUS. INSIDER (Aug. 23, 2017, 11:00 AM), <https://www.businessinsider.com/hirevue-ai-powered-job-interview-platform-2017-8> [<https://perma.cc/3R8D-Y6QN>].

34. See generally FREDERIK WINSLOW TAYLOR, PRINCIPLES OF SCIENTIFIC MANAGEMENT (1911); cf. Ifeoma Ajunwa, Kate Crawford & Joel Ford, *Health and Big Data: An Ethical Framework for Health Information Collection by Corporate Wellness Programs*, 44 J.L. MED. & ETHICS 474 (2016) (positing that workforce science, as an iteration of Taylorism, now focuses on the worker’s body rather than the job task).

35. See, e.g., Rebecca Greenfield, *The Rise of the (Truly Awful) Webcam Job Interview*, BLOOMBERG (Oct. 12, 2016, 7:00 AM), <https://www.bloomberg.com/news/articles/2016-10-12/the-rise-of-the-truly-awful-webcam-job-interview> [<https://perma.cc/M93J-QTY8>].

36. *Id.*

37. See, e.g., Tess Townsend, *Most Engineers Are White — and So Are the Faces That They Use to Train Software*, VOX: RECODE (Jan. 18, 2017, 11:45 AM), <https://www.vox.com/2017/1/18/14304964/data-facial-recognition-trouble-recognizing-black-white-faces-diversity> [<https://perma.cc/HG4C-SEP6>] (“A lack of diversity in the training set leads to an inability to easily characterize faces that do not fit the normal face derived from the training set.” (emphasis omitted)).

38. See Thor Benson, *Your Next Job Interview Could Be with a Racist Bot*, DAILY BEAST (Apr. 20, 2018, 11:01 PM), <https://www.thedailybeast.com/your-next-job-interview-could-be-with-a-racist-bot> [<https://perma.cc/QRG3-D3WU>].

39. See FRANK PASQUALE, THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION 16 (2015) (arguing that unregulated and opaque data collection is contributing to social inequality).

lack of worker’s agency and control over the portability of the data. As Dan Lyons notes in his book, *Lab Rats*:

HireVue’s robot recruiting system is building a database of deep, rich psychographic information on millions of people. Moreover, the data is not anonymous. Your psychographic blueprint is connected to all of your personal information — name, address, email, phone number, work history, education. And they have you on video. Everything you say in an interview can follow you around for the rest of your life.⁴⁰

Yet, there are no federal regulations as to the collection, storage, or use of data from automated hiring platforms, and in effect, employers have *carte blanche* to adopt self-serving practices.⁴¹

In their seminal essay on privacy law, Samuel D. Warren and Louis L. Brandeis argue that Americans should have the “right to be let alone.”⁴² The scholars start by writing “[t]hat the individual shall have full protection in person and in property is a principle as old as the common law; but it has been found necessary from time to time to define anew the exact nature and extent of such protection.”⁴³ Thus, they suggest molding common law to fit the times — including the political, social, and economic changes that regularly occur.⁴⁴ I note here the growing tendency to deny this “right to be let alone” to workers. Increasingly, workers are being called upon to exchange their privacy for the mere opportunity to be considered for employment.⁴⁵ With recent technological advances in automated hiring, and especially given the current trend towards automated video interviewing which accumulates even more data about the candidate’s person than could have previously been imagined, employment antidiscrimination law is in dire need of updates. In this Article, I argue that such updates to the law should not just acknowledge the auditing imperative, but also recognize worker’s agency to control the end uses and portability of

40. DAN LYONS, *LAB RATS: HOW SILICON VALLEY MADE WORK MISERABLE FOR THE REST OF US* 159 (2019).

41. See, e.g., Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 *GEO. L.J.* 1147, 1160 (2017) (“Despite this interpretive limitation, machine-learning algorithms have been implemented widely in private-sector settings. Companies desire the savings in costs and efficiency gleaned from these techniques.”).

42. Samuel D. Warren & Louis D. Brandeis, *The Right to Privacy*, 6 *HARV. L. REV.* 193, 193 (1890).

43. *Id.*

44. *Id.*

45. Ifeoma Ajunwa, Kate Crawford & Jason Schultz, *Limitless Worker Surveillance*, 105 *CAL. L. REV.* 735, 736 (2017).

data (much of it now biometric) subsumed by the algorithmic hiring apparatus.⁴⁶

In this context, it is alarming that a recent study by the Pew Research Center found that most Americans underestimate the prevalence of these automated hiring platforms in the workplace.⁴⁷ The study revealed that “fewer than half of Americans are familiar with the concept of computer programs that can review job applications without any human involvement.”⁴⁸ In fact, 57% of Americans say that they have heard nothing at all about automated hiring platforms in the past.⁴⁹ Of the respondents who were aware of automated hiring systems, 76% stated that they would not want to apply for jobs through such a system.⁵⁰ The given reasons for that response varied, but most commonly, the individuals expressed the belief that computer systems could not capture everything about an applicant.⁵¹ One woman wrote, “[a] computer cannot measure the emotional intelligence or intangible assets that many humans have.”⁵² Another stated, “I do believe that hiring people requires a fair amount of judgment and intuition that is not well automated.”⁵³ On the other side of this spectrum, however, 22% of the individuals surveyed reported that they would want to apply for jobs that use a computer program to make hiring decisions.⁵⁴ The most common rationale for this response was the belief that software would be less biased than human reviewers.⁵⁵

I have previously argued that a misguided belief in the objectivity of automated decision-making has ushered in automated hiring as an anti-bias intervention.⁵⁶ I have further argued that the framing of discovered bias in automated decision-making systems as a technical problem, rather than a legal problem, has stymied attempts at solving the problem.⁵⁷ Professor Sandra Mayson has also argued that “the source of racial inequality in risk assessment [which is a type of automated decision-making] lies neither in the input data, nor in a particular algorithm, nor in algorithmic methodology per se.”⁵⁸ Rather, “the deep problem is the nature of prediction itself. All prediction looks

46. *See infra* Parts IV, V.

47. AARON SMITH & MONICA ANDERSON, PEW RSCH. CTR., AUTOMATION IN EVERYDAY LIFE 50 (2017), http://assets.pewresearch.org/wp-content/uploads/sites/14/2017/10/03151500/PI_2017.10.04_Automation_FINAL.pdf [<https://perma.cc/D4E4-B47W>].

48. *Id.*

49. *Id.*

50. *Id.* at 52.

51. *Id.*

52. *Id.*

53. *Id.*

54. *Id.*

55. *Id.*

56. Ajunwa, *supra* note 6, at 1671.

57. *Id.*

58. *See* Mayson, *supra* note 4, at 2218.

to the past to make guesses about future events. In a racially stratified world, any method of prediction will project the inequalities of the past into the future.”⁵⁹ For automated decision-making in employment, I argue that not only is the nature of prediction problematic (particularly given historical employment discrimination), but also, the manner in which such prediction is accomplished further creates opportunities for unlawful discrimination and exclusion.

I identify four major problems with automated hiring: (1) the design features of automated hiring platforms may enable them to serve as culling systems that discreetly eliminate applicants from protected categories without retaining a record; (2) automated hiring systems that allow for the deployment of proxies for protected categories, like gender or race, can be used to present discriminatory employment results as fair; (3) intellectual property law, specifically trade secret, protects automated hiring systems from outside scrutiny and allows discrimination to go undetected; and (4) a worker’s lack of control over the portability of applicant data captured by automated hiring systems increases the chance of repeated employment discrimination, thus raising the specter of an algorithmically permanently excluded class⁶⁰ of job applicants, meaning that certain applicants might find themselves “algorithmically blackballed.”⁶¹

When it comes to using litigation to redress employment discrimination, these problematic features of automated hiring present obstacles to workers: (1) at higher levels of automation, it becomes difficult to determine intent to discriminate, which is required for finding liability under the disparate treatment cause of action under Title VII;⁶² (2) when bringing suit under the disparate impact cause of action, the design features of automated hiring systems, as well as trade secret claims that may arise, impede the plaintiff’s ability to provide the statistical proof required to establish a prima facie case; and (3) litigation remedies in employment antidiscrimination law do not address privacy and discrimination issues associated with the collection of personal and biometric data from job candidates, as enabled by automated video interviewing. I argue then that employment law, with its emphasis on litigation as redress for employment discrimination, is

59. *Id.*

60. Richard A. Bales & Katherine V.W. Stone, *The Invisible Web at Work: Artificial Intelligence and Electronic Surveillance in the Workplace*, 41 BERKELEY J. LAB. & EMP. L. 1, 1 (2020) (“The data collected is transformed by means of artificial intelligence (AI) algorithms into a permanent electronic resume that can identify and predict an individual’s performance as well as their work ethic, personality, union proclivity, employer loyalty, and future health care costs.”).

61. *See infra* Section V.C.4.

62. Sullivan, *supra* note 14, at 397 (exploring the legal difficulties of assigning intent to a machine learning automated hiring system, when the machine can learn from previous decisions and write its own follow-on models).

limited in its capacity to address the full spectrum of identified problems with automated hiring.

This Article pushes the boundaries of existing employment law scholarship by proposing alternative approaches to solving the issue of bias in automated employment decision-making, in addition to offering methods for strengthening existing litigation redress mechanisms. Alternative approaches to litigation represent an important contribution given that employment discrimination plaintiffs generally do not fare well in court.⁶³ Thus, I argue that administrative measures, such as mandated audits, are necessary and currently under-utilized means for achieving the bedrock legal principle of equal opportunity in employment. In addition, I propose labor law processes, such as collective bargaining, which have also been found to influence business practices for the better⁶⁴ and could be instrumental in both clarifying workers' rights and delineating employers' responsibilities under an automated hiring regime.

The Article is then organized as follows. Part II reviews the business case for automated hiring as well as the potential for misuse of automated hiring systems. Part III parses some solutions that focus on some of the technological shortcomings of automated hiring systems and notes the limitations of such techno-solutionist approaches. Part IV discusses the gaps in current employment law framework for addressing bias in automated hiring — notably, disparate impact claims present a high hurdle for plaintiffs, especially in the case of automated hiring systems when the means of proof is solely under the control of the employer. Part V examines the potential for a hybrid approach to tackling bias in employment discrimination that combines *ex post* approaches (in particular internal and external auditing mandates) with *ex ante* approaches, such as (1) contractual protections for employers

63. See Michael J. Zimmer, *The New Discrimination Law: Price Waterhouse is Dead, Whither McDonnell Douglas?*, 53 EMORY L.J. 1887, 1944 (2004) (“The 5.8% reversal rate of defendant trial victories is smaller in employment discrimination cases than any other category of cases except prisoner habeas corpus trials.”); see also Ruth Colker, *The Americans with Disabilities Act: A Windfall for Defendants*, 34 HARV. C.R.-C.L. L. REV. 99, 100 n.9 (1999) (finding that between 1992 and 1998, defendants prevailed in more than 92% of cases decided at the trial court level and were more likely to be affirmed on appeal); Theodore Eisenberg, *Litigation Models and Trial Outcomes in Civil Rights and Prisoner Cases*, 77 GEO. L.J. 1567, 1578 (1989) (noting that only claims filed by prisoners have a lower success rate than that of employment discrimination plaintiffs); cf. Michael Selmi, *The Evolution of Employment Discrimination Law: Changed Doctrine for Changed Social Conditions*, 2014 WIS. L. REV. 937, 938 (2014) (“Employment discrimination law has long been ripe for updating. Many of the core cases regarding how discrimination is defined and proved arose in the 1970s in a very different era and were designed to address very different kinds of discrimination.”).

64. See Alison D. Morantz, *What Unions Do for Regulation*, 13 ANN. REV. L. & SOC. SCI. 515, 527–28 (2017) (surveying literature from an array of regulatory domains — antidiscrimination, environmental protection, product quality, corporate governance, law enforcement, tax compliance, minimum wage and overtime protection, and occupational safety and health — to show that unions tend to increase the level of regulatory compliance).

who rely on vendor representations of bias reduction, (2) fairness-by-design principles that could be implemented as part of Employment Opportunity Commission (“EEOC”) guidelines to prevent discrimination in automated hiring, and (3) collective bargaining that would address both data input into automated hiring systems and worker control over the afterlife of the data created by these systems.

II. AUTOMATED HIRING AS BUSINESS PRACTICE

In this Part, I discuss the business case for the trend towards automated hiring. I also note the potential for automated hiring systems to be misused to produce unlawful employment discrimination. Furthermore, I describe how such systems may serve to mask employment discrimination or impede its detection.

A. The Business Case

Automated hiring systems have proliferated because they are perceived as both cost-effective and efficient. A Forbes article notes that artificial intelligence (“AI”) will quickly emerge as a key tool for human resources (“HR”) because of the current talent scarcity and low unemployment.⁶⁵ Companies on average spend approximately four thousand dollars per candidate on the hiring process, including interviewing, scheduling, and conducting assessments.⁶⁶ However, the adoption of automated hiring makes the hiring process much less costly. This might be why, according to a Deloitte Bersin report, companies that use technologies, such as AI and predictive data analytics, are more successful than those who do not.⁶⁷ For instance, one report indicates that the companies using AI technology show 18% higher revenue and 30% greater profitability compared to those without the tools.⁶⁸

A report by Ideal demonstrates how automated hiring allows companies to be efficient in hiring by detailing the time commitment

65. Gal Almog, *Recruiting Isn't Enough: How AI Is Changing the Rules in the Human Capital Market*, FORBES (Feb. 9, 2018, 8:50 AM), <https://www.forbes.com/sites/groupthink/2018/02/09/traditional-recruiting-isnt-enough-how-ai-is-changing-the-rules-in-the-human-capital-market/#729e2624274a> [<https://perma.cc/EXB3-XLH7>].

66. *See id.* (citing DELOITTE DEV. LLC, *THE RISE OF THE SOCIAL ENTERPRISE: 2018 DELOITTE GLOBAL HUMAN CAPITAL TRENDS* (2018), <https://www2.deloitte.com/content/dam/Deloitte/global/Documents/HumanCapital/gx-hc-trends-rise-social-enterprise.pdf> [<https://perma.cc/XU3N-2QXR>]).

67. *See Almog, supra* note 65 (citing DELOITTE DEV. LLC, *supra* note 66).

68. *See* DENISE MOULTON & ROBIN ERICKSON, *USING TALENT ACQUISITION TO DRIVE CRITICAL TALENT RESULT 2–3* (2018), <https://www2.deloitte.com/content/dam/Deloitte/us/Documents/human-capital/us-hc-using-talent-acquisition-to-drive-critical-talent-results.pdf> [<https://perma.cc/8APZ-ZGJC>]; *see also* Almog, *supra* note 65.

required for traditional hiring.⁶⁹ On average, companies spend fourteen hours per week manually completing tasks that could be automated.⁷⁰ Twenty-eight percent indicate that they spend twenty hours or more, and 11% spend thirty hours or more on such tasks.⁷¹ Also, 41% of HR managers say not fully automating their manual hiring processes has led to lower productivity, and 35% have experienced higher costs for the same reason.⁷² In addition to lower efficiency and productivity, not fully automating manual processes in HR seems to have affected hiring decisions regarding the best talent, as 17% of HR managers state that it has led to a poor candidate experience.⁷³

Other articles also tout the benefits of adopting automated hiring processes. For instance, a LinkedIn Talent Blog post claims that a recruiting algorithm increases the accuracy of selecting productive employees by more than 50%.⁷⁴ An article by Monster.com, a global employment website, boasts that using big data to evaluate candidates has lowered turnover for companies, with a median reduction of 38%.⁷⁵ Furthermore, in the article *In Hiring, Algorithms Beat Instinct*, the authors argue that hiring algorithms produce more objective outcomes than do human decision makers.⁷⁶ The authors note that although humans are adept at specifying qualifications for a job and drawing out information from candidates, HR managers find it difficult to weigh the results;⁷⁷ according to one analysis, a simple equation performed better than human decisions, regardless of the number of candidates and types of jobs.⁷⁸ Another study found that although hiring managers can be greatly familiar with their organizations and have more insight beyond

69. Ji-A Min, *12 Revealing Stats on How Recruiters Feel About AI*, IDEAL (Feb. 1, 2019), <https://ideal.com/how-recruiters-feel-about-ai/> [<https://perma.cc/RLZ8-DT6L>].

70. *See id.*

71. *See id.*

72. *See id.*

73. *See id.*

74. Maren Hogan, *8 Hiring Stats That Will Change the Way You Recruit*, LINKEDIN: TALENT BLOG (Sept. 8, 2016), <https://business.linkedin.com/talent-solutions/blog/trends-and-research/2016/8-hiring-stats-that-will-change-the-way-you-recruit-today> [<https://perma.cc/3N4X-WEJD>]; *see also* Roy Maurer, *Using Data to Make Better Hires*, SHRM (Jan. 29, 2016), <https://www.shrm.org/resourcesandtools/hr-topics/talent-acquisition/pages/using-data-make-better-hires.aspx> [<https://perma.cc/49DA-G2PP>] (citing Nathan R. Kuncel, Deniz S. Ones & David M. Klieger, *In Hiring, Algorithms Beat Instinct*, HARV. BUS. REV., May 2014, <https://hbr.org/2014/05/in-hiring-algorithms-beat-instinct> [<https://perma.cc/5Y9P-C6XD>]).

75. John Rossheim, *Algorithmic Hiring: Why Hire by Numbers?*, MONSTER, <https://hiring.monster.com/hr/hr-best-practices/recruiting-hiring-advice/strategic-workforce-planning/hiring-algorithms.aspx> [<https://perma.cc/7MD2-4F6J>].

76. *See* Kuncel, Ones & Klieger, *supra* note 74.

77. *Id.*

78. *See id.* (“Our analysis of 17 studies of applicant evaluations shows that a simple equation outperforms human decisions by at least 25%. The effect holds in any situation with a large number of candidates, regardless of whether the job is on the front line, in middle management, or (yes) in the C-suite.”).

a two-dimensional job description, they are also easily distracted by marginal things, such as applicants' compliments, and "use information inconsistently."⁷⁹ Yet another study found that a job-screening algorithm "favored 'nontraditional' candidates" much more than human screeners did, "exhibit[ing] significantly less bias against candidates that were underrepresented at the firm."⁸⁰ Some other algorithmic studies related to credit applications, criminal justice, public resource allocations, and corporate governance all concluded that "[a]lgorithms are less biased and more accurate than the humans they are replacing."⁸¹

Given these results, some legal scholars have challenged the focus of legal scholarship on the bias discovered in automated decision-making.⁸² As these scholars argue, the original intent of automated decision-making is "to improve upon human decision-making by suppressing biases to make the most efficient and least discriminatory decisions."⁸³ Thus, arguably, there is no implicit promise that automated decision-making could eliminate all bias; rather, the function of automated decision-making is merely to improve upon human decision-making. This assertion should be accepted at face value. My purpose for this Article is not to argue that automated decision-making can or should eliminate all bias in decision-making; rather, my aim is to argue that automated decision-making, even when it does offer some improvement on human decision-making, still merits legal oversight,⁸⁴ particularly when such decision-making holds the potential to limit the access to earning a livelihood for people of protected categories.

B. How Automated Is Automated Hiring?

Although this Article uses the term "automated hiring," I contend that this term can be misleading as it elides the continued role of human input, the human hand. As I have previously noted, to argue against or for automated decision-making versus human decision-making rests on the false assumption that the two could be wholly disentangled.⁸⁵ As

79. *See id.*

80. Alex P. Miller, *Want Less-Biased Decisions? Use Algorithms*, HARV. BUS. REV. (July 26, 2018), <https://hbr.org/2018/07/want-less-biased-decisions-use-algorithms> [<https://perma.cc/J6YW-Y5Q9>].

81. *Id.*

82. *See, e.g.*, Stephanie Bornstein, *Antidiscriminatory Algorithms*, 70 ALA. L. REV. 519, 520 (2018).

83. *Id.* at 520.

84. Professor Julie Cohen has extensively made the point that automated systems merit greater legal oversight in her breadth of scholarship. *See, e.g.*, Cohen, *supra* note 7.

85. Ajunwa, *supra* note 6, at 1711, 1718.

Professor Mayson notes, automated decision-making is merely a reflection of all past decisions:

All prediction functions like a mirror. . . . Algorithmic prediction produces a precise reflection of digital data. Subjective prediction produces a cloudy reflection of anecdotal data. But the nature of the analysis is the same. To predict the future under status quo conditions is simply to project history forward.⁸⁶

I agree here with the conclusion that algorithmic decision-making posits history as the best diviner of the future, but I also urge for a better understanding of how human decision-making remains entangled in automated decision-making. Such an understanding, I believe, would help to quell the reification of automated decision-making as better than human decision-making and also to negate what I call “automation exceptionalism,” which is the idea that automated decision-making is somehow *set apart* and should not be subjected to the same scrutiny or skepticism as human decision-making.

To illustrate this point, I point to the example of Amazon’s experience with one hiring algorithm.⁸⁷ In that case, a whistleblower revealed that Amazon had created and then abandoned an automated hiring system that was returning biased results for women candidates.⁸⁸ I cannot believe that Amazon would build an automated hiring system to intentionally discriminate against women, yet that is alleged to have happened in practice.⁸⁹

Most automated decision-making requires human input at some stage. Some might argue that a crucial stage is *ex post*, when human interveners may choose to ignore or make exceptions for the automated result. However, note that for all automated decision-making, there is always *ex ante* human input, when human decision-making directly dictates the design of the automated decision-making system, including deciding what variables should be considered, and deciding how said variables should be measured. In the Amazon case, albeit that there was no intention to discriminate, one possible cause for the discriminatory results is human intervention in the way the computer models were trained.⁹⁰ Thus, despite some of the proven benefits of automated

86. Mayson, *supra* note 4, at 2224.

87. Isobel Asher Hamilton, *Amazon Built an AI Tool to Hire People but Had to Shut It Down Because It Was Discriminating Against Women*, INSIDER: BUS. (Oct. 10, 2018, 5:47 AM), www.businessinsider.com/amazon-built-ai-to-hire-people-discriminated-against-women-2018-10 [https://perma.cc/VB44-Z95T].

88. *Id.*

89. *Id.*

90. *See id.* (finding that the automated hiring system “reportedly downgraded résumés containing the words ‘women’s’ and filtered out candidates who had attended two women-

hiring, there remains the potential for misuse, resulting from the opportunities to introduce human bias at any stage of the automated hiring process — from design, to implementation, and finally, to the interpretation of results.

C. Potential for Misuse

Although automated hiring offers some business utility, the potential for the misuse of algorithmic hiring to accomplish (un)intended unlawful discriminatory results remains. Hiring technologies can play various roles in the process; for example, in the early stages of recruiting, automated predictions can “steer job advertisements and personalized job recommendations to jobseekers from particular demographic groups.”⁹¹ Also, although employers might adopt hiring technology to “increase efficiency, and in hopes that they will find more successful — and sometimes, more diverse — employees,”⁹² this might be a superficial stop gap to addressing issues of inequity embedded in organizational practices. Thus, the belief that recruiters will be able to “make fairer and more holistic hiring decisions” because the tools will “reduce bias by obscuring applicants’ sensitive characteristics,”⁹³ centers on individual human prejudice, while obviating institutional, structural, and other forms of bias that become systemic in any given organization.⁹⁴ To illustrate the historical and structural nature of bias in hiring, consider this: “[A] company that tends to hire from a privileged and homogeneous community and then uses ‘culture fit’ as a factor in hiring decisions could end up methodically rejecting otherwise qualified candidates who come from more diverse backgrounds.”⁹⁵

The fact remains that there are myriad of ways that automated hiring could systematically replicate biases that have calcified from organizational practice.⁹⁶ First, if the training data for a model is itself

only colleges”); *see also* Ifeoma Ajunwa, *The Paradox of Automation as Anti-Bias Intervention*, 41 *CARDOZO L. REV.* 1671, 1674 (2020) (describing the Amazon case and noting “[a] potential cause: The computer models were trained on predominantly male resumes, with the result that the system concluded that men were preferred candidates”).

91. MIRANDA BOGEN & AARON RIEKE, *UPTURN, HELP WANTED: AN EXAMINATION OF HIRING ALGORITHMS, EQUITY, AND BIAS* 3 (2018), <https://www.upturn.org/static/reports/2018/hiring-algorithms/files/Upturn%20--%20Help%20Wanted%20-%20An%20Exploration%20of%20Hiring%20Algorithms,%20Equity%20and%20Bias.pdf> [<https://perma.cc/BY4E-FXDL>].

92. *Id.* at 6.

93. *Id.* at 7.

94. For example, Professor Pauline Kim argues: “algorithms will not counteract structural forms of workplace bias.” *Data-Driven Discrimination at Work*, *supra* note 5, at 871.

95. BOGEN & RIEKE, *supra* note 91, at 7.

96. As other scholars have argued: “It should not be surprising that trying to predict qualities of good future workers based on the qualities of current workers and existing work culture will not lead to change. In other words, people analytics runs the risk of homosocial

inaccurate, non-representative, or biased, the resulting model and the predictions could reflect skewed results.⁹⁷ Second, a phenomenon known as “automation bias” occurs when people “give undue weight to the information coming through their monitors.”⁹⁸ A third issue is when algorithms are trained to evaluate the criteria used for selection in a manner that benefits one group of applicants. This is especially true for automated video interviewing which is the latest trend in automated hiring.

Automated video interviews involve the video capture of the word choices, speech patterns, and facial expressions of job applicants, which is then used to evaluate their fit for a job position and their cultural fit within the organization.⁹⁹ A survey of 506 companies in 2011 showed that 47% use video interviewing to shorten the hiring timeframe and save costs, and 22% would consider it for interviewing non-local candidates.¹⁰⁰ And more recently in 2018, 60% of organizations surveyed confirmed that they are turning to video interviews for recruitment.¹⁰¹ For example, HireVue is one such technology used to conduct virtual interviews, and the claim is that it can identify facial expressions, vocal indications, word choice, and more.¹⁰² However, “[s]peech recognition software can perform poorly” for certain groups of people if the algorithms have not been trained for those groups, and “[f]acial analysis systems can struggle to read the faces of women with darker skin.”¹⁰³ The legitimacy of considering physical features and facial expressions as part of the hiring process is questionable given a lack of scientific studies establishing any causal relationship between those attributes and workplace success.¹⁰⁴

reproduction, or replacement of workers with workers that look like them, on a grand scale.” Matthew T. Bodie, Miriam A. Cherry, Marcia McCormack & Jintong Tang, *The Law and Policy of People Analytics*, 88 U. COLO. L. REV. 961, 1013 (2017); see also Alan G. King & Marko J. Mrkonich, “Big Data” and the Risk of Employment Discrimination, 68 OKLA. L. REV. 555, 574 (2016) (“[I]f incumbents are older than applicants, then the social-media profile of this older group may differ markedly from that of younger job applicants. Accordingly, an algorithm highly accurate in sorting *incumbents* for their proficiency may yield *applicants* notable only for their ‘retro’ tastes and lifestyles.”).

97. BOGEN & RIEKE, *supra* note 91, at 8.

98. *Id.* at 9 (quoting Raja Parasuraman & Victor Riley, *Humans and Automation: Use, Misuse, Disuse, Abuse*, 39 HUM. FACTORS 230 (1997)).

99. *How AI Changes Recruiting Strategies Right Now*, RECRUITMENT PROCESS OUTSOURCING ASS’N (Oct. 10, 2019), <https://blog.rpoassociation.org/blog/how-ai-changes-recruiting-strategies-right-now> [<https://perma.cc/2LCD-P8WF>].

100. Heather O’Neill, *Video Interviewing Cuts Costs, but Bias Worries Linger*, WORKFORCE.COM (Oct. 5, 2011), <https://www.workforce.com/news/video-interviewing-costs-costs-but-bias-worries-linger> [<https://perma.cc/GB3G-FNMQ>].

101. Nilam Oswal, *The Latest Recruitment Technology Trends and How to Really Use Them*, PC WORLD (Feb. 9, 2018), <https://www.pcworld.idg.com.au/article/633219/latest-recruitment-technology-trends-how-really-use-them/> [<https://perma.cc/HQ8Q-ZNKW>].

102. See BOGEN & RIEKE, *supra* note 91, at 36.

103. *Id.* at 37.

104. See *id.* at 37–38.

Yet, a cursory survey¹⁰⁵ shows that a wide range of companies are already using automated video interviewing as part of their hiring process:

- (1) **HireVue:** A pioneer in video interviewing and a platform for applicant management, candidate assessment and video interviewing that promises employer benefits of 24% cost savings and 25–40% time savings.¹⁰⁶ HireVue claims that the technology captures more than a million meaningful data elements about a job candidate in each minute of video and can tell managers things about candidates' truthfulness and confidence in answering questions. HireVue records candidates' responses to preset questions and then analyzes and scores them based on tone, body language, and keyword¹⁰⁷ and criteria that are proven to be predictive of job performance.¹⁰⁸ This platform is mostly used by organizations in retail, customer service, and hospitality for volume hiring. HireVue now has more than six hundred customers and has delivered more than five million video interviews.¹⁰⁹
- (2) **Talview:** An AI-enabled video interviewing technology used by many Fortune 500 companies and clients across more than 102 countries.¹¹⁰ Popular clients include Amazon, Cognizant, Whirlpool, and Sephora, among others.¹¹¹

105. I also shared this survey in my written testimony to Congress. *See The Future of Work: Protecting Workers' Rights in the Digital Age, Hearing Before the Subcomm. on C.R. and Hum. Serv's. of the H. Comm. on Educ. and Lab.*, 116th Cong. (2020) (statement of Ifeoma Ajunwa, then-Assistant Professor, Cornell University Industrial and Labor Relations School), <https://www.congress.gov/116/meeting/house/110438/witnesses/HHRG-116-ED07-Wstate-AjunwaJDPHDI-20200205.pdf> [<https://perma.cc/6XXK-GX5E>].

106. Janine Woodworth & Jake Bauer, *Digital Interviewing: The Voice of the Candidate*, HIREVUE 7 (2014), <http://www.thetalentboard.org/wp-content/uploads/2014/06/Digital-Interviewing-The-Voice-of-the-Candidate.pdf> [<https://perma.cc/LY2K-PJAG>].

107. Dandan Chen, Pedro Galicia, Daniel Manjarrez & Lauren Sims, *The Growing Role of Technology in Talent Acquisition* 4 (Feb. 2018) (MILR paper, Cornell University), https://est05.esalestrack.com/esalestrack/Content/Content.ashx?aid=2181&system_filename=58ee0e8c-aabf-412f-afbd-d5b34a20c727.pdf [<https://perma.cc/ZTV6-JY5P>].

108. Monika, *Recruiting Software — All You Need to Know*, HARVER (Aug. 23, 2019), <https://harver.com/blog/recruiting-software/> [<https://perma.cc/QCG2-3346>].

109. Josh Bersin, *AI Comes to Recruiting: Will Interviews Go the Way of the Dinosaur?*, JOSH BERSIN (Nov. 7, 2018), <https://joshbersin.com/2018/11/ai-comes-to-recruiting-will-interviews-go-the-way-of-the-dinosaur/> [<https://perma.cc/U873-WZWH>].

110. *Top 40+ Pre-Employment Assessment Tools*, ACADEMY TO INVIGORATE HR (AIHR) DIGITAL (July 2020), <https://www.digitalhrtech.com/top-pre-employment-assessment-tools/> [<https://perma.cc/A22R-43NP>].

111. *Customers*, TALVIEW, <https://www.talview.com/customers> [<https://perma.cc/KA5U-A448>].

- (3) **Spark Hire:** A popular video interviewing software with over 5,000 customers that uses on-demand video interviews to screen job candidates and help recruiters identify the best candidates for a job earlier in the hiring process. Popular clients include the United States Postal Service, IKEA, and Volkswagen.¹¹²
- (4) **Wepow:** This technology allows employers to pre-record or schedule live video interviews with candidates and compare and rank them based on predefined criteria. It also analyzes the recruitment process and highlights areas for improvement. Top customers include Heineken, Genentech, Virgin Atlantic, Walmart, Adidas, and many more.¹¹³

The use of automated interviewing is legally fraught for several reasons. First, algorithms have “limited ability to parse the nuanced meaning of human communication.”¹¹⁴ Second, such checks could “surface details about an applicant’s race, sexual identity, disability, pregnancy, or health status, which employers should not consider during the hiring process.”¹¹⁵ And third, the training of such algorithms could skew the results for protected classes given that many software engineers are white males, and thus tend to use white male faces and voices as their training models.¹¹⁶

Beyond evaluation, automated hiring provides other opportunities for human bias to creep in. For example, as the last step of the hiring process, employers make offers to applicants using automated hiring systems. The software programs predict the likelihood a candidate will accept a job offer, and what the employer can do to increase the rate of acceptance. The employer can “adjust salary, bonus, stock options, and other benefits to see in real time how the prediction changes.”¹¹⁷ Although these functions could be helpful for an effective hiring process, they might also amplify pay gaps for women and minority job

112. *Hear It from Our Happy Customers*, SPARK HIRE, <https://www.sparkhire.com/customers> [<https://perma.cc/BAN5-HFWR>].

113. *Your Success Is Our Success . . . We Power You*, WEPow, <https://www.wepow.com/en/customers> [<https://perma.cc/CP4L-MAA7>].

114. BOGEN & RIEKE, *supra* note 91, at 40 (quoting Natasha Duarte, Emma Llanso & Anna Loup, *Mixed Messages? The Limits of Automated Social Media Content Analysis*, CTR. FOR DEMOCRACY & TECH. 3 (Nov. 2017), <https://cdt.org/files/2017/11/Mixed-Messages-Paper.pdf> [<https://perma.cc/HPU5-294N>]).

115. *Id.*

116. See Kari Paul, ‘Disastrous’ Lack of Diversity in AI Industry Perpetuates Bias, *Study Finds*, GUARDIAN (Apr. 16, 2019), <https://www.theguardian.com/technology/2019/apr/16/artificial-intelligence-lack-diversity-new-york-university-study> [<https://perma.cc/H2TN-4V32>].

117. BOGEN & RIEKE, *supra* note 91, at 41.

candidates.¹¹⁸ Such predictive salary offers also undermine “laws that bar employers from considering candidates’ salary histories.”¹¹⁹

As Rachel Goodman of the American Civil Liberties Union (“ACLU”) writes, the flaws of automated hiring remain because of limitations in the law. For one, although vendors who market the hiring tools claim that these hiring tools are less biased than humans, the software is proprietary, and there is currently no way to verify these claims.¹²⁰ This lack of transparency makes it difficult for job applicants to bring suit based on a disparate impact theory in “failure-to-hire” cases, as applicants are unable to identify a policy or practice that led to their rejection.¹²¹ One suggestion is that “outside auditors may be able to uncover bias.”¹²² However, such research by outside auditors is thwarted by various obstacles, one of them being that federal laws, such as the Computer Fraud and Abuse Act, may criminalize certain types of testing of employment websites for discrimination.¹²³ Given these obstacles, there are calls for the EEOC to expand its efforts to govern workplace algorithms.¹²⁴ Later, I will outline some federal measures that could provide true protections for job applicants subjected to an automated hiring regime.¹²⁵ But first, I will parse some other solutions that I think fall short of the ultimate goal of equal opportunity for all job applicants.

118. *See id.*

119. *Id.*

120. Rachel Goodman, *Why Amazon’s Automated Hiring Tool Discriminated Against Women*, AM. C.L. UNION (Oct. 12, 2018, 1:00 PM), <https://www.aclu.org/blog/womens-rights/womens-rights-workplace/why-amazons-automated-hiring-tool-discriminated-against> [https://perma.cc/UW9P-QSBJ].

121. *Id.*

122. *Id.*

123. *Id.*; Sandvig v. Barr — *Challenge to CFAA Prohibition on Uncovering Racial Discrimination Online*, AM. C.L. UNION (May 22, 2019), <https://www.aclu.org/cases/sandvig-v-barr-challenge-cfaa-prohibition-uncovering-racial-discrimination-online> [https://perma.cc/6ASQ-A2WS].

124. *See Goodman, supra* note 120.

125. *See infra* Section V.B.

III. EX MACHINA: TECHNO-SOLUTIONIST APPROACHES

Even as legal scholars have called for more transparency¹²⁶ and accountability¹²⁷ for machine learning algorithms, increasingly, attention has shifted towards technological approaches to combating algorithmic capture in employment. These techno-solutionist approaches generally fall into two categories: (1) the adjustment of human job search behavior to “game” machine learning algorithms and (2) the creation of new algorithms that promise to eliminate bias. This section notes the limitations of such approaches and cautions that techno-solutionist approaches will never be effective for problems that are, at their root, derived from socio-technical interactions arising from structural bias and societal prejudices.

A. Humans Conform to the Machine

One approach to counteracting the biased effects of hiring algorithms is to cheat the system. Thus, humans devise strategies to hurdle routine machine learning errors and other encoded biases. In a recent *LinkedIn* article, a recruiting manager counseled job applicants on how to avoid getting axed by the applicant tracking system (“ATS”).¹²⁸ 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 advertisement to ensure that an unsophisticated algorithm does not reject the application simply because the algorithm was designed to only recognize a narrow list of words provided for in a keyword search.¹²⁹

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

126. Hannah Bloch-Wehba, *Access to Algorithms*, 88 *FORDHAM L. REV.* 1265, 1269 (2020) (“These features . . . have prompted calls for new mechanisms of transparency and accountability in the age of algorithms.”); Robert Brauneis & Ellen P. Goodman, *Algorithmic Transparency for the Smart City*, 20 *YALE J.L. & TECH.* 103, 132 (2018) (“Such accountability requires not *perfect* transparency . . . but . . . *meaningful* transparency.”); see Danielle Keats Citron & Frank A. Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 *WASH. L. REV.* 1, 25 (2014) (discussing the need for oversight of algorithms); Alyssa M. Carlson, *The Need for Transparency in the Age of Predictive Sentencing Algorithms*, 103 *IOWA L. REV.* 303, 326 (2017) (arguing that transparency increases accuracy); Maayan Perel & Niva Elkin-Koren, *Accountability in Algorithmic Copyright Enforcement*, 19 *STAN. TECH. L. REV.* 473, 482 (2016) (discussing the lack of transparency in algorithms).

127. See, e.g., Kroll et al., *supra* note 21, at 636.

128. Jan Tegze, *Modifying Your Resume to Beat ATS Algorithms*, *LINKEDIN* (Sept. 10, 2015), <https://www.linkedin.com/pulse/modifying-your-resume-beat-ats-algorithms-jan-tegze/> [<https://perma.cc/HM2B-2VUD>].

129. *Id.*

of automated hiring.¹³⁰ Although some question the reliability of personality tests,¹³¹ the tests remain a popular part of automated hiring systems. Some experts have estimated that “as many as 60 percent of workers are now asked to take workplace assessments” and that “[t]he \$500-million-a-year industry has grown by about 10 percent annually in recent years.”¹³² While many organizations use personality testing for career development, about 22% use it to evaluate job candidates, according to the results of a 2014 survey of 344 Society for Human Resource Management members.¹³³ While some lawsuits have sought to eliminate the tests, most workers have resigned themselves to encountering the test as part of the hiring process and have come to rely on online “answer keys” created to beat the tests.¹³⁴ These “answer keys,” however, represent conformity to the unfair practices of automated hiring, rather than a true protest of 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.¹³⁵

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-ups¹³⁶ are hawking new ways to automate hiring. Some of these companies also claim that their technological approaches ensure employment decisions that are non-discriminatory.¹³⁷ Although these start-ups may very well have the good intention of eliminating human bias in hiring, I argue that the lack of any established internal or external auditing protocols means that those good intentions cannot be verified

130. See Melanie Shebel, *Unicru Personality Test Answer Key: Read This and Get Hired*, TOUGH NICKEL (May 8, 2018), <https://toughnickel.com/finding-job/Unicru> [<https://perma.cc/4DPV-MEAK>]; Timothy Horrigan, *Some Answers to Unicru Personality Test*, TIMOTHY HORRIGAN (Jan. 27, 2009), <http://www.timothyhorrigan.com/documents/unicru-personality-test.answer-key.html> [<https://perma.cc/72D8-LYU4>].

131. See, e.g., Gill Plimmer, *How to Cheat a Psychometric Test*, FIN. TIMES (Apr. 2, 2014), <https://www.ft.com/content/eeda84e4-b4f6-11e3-9166-00144feabdc0> [<https://perma.cc/LDH9-7Z6Z>].

132. Dori Meinert, *What Do Personality Tests Really Reveal?*, SOC’Y FOR HUM. RESOURCE MGMT. (June 1, 2015), <https://www.shrm.org/hr-today/news/hr-magazine/pages/0615-personality-tests.aspx> [<https://perma.cc/3S6U-HZDB>].

133. *Id.*

134. See Shebel, *supra* note 130.

135. See *infra* Section III.C.

136. See, e.g., HIREVUE, <http://hirevue.com> [<https://perma.cc/YU54-6ZK7>].

137. Aarti Shahani, *Now Algorithms Are Deciding Whom to Hire, Based on Voice*, NPR: ALL TECH CONSIDERED (Mar. 23, 2015, 4:40 PM), <http://www.npr.org/sections/alltechconsidered/2015/03/23/394827451/now-algorithms-are-deciding-whom-to-hire-based-on-voice> [<https://perma.cc/B68N-FLWF>].

in practice, and I remain steadfast in my belief that any solely technosolutionist attempts at a solution without legal oversight will fall short. Thus, calls for improving the transparency of algorithms do not adequately address the full scope of the problem.

Legal scholars have called for greater transparency for hiring algorithms,¹³⁸ with the belief that “greater disclosure of how [algorithms] operate” will help avoid unfairness.¹³⁹ Professor Frank Pasquale suggests that a solution to the problem of algorithmic discrimination is transparency; he uses the metaphor of the “black box” and proposes that algorithms should not operate as black boxes but should be opened up for examination.¹⁴⁰ However, some argue that this call for transparency is not sufficient for algorithms to be completely fair in regard to legal standards.¹⁴¹ This is because transparency alone does not fully explain why a particular decision was made or how fairly the system operates.¹⁴² Rather, those scholars argue that governing algorithms requires design principles that provide checks for bias. Professor Joshua A. Kroll and his co-authors suggest technical strategies that would help overcome hidden biases in the algorithms.¹⁴³ 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 well, “the validity of the initial assumptions can be tested and the accuracy and fairness of the whole system will benefit over time.”¹⁴⁴

Professors Solon Barocas and Andrew Selbst join this debate to note that the inscrutability and the nonintuitive nature of machine learning algorithms are both factors in automated decision-making. They define “inscrutability” as “a situation in which the rules that govern decision-making are so complex, numerous, and interdependent that they defy practical inspection and resist comprehension.”¹⁴⁵ The legal problem with inscrutability, I argue, is that ultimately it muddles

138. See Citron & Pasquale, *supra* note 126, at 24–25.

139. *Auditing Algorithms*, *supra* note 21, at 189.

140. See, e.g., Frank Pasquale, *Bittersweet Mysteries of Machine Learning (A Provocation)*, LONDON SCH. ECON. & POL. SCI.: MEDIA POL’Y PROJECT (Feb. 5, 2016), <https://blogs.lse.ac.uk/mediapolicyproject/2016/02/05/bittersweet-mysteries-of-machine-learning-a-provocation/> [<https://perma.cc/72CC-PQTE>]; see also Anupam Chander, *The Racist Algorithm?*, 115 MICH. L. REV. 1023, 1039 (2017).

141. See Kroll et al., *supra* note 21, at 633.

142. As some scholars have noted, the need for explainability is especially important in the context of automated hiring. See, e.g., James Grimmelman & David Westreich, *Incomprehensible Discrimination*, 7 CALIF. L. REV. ONLINE 164, 177 (2017) (“Applicants who are judged and found wanting deserve a better explanation than, ‘The computer said so.’”); Andrew Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085, 1085 (2018) (noting that “algorithmic decision-making has become synonymous with inexplicable decision-making”).

143. See Kroll et al., *supra* note 21, at 640.

144. *Id.* at 684.

145. Selbst & Barocas, *supra* note 142, at 1094.

any attempt to determine intent. In addition to inscrutability which becomes an issue when machine learning algorithms are creating de novo rules on their own, another important problem is the non-intuitive nature of automated decision-making. As the authors note, the human need to understand the intuitive relationship between any given automated decision and the underlying data is “not the demand for disclosure or accessible explanations; it is a demand that decision-making rely on reasoning that comports with intuitive understanding of the phenomenon in question.”¹⁴⁶ I argue that this human need for “intuitive understanding” is a desire for justice, rather than a quest for technical redress. There is both a human need to understand the factors under which one is judged (especially for access to livelihood) and a desire to see factors done away with that do not conform to principles of fairness.

A recent Illinois law represents one attempt at transparency for automated hiring and also highlights the limitations of that approach. Effective January 1, 2020, the Artificial Intelligence Video Interview Act (“AIVIA”)¹⁴⁷ is the governing law in Illinois for any employer who chooses to “use artificial intelligence (AI) to analyze video interview by job candidates.”¹⁴⁸ Under AIVIA, employers are required to provide advance notice to the applicant of the use of the video interview technology, and further to “explain to the applicant ‘how the [AI] works’ and what general characteristics the technology uses to evaluate applicants.”¹⁴⁹ This call for transparency is facially valuable.¹⁵⁰ However, many AI video analytics providers do not publish adequate information on the workings of their products. Thus, the effects of this part of the law may take one of two paths: Either AI video providers will be forced to publish more information about their algorithms or the standard for meeting this transparency mandate will be effectively so low as to become meaningless.

Beyond transparency, the law requires that employers “obtain, in advance, the applicant’s consent to use the technology.”¹⁵¹ The law also features provisions for data protection. It imposes limits on “the distribution and sharing of the video,” granting access “only to those

146. *Id.* at 1097.

147. 820 ILL. COMP. STAT. 42 (2020).

148. Nicole Mormilo, Matthew Jedreski, K.C. Halm & Jeffrey S. Bosley, *Employers Using AI in Hiring Take Note: Illinois’ Artificial Intelligence Video Interview Act Is Now in Effect*, DAVIS WRIGHT TREMAINE LLP (Feb. 10, 2020), <https://www.dwt.com/blogs/artificial-intelligence-law-advisor/2020/02/illinois-aivia-compliance> [https://perma.cc/JL6E-RUQZ].

149. Matthew Jedreski, Jeffrey S. Bosley & K.C. Halm, *Illinois Becomes First State to Regulate Employers’ Use of Artificial Intelligence to Evaluate Video Interviews*, DAVIS WRIGHT TREMAINE LLP (Sept. 3, 2019), <https://www.dwt.com/blogs/artificial-intelligence-law-advisor/2019/09/illinois-becomes-first-state-to-regulate-employers> [https://perma.cc/46JD-2T32].

150. *See infra* Section IV.B.

151. Jedreski, Bosley & Halm, *supra* note 149.

persons ‘whose expertise or technology’ is necessary to evaluate the applicant.”¹⁵² Further, candidates are given some control over what happens to the video after their assessment. Employers are required to “destroy the video (and all backup copies) within 30 days” of the applicant requesting its destruction.¹⁵³

The law firm Davis Wright Tremaine, LLP (“DWT”) identifies a few key issues with the law. Chiefly, the law fails to define “artificial intelligence” and “artificial intelligence analysis” along with other key terms.¹⁵⁴ This ambiguity may mean that certain employer AI use cases, such as “to track data about its candidates,” may not be covered.¹⁵⁵ Further, ambiguity in the transparency mandate of the law may, as suggested above, pose serious problems for its effective use. DWT notes that the law does not go in depth to specify “how much detail an employer must provide when ‘explaining how artificial intelligence works’ to an applicant” or what “‘characteristics’ of the AI employers must disclose.”¹⁵⁶ Therefore, employers may be permitted to use broad, cursory statements such as “AI will assess a candidate’s performance” to satisfy this requirement, statements which do not serve the true spirit of transparency. DWT finds the law to be unclear in several other aspects as well. It notes that there is no requirement that candidates provide express written consent.¹⁵⁷ Further, the law “does not include a private right of action or any explicit penalties,” which could raise serious issues in enforcing its provisions.¹⁵⁸ As for data destruction, DWT points out that it is not clear if “data that an employer extracts or derives from the video interview . . . is subject to the destruction duty under the law.”¹⁵⁹ If such data is not protected by the AIVIA, then the extent to which the act allows candidates control over their interview data is potentially limited. Lastly, DWT points out that “there is no guidance on what it means for a job to be ‘based in’ Illinois, and the statute is silent as to whether employees may refuse to consider applicants who refuse to consent.”¹⁶⁰

Ultimately, AIVIA is a step in the right direction, as it touches on the serious concerns of transparency and data rights. However, the primary, overarching issue with the law is its lack of specificity. Failing to define key terms, to expand on essential provisions, or to stipulate any enforcement mechanism means that the effective impact of the transparency and data rights measures is limited, and employers who

152. *Id.*

153. *Id.*

154. *Id.*

155. *Id.*

156. Mormilo, Jedreski, Bosley & Halm, *supra* note 148.

157. *See* Jedreski, Bosley & Halm, *supra* note 149.

158. *Id.*

159. *Id.*

160. *Id.*

wish to evade the law may do so. Further, while some employers may surely make a good faith effort to comply, many employers themselves are not privy to how the AI they use truly works. Companies such as HireVue keep a close guard over their algorithms and technologies to protect their market share, to the detriment of clients and candidates alike.¹⁶¹ In order to push AI video interview companies to be more transparent, the law must put in place effective penalties such that employers would not choose to use technology unless AI companies provided enough information. Effective legislation must hold enough weight to impact all stakeholders in the AI video interview universe. Again, it is important to reiterate that Illinois is “at the forefront of regulating technology and personal data.”¹⁶² AIVIA should be commended as first-of-its-kind legislation that is shedding light on critical issues of public interest. It simply needs to go further to counterbalance the immense power which the AI sphere currently holds.

C. *The Perils of Techno-Solutionism*

In the specific case of automated hiring systems, techno-solutionist methods fail to address the bias encoded in the business practices deployed in the hiring process. In fact, those methods may even serve to replicate the shortcomings of human decision-making processes in hiring. For example, although the websites providing “answer keys” to beat employment personality tests 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 be futile attempts to combat “algorithmic governmentality,” which as one scholar has argued “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.”¹⁶³ This suggests a need for remedies that do not unquestioningly privilege technological innovation, but which uphold the goals of antidiscrimination laws through careful legal oversight. As other scholars have noted, techno-solutionist approaches to societal problems are foiled by the “bias in, bias out” problem.¹⁶⁴ That is, techno-solutionist approaches that fail to

161. See *infra* Section IV.B.

162. Jedreski, Bosley & Halm, *supra* note 149.

163. Douglas Spencer, *Proletarianisation Isn't Working*, RADICAL PHIL. (Feb. 2018), <https://www.radicalphilosophy.com/reviews/individual-reviews/proletarianisation-isnt-working> [<https://perma.cc/E3JC-9S52>].

164. Mayson, *supra* note 4, at 2224; Robert Brauneis & Ellen Goodman, *Algorithmic Transparency for the Smart City*, 20 YALE J.L. & TECH. 103, 122 (2018); see Anjanette H. Raymond, Emma Arrington Stone Young & Scott J. Shackelford, *Building a Better HAL*

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.

IV. DO EMPLOYMENT LAWS ADEQUATELY ADDRESS AUTOMATED HIRING?

In this section, I discuss the limitations of employment law in protecting job applicants who experience an adverse impact from automated hiring systems. I review employment law scholarship that offers empirical evidence of the difficulty of proving employment discrimination based on a disparate impact cause of action and the theories proffered by legal scholars as to why this might be the case. Given that the means of proving discrimination by automated hiring systems remains solely under the control of employers, I argue that there is a necessity for compulsory data retention by employers making use of automated hiring systems and that, furthermore, such data retention should facilitate both mandated and voluntary audits.¹⁶⁵ Finally, I note the potential for trade secret law to be used as a shield against such audits, and I argue that audits by an independent auditing body would serve to allay any fears as to the misuse of proprietary information. These measures will aid in data retention to help compile the statistical proof required by disparate impact claimants, and an independent external auditing mandate would help to maintain the intellectual property law shield for proprietary automated systems. They will also level the field for disparate impact claimants and eliminate the current Sisyphean climb to proving discrimination on the basis of disparate impact.

A. The Uphill Climb for Disparate Impact Claims

As several legal scholars have demonstrated through empirical data, plaintiffs aiming to bring an employment discrimination claim on a theory of disparate impact, rather than disparate treatment, face an uphill battle.¹⁶⁶ Professor Michael Selmi assesses the disparate impact theory's legacy.¹⁶⁷ Based on an extensive empirical analysis of court cases, his article employs detailed statistics to demonstrate the

9000: *Algorithms, the Market, and the Need to Prevent the Engraining of Bias*, 15 NW. J. TECH. & INTELL. PROP. 215, 222 (2018).

165. See *infra* Part V.

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

167. Michael Selmi, *Was the Disparate Impact Theory a Mistake?*, 53 UCLA L. REV. 701 (2006).

difficulty of proving disparate impact cases.¹⁶⁸ The disparate impact theory initially arose to deal with specific practices, such as seniority systems and written tests, that were perpetuating intentional discrimination.¹⁶⁹ Even though courts have not restricted the theory to those particular contexts, it has “proved an ill fit for any challenge other than to written examinations.”¹⁷⁰

Selmi finds that the Supreme Court “had rejected more challenges than it had accepted, and it had largely limited the theory to its origins — namely testing claims and perhaps some other objective procedures capable of formal validation,” by the end of the first decade of disparate impact theory.¹⁷¹ The following two decades further confirmed the theory’s limited reach.¹⁷² This limited reach is “particularly significant,” considering that employment discrimination claims in general are already “notoriously difficult to prove.”¹⁷³ Selmi notes that “if intentional discrimination is difficult to prove with existing circumstantial evidence,” it will be even more difficult for society to accept unintended negatives effects as racism.”¹⁷⁴ Based on the belief that the disparate impact theory was a mistake, Selmi suggests that a broader judicial definition of intent would have “opened our eyes to the persistence of discrimination in a way that the disparate impact theory could not.”¹⁷⁵

Similarly, Professor Sandra Sperino provides exhaustive case law evidence of a defendant-friendly bias to the adjudication of disparate impact cases and discusses the development of disparate impact theory.¹⁷⁶ For example, the Supreme Court in *Griggs v. Duke Power Co.* recognized the disparate impact theory of employment discrimination under Title VII by indicating that “good intent or absence of discriminatory intent does not redeem employment procedures or testing mechanisms that operate as ‘built-in headwinds’ for minority groups and are unrelated to measuring job capability.”¹⁷⁷ Later, in *Wards Cove Packing Co. v. Atonio*, the Court “tipp[ed] the scales in favor of employers” by “placing the burden of persuasion on the plaintiff and by requiring the employer only to articulate a legitimate reason for its conduct.”¹⁷⁸ Moreover in *Smith v. City of*

168. *See id.* at 734–39.

169. *See id.* at 705.

170. *Id.*

171. *Id.* at 733.

172. *Id.* at 734.

173. *See id.*

174. *Id.* at 768.

175. *Id.* at 782.

176. Sandra F. Sperino, *Disparate Impact or Negative Impact?: The Future of Non-Intentional Discrimination Claims Brought by the Elderly*, 13 *ELDER L.J.* 339 (2005).

177. *Id.* at 348 (quoting *Griggs v. Duke Power Co.*, 401 U.S. 424, 432 (1971)).

178. *Id.* at 349 (quoting *Wards Cove Packing Co. v. Atonio*, 490 U.S. 642, 673 (1989) (Stevens, J., dissenting)).

Jackson, the Supreme Court, while recognizing that disparate impact is a viable claim under the Age Discrimination in Employment Act of 1967 (“ADEA”),¹⁷⁹ “affirmed the dismissal of the petitioners’ claims, finding that they had not produced enough evidence to prevail on a disparate impact claim.”¹⁸⁰ According to Justice O’Connor, the Court in *Wards Cove Packing* signaled a defendant-friendly analysis by first requiring the plaintiff to establish that the application of a particular employment practice created a disparate impact, then requiring the employer to produce evidence that “its action was based on a reasonable nonage factor,” and lastly mandating the plaintiff to bear the burden of disproving the company’s assertion.¹⁸¹

Sperino notes that, in reality, disparate impact claims appear to have been disfavored even before the *Smith* case.¹⁸² Litigants arguing a disparate impact case “face significant initial costs that are either absent or are less significant in a disparate treatment case”; “the reliance on statistical evidence requires plaintiffs to obtain large amounts of data from the defendant and other sources.”¹⁸³ Furthermore, the necessary evidence required by the plaintiff “is largely in the hands of the defendant and must be sought through the discovery process.”¹⁸⁴ Because defendants are often reluctant to produce the information voluntarily, the process of collecting and analyzing statistical evidence is “both complex and arduous.”¹⁸⁵

Both Selmi’s and Sperino’s research offers grist for a re-imagining of redress mechanisms for employment discrimination. First, I concur with Selmi’s conclusions here regarding the need for a more expansive definition of intent in proving employment discrimination cases. This is why, in another article, I have proposed a new theory of action, *discrimination per se*, which takes into account the particular difficulties of proof presented when a plaintiff is seeking to challenge an employer’s use of an automated hiring system for employment discrimination.¹⁸⁶ Discrimination *per se* would effectively operate as a third cause of action under Title VII.¹⁸⁷ Per my proposal,

179. *Id.* at 354 (citing *Smith v. City of Jackson*, 544 U.S. 228, 228 (2005)).

180. *Id.* (quoting *Smith*, 544 U.S. at 242).

181. *See id.* at 359 (citing *Smith*, 544 U.S. at 252 (O’Connor, J., concurring)).

182. *See id.* at 359–60.

183. *Id.* at 360.

184. *Id.* at 360–61.

185. *Id.* at 361 (quoting *Hill v. Miss. State Emp’t Serv.*, 918 F.2d 1233, 1238 (5th Cir. 1990)).

186. *See Ajunwa, supra* note 6, at 1727–28.

187. Title VII of the Civil Rights Act of 1964 protects the job applicant against discrimination on the basis of sex, race, color, national origin, and religion. *See* 42 U.S.C. §§ 2000e–2000e-17. Plaintiffs must establish that “a respondent uses a particular employment practice that causes a disparate impact on the basis of [a protected characteristic] and the respondent fails to demonstrate that the challenged practice is job related for the position in question and consistent with its business necessity.” 42 U.S.C. § 2000e-2(k)(1)(A)(i).

a plaintiff can assert that a hiring practice (for example, the use of proxy variables in automated hiring resulting in or *with the potential to result in* adverse impact to protected categories) is so egregious as to amount to *discrimination per se*, and this would shift the burden of proof from the plaintiff to the defendant (employer) to show that its practice is non-discriminatory.¹⁸⁸

This burden-shifting eliminates the uphill climb confronting disparate impact claimants during which they must procure sufficient statistical evidence of disproportionate impact.

However, even with the proposed theory of discrimination *per se* as help for the plaintiff, Sperino's point that plaintiffs of employment discrimination cases are disadvantaged by the necessary reliance on the employer to provide the very data they need to prove their case still stands. A major thread that runs through the dismissed cases on automated hiring is the court's finding of a lack of evidence or the inability of the plaintiff to provide proof of their allegations of discrimination.

Consider the case of *Gladden v. Bolden*.¹⁸⁹ Warren Gladden, an African American male, filed suit against NASA alleging race and age discrimination in violation of Title VII and ADEA.¹⁹⁰ He argued that the automated hiring system used by NASA, Resumix, had a selection process that was discriminatory as his resume was not moved forward in the hiring process even though he claimed he had "extensive" experience.¹⁹¹ However, NASA testified that the Resumix system did not take race, gender, or age into account when it was analyzing and scoring resumes.¹⁹² The court thus dismissed the plaintiff's complaint, citing a lack of evidence.¹⁹³

In yet another case, *Vazirabadi v. Denver Health*,¹⁹⁴ the plaintiff Alireza Vazirabadi brought suit against Denver Health alleging discrimination on the basis of age and national origin. Vazirabadi alleged that he had selected "yes" for a voluntary question on the online application which asked if he was more than forty years old.¹⁹⁵ Also, another question on the online application form asked about foreign

188. Ajunwa, *supra* note 6, at 1728.

189. 802 F. Supp. 2d 209 (D.D.C. 2011).

190. *Id.* at 210.

191. *Id.* at 211.

192. *See id.*

193. *Id.* at 214–15.

194. *Vazirabadi v. Denver Health & Hosp. Auth.*, No. 17-cv-01737, 2018 U.S. Dist. LEXIS 229111, at *2–3 (D. Colo. Oct. 11, 2018).

195. *Id.* at *2.

language skills, and he had indicated that he was fluent in Farsi.¹⁹⁶ Vazirabadi submitted a charge of discrimination with the EEOC when he was not hired and the company hired a 34-year-old Caucasian and a 28-year-old Hispanic, for the two positions he had applied for.¹⁹⁷ The court found, however, that Vazirabadi had not provided sufficient evidence to support his claim, and that his allegations were based “solely on conjecture.”¹⁹⁸ Thus, the court approved the hospital’s motion for summary judgment and dismissed the case.¹⁹⁹

The difficulties of proof for applicants regarding discrimination via automated hiring systems are further exacerbated by intellectual property law and the CFAA.

B. Intellectual Property Law and the CFAA

Any attempt by plaintiffs to access proof of discrimination in automated hiring systems may be stymied by extant laws, such as intellectual property law and the Computer Fraud and Abuse Act (“CFAA”), both of which have been invoked by the makers of automated decision-making systems as shields to scrutiny.²⁰⁰ Corporations, claiming trade secret, have invoked intellectual property law to prevent the disclosure of information related to their proprietary algorithms.²⁰¹ Similarly, the CFAA could be read to protect automated systems from outside audits with the argument that such audits violate the terms of service for the systems.²⁰² Although the ACLU has brought

196. *See id.*

197. *Id.* at *2–3.

198. *Id.* at *24.

199. *See id.* at *25.

200. As an example of intellectual property law, Section 1201 of the Digital Millennium Copyright Act (“DMCA”) creates liability for hacking or reverse engineering an automated system protected under copyright law. 17 U.S.C. § 1201; *see also* Perel & Elkin-Koren, *supra* note 126, at 526 (noting the chilling effect on researchers who would like to reverse engineer automated processes, given the potential to incur liabilities); Rebecca Wexler, *Life, Liberty, and Trade Secrets: Intellectual Property in the Criminal Justice System*, 70 STAN. L. REV. 1343, 1395 (2018); Rebecca Wexler, *When a Computer Program Keeps You in Jail*, N.Y. TIMES (June 13, 2017), <https://www.nytimes.com/2017/06/13/opinion/how-computers-are-harming-criminal-justice.html> [<https://perma.cc/BMW4-XPQ6>]; Elizabeth E. Joh, *The Undue Influence of Surveillance Technology Companies on Policing*, 92 N.Y.U. L. REV. 19, 43 (2017) (discussing how trade secret law can protect policing algorithms from scrutiny); Sonia Katyal, *supra* note 4, at 117 (discussing the same and suggesting a whistleblowing framework to enable disclosure of biased algorithms).

201. For example, Nicole Wong, in her role as Google’s Associate General Counsel, has stated that “Google avidly protects every aspect of its search technology from disclosure.” Nicole Wong, *Response to the DoJ Motion*, OFFICIAL GOOGLE BLOG (Feb. 17, 2006), <https://googleblog.blogspot.com/2006/02/response-to-doj-motion.html> [<https://perma.cc/SC5K-72T8>].

202. 18 U.S.C. § 1030(a)(2)(C). Circuits have interpreted the CFAA in divergent ways. *Compare* *Brown Jordan Int’l, Inc. v. Carmicle*, 846 F.3d 1167, 1174–75 (11th Cir. 2017), *and* *United States v. John*, 597 F.3d 263, 272 (5th Cir. 2010), *and* *Int’l Airport Ctrs., L.L.C. v. Citrin*, 440 F.3d 418, 420–21 (7th Cir. 2006), *and* *EF Cultural Travel BV v. Explorica, Inc.*,

suit on behalf of several academic researchers aiming to audit such systems and has alleged that the CFAA is unconstitutionally overbroad,²⁰³ there has yet to be a proposed solution to the argument that trade secret laws may also serve as an impediment to the auditing of decision-making algorithms.²⁰⁴

Similarly, Professors Lilian Edwards and Michael Veale discuss the concerns about the disparate impact of machine learning algorithms and the attendant calls for transparency.²⁰⁵ They claim that the argument against opacity as “right to an explanation” under the General Data Protection Regulation (“GDPR”) of the European Union is ineffective and blocks the ability for recourse.²⁰⁶ The authors also suggest the need for “subject-centric” explanations, which focus on a select region of a model, as explanation systems, because such explanations can not only reveal more but could also circumvent any developer’s intellectual property or trade secret concerns.²⁰⁷

Given that it would take time to carve out exceptions to intellectual property law and the CFAA framework,²⁰⁸ I argue then, that as a pragmatic matter, an independent third-party auditor, that pledges to keep secret any trade secret information it obtains in the auditing process, and which is buoyed by the labor market preferences of job applicants, may afford a more immediate approach to addressing the issues of transparency and accountability for automated hiring systems.

274 F.3d 577, 582–84 (1st Cir. 2001) (adopting a broad interpretation of “exceed[ing] authorized access”), *with* *United States v. Valle*, 807 F.3d 508, 528 (2d Cir. 2015), *and* *United States v. Nosal*, 676 F.3d 854, 862–63 (9th Cir. 2012), *and* *WEC Carolina Energy Sols. LLC v. Miller*, 687 F.3d 199, 207 (4th Cir. 2012) (rejecting a broader interpretation). And despite its holding in *Nosal* rejecting a broad interpretation of the CFAA, the Ninth Circuit recently held that continuing to access a website after receiving a cease-and-desist letter created liability under the CFAA. *Facebook, Inc. v. Power Ventures, Inc.*, 844 F.3d 1058, 1069 (9th Cir. 2016) (“But when Facebook sent the cease-and-desist letter, Power, as it conceded, knew that it no longer had permission to access Facebook’s computers at all. Power, therefore, knowingly accessed and without permission took, copied, and made use of Facebook’s data.”). The Supreme Court recently denied Power Ventures’ petition for certiorari, *Power Ventures, Inc. v. Facebook, Inc.*, 138 S. Ct. 313 (2017) (mem.); *Power Ventures* would have provided the Court with its first opportunity to bridge the gulf between broad and narrow interpretations of 18 U.S.C. § 1030(a)(2)(C).

203. *See* Complaint at 4, *Sandvig v. Lynch*, No. 16-cv-01368 (D.D.C. June 29, 2016).

204. Wexler, *Life, Liberty, and Trade Secrets*, *supra* note 200, at 1429.

205. Lilian Edwards & Michael Veale, *Slave to the Algorithm: Why a Right to an Explanation Is Probably Not the Remedy You Are Looking for*, 16 DUKE L. & TECH. REV. 18, 19–22 (2017).

206. *Id.* at 44.

207. *Id.* at 56–57.

208. Note that one scholar advocates for exceptions to copyright law that would allow for scrutiny of decision-making algorithms by third parties without violating the CFAA and also allow for otherwise copyrighted material to be used as part of the training data for algorithmic systems. Amanda Levendowki, *How Copyright Law Can Fix Artificial Intelligence’s Implicit Bias Problem*, 93 WASH. L. REV. 579, 594–96 (2018). My approach focuses on the idea of a certified third-party auditor that would alleviate the concerns regarding proprietary information and does not necessarily require a change in existing framework — a fraught and contentious process. *See infra* Section V.

C. Recognizing an Affirmative Duty

I argue here that any affirmative duty of care imposed on an employer should carry also an auditing imperative for automated hiring systems. But first: Is there an affirmative duty of care for employers? From what legal basis is this duty of care derived?

Over the last several decades, legal scholars have begun calling for the application of tort law to the framework through which we understand employment discrimination. Professor David Benjamin Oppenheimer first noted that the Supreme Court's primary theories of employment discrimination could readily be analogized to intentional tort and strict liability doctrines.²⁰⁹ Then, Oppenheimer elaborates on this analogy, arguing that employment discrimination can most aptly be compared to the tort doctrine of negligence.²¹⁰

First, Oppenheimer argues that the theory of unconscious racism must be applied to employment discrimination.²¹¹ Through this theory, Oppenheimer explains that racist acts are often the product of unconscious bias and stereotyping — not conscious decisions.²¹² As such, humans may not even be aware that they are making such judgments, while their actions still reflect their unconscious perceptions.²¹³ Effectively, this opens the door for people to have unconscious biases that impact others in a negative way.²¹⁴

Oppenheimer then parallels this notion to the idea of employment discrimination, arguing that employers may not consciously hold racist or discriminatory views, but nonetheless discriminate in their conduct towards employees.²¹⁵ He observes a swift upward trend towards most white Americans professing a commitment to nondiscrimination in employment.²¹⁶ Yet, Title VII and other statutory prohibitions of race discrimination are still necessary because racism is often an unconscious bias.²¹⁷ Furthermore, supporting the principle of nondiscrimination in employment does not necessarily mean that all white Americans are also in support of federal enforcement of employment discrimination laws.²¹⁸ In fact, based on one study,

209. See *Negligent Discrimination*, *supra* note 28, at 899.

210. *Id.*

211. *Id.* at 900–01.

212. *Id.* In fact, a person's attempt to understand his or her relationship to the world often necessarily means the person must categorize other individuals and draw comparisons between himself or herself and others. *Id.* at 901. People learn this skill from a very young age, such that making snap judgments about others becomes part of the way their brains work. *Id.* at 902.

213. *Id.*

214. See *id.*

215. *Id.*

216. *Id.* at 903.

217. See *id.*

218. See *id.* at 905.

Oppenheimer suggests that 97% of the support for nondiscrimination is an “empty gesture,” meaning white Americans often do not back up the “support” they suggest in surveys.²¹⁹ Similarly, while many white Americans had attested that they were committed to nondiscrimination, they were similarly more likely to describe African Americans as being more “lazy” and less “honest” than other Americans.²²⁰ Using these studies, Oppenheimer concludes that white Americans are frequently unaware of their own internal racism.²²¹

Oppenheimer then argues that a theory of employment discrimination that focuses on intent to discriminate can provide no remedy for most discrimination, because there often is no intent involved.²²² The intent requirement is ultimately based on a false binary — “[w]hen Congress enacted Title VII it provided little guidance on the standard that courts should require for proof of discrimination.”²²³ The Supreme Court supplemented this by dividing discrimination cases into claims that looked like intentional torts, and others that looked more like strict liability.²²⁴

With this in mind, Oppenheimer provides an analysis of *Griggs v. Duke Power Co.*, a case applying the strict liability employment law theory.²²⁵ Here, the Supreme Court emphasized the importance of the “consequences of employment practices, not simply the motivation.”²²⁶ As such, it found that the employer was strictly liable for its unintended but harmful conduct, without using the words “strict liability.”²²⁷

Next, Oppenheimer delves into the idea of the intentional tort, which presented itself in the *McDonnell Douglas* case.²²⁸ In this case, the Supreme Court held that in an individual discrimination case, the plaintiff must prove an intent to discriminate by showing, for example, that “she was qualified for an open job which remained open after her rejection.”²²⁹ After this point, employers can defend themselves by showing that there was a legitimate nondiscriminatory reason for their decisions.²³⁰

219. *Id.*

220. *Id.* at 910.

221. *Id.* at 916.

222. *Id.*

223. *Id.* at 919.

224. *Id.* (citing *McDonnell Douglas Corp. v. Green*, 411 U.S. 792 (1973) (explaining that where an employee challenges a specific employment decision, she must prove it was motivated by an intent to discriminate); *Griggs v. Duke Power Co.*, 401 U.S. 424 (1971) (explaining that where an employee challenges policies or procedures that have a discriminatory effect, she may rely on strict liability theory rather than having to prove intentional discrimination)).

225. *Id.* at 920 (citing *Griggs*, 401 U.S. 424).

226. *See id.* at 921 (quoting *Griggs*, 401 U.S. at 432).

227. *See id.*

228. *See id.* at 922.

229. *See id.* (citing *McDonnell Douglas*, 411 U.S. at 802).

230. *See id.* at 922–23 (citing *McDonnell Douglas*, 411 U.S. at 802).

Yet the Supreme Court began to articulate a third approach to the adverse impact and strict liability doctrines — the less discriminatory alternative doctrine.²³¹ In these cases, a plaintiff could prevail if she could show that “other selection devices without a similar discriminatory effect would also serve the employer’s legitimate interest.”²³² Oppenheimer argues that this test opened the door for the application of the doctrine of negligence to employment discrimination case.²³³ He explains that “[n]egligence, at its core, is the breach of a duty recognized by law for the protection of others.”²³⁴ Employers often have this duty — for example, the duty to provide a safe workplace or to protect employees from unfit co-employees or supervisors.²³⁵ Then, he argues that the employment relationship is a “special relationship,” such that both employees and employers enter into the employment relationship with care and owe each other certain duties.²³⁶ Here, employers could be responsible for not protecting employees from discriminatory practices.²³⁷

Oppenheimer also compares this duty to the duty to accommodate differences, found in *Teamsters*, where the Court discussed the liability of failing to act.²³⁸ Though the duty of care has largely been used in the context of religious accommodations, any employer who failed to prevent discrimination from occurring could ostensibly be held liable.²³⁹ In fact, after years of unsuccessful sexual harassment claims, the EEOC began applying the liability for failure to act — for example, in the case of workplace sexual harassment, an employer may be responsible for the acts of non-employees, with respect to “sexual harassment . . . in the workplace, where the employer . . . knows or should have known of the conduct and fails to take immediate and appropriate corrective action.”²⁴⁰ Through an evolving landscape of the law, Oppenheimer demonstrates that negligent discrimination is potentially closer to practice than we think.

Oppenheimer’s ideas opened the door for other legal scholars to explore the application of tort law to employment discrimination, as well as the possibility of a duty for employers to prevent discrimination.

231. *See id.* at 931.

232. *See, e.g.,* *Grant v. Bethlehem Steel Corp.*, 635 F.2d 1007, 1015 (2d Cir. 1980).

233. *See Negligent Discrimination, supra* note 28, at 932.

234. *Id.*

235. *Id.* (citing *Hentzel v. Singer Co.*, 188 Cal. Rptr. 159, 164 (Cal. Ct. App. 1982) (safe workplace); *Najera v. S. Pac. Co.*, 13 Cal. Rptr. 146, 148 (Cal. Ct. App. 1961) (unfit co-employees and supervisors)).

236. *Id.* at 932–33 (citing RESTATEMENT (SECOND) OF TORTS § 314B (1965)).

237. *See id.* at 933.

238. *See id.* at 936.

239. *See Dewey v. Reynolds Metals Co.*, 429 F.2d 324, 330 (6th Cir. 1970), *aff’d*, 402 U.S. 689 (1971) (per curiam) (testing the duty to accommodate religious beliefs).

240. 29 C.F.R. § 1604.11(e) (2020); *see also Negligent Discrimination, supra* note 28, at 956.

One example of such exploration is a 2009 article by Professor Noah D. Zatz, which confronted the idea that employers have a duty to do more than simply respond when employees are harassed or discriminated against by outsiders.²⁴¹ To begin, Zatz explains the case of *Dunn v. Washington County Hospital*, in which an employee sued her employer for sex discrimination after she made a complaint to the hospital that an independent contractor at the hospital — therefore, a third party — was sexually harassing her and the hospital did not act.²⁴² Here, the Seventh Circuit stated that “[t]he employer’s responsibility is to provide its employees with nondiscriminatory working conditions. The genesis of inequality matters not; what *does* matter is how the employer handles the problem.”²⁴³ This notion seems to expand far beyond that of an employer’s duty to maintain a non-discriminatory environment, extending even to actors outside of the employer’s direct control.²⁴⁴

Interestingly, Zatz’s theory also rejects some long-held beliefs about Title VII — notably that there has to be either disparate treatment or disparate impact in order to prove discrimination, an idea which Oppenheimer had also rejected in his analysis of *Griggs* and *McDonnell Douglas*.²⁴⁵ In fact, by analyzing the treatment of third parties in discrimination cases, Zatz suggests that there is, and should be, an entirely separate doctrine for cases of non-accommodation, where the employer refuses to reasonably accommodate employee’s complaints of discrimination.²⁴⁶ To make this point, Zatz argues that by providing reasonable accommodations and refraining from disparate treatment, employers can prevent “membership causation,” a phrase used to describe when an employee suffers workplace harm due to her membership in a protected class, regardless of where that harm comes from.²⁴⁷ Then, because the employer is capable of preventing membership causation, Zatz explains that the employer should be liable for workplace harm when it does occur.²⁴⁸ Though Zatz focuses primarily on the application of this doctrine to third parties, his message is clear — employers have a duty to prevent discrimination in the workplace, and should be held liable when they fail to do so.

In addition to Professors Oppenheimer and Zatz, Professor Charles Sullivan similarly finds a corollary between tort law and employment law regarding the question of imposed duties for employers. In his 2012 article, Sullivan focuses primarily on the idea of discrimination as an

241. *Managing the Macaw*, *supra* note 29, at 1359.

242. *Id.* at 1359 (citing *Dunn v. Wash. Cnty. Hosp.*, 429 F.3d 689, 689–90 (7th Cir. 2005)).

243. *Id.* (quoting *Dunn*, 429 F.3d at 691).

244. *See id.* at 1360.

245. *See Negligent Discrimination*, *supra* note 28, at 919.

246. *See Managing the Macaw*, *supra* note 29, at 1362.

247. *See id.*

248. *See id.* at 1364.

intentional tort.²⁴⁹ The article primarily details one case, *Staub v. Proctor Hospital*, in which the Supreme Court further wrote tort law into antidiscrimination statutes by explicitly adopting tort law's definition of intent for statutory discrimination cases.²⁵⁰ However, instead of easing the notion of discriminatory intent like many perceived *Staub* to do, Sullivan argues that *Staub* actually adds another layer to the plaintiff's burden.²⁵¹

The plaintiff in *Staub* was fired by his employer because of his service in the military,²⁵² which was unlawful under the Uniformed Services Employment and Reemployment Rights Act.²⁵³ Sullivan notes that *Staub* will govern cases under more traditional antidiscrimination statutes, including Title VII, as they provide similar language for antidiscrimination claims.²⁵⁴ Both statutes place the burden of persuasion on the plaintiff, and will not allow damages if the employer meets its burden of showing that it would have made the same decision regardless of the protected characteristic.²⁵⁵

Analyzing the employment discrimination claim, Justice Scalia held that if a supervisor performed an act motivated by discriminatory animus that was "intended by the supervisor to cause an adverse employment action, and if that act is a proximate cause of the ultimate employment action, then the employer is liable."²⁵⁶ As Sullivan notes, this is the first time the language of tortious intent had been brought directly into the employment law context.²⁵⁷ Sullivan argues that this case left open many questions as to what the employer's actual duties are.²⁵⁸ For example, where Zatz had argued for liability arising from third parties, Sullivan notes that under this intent-based analysis, it is unclear whether an employer could even be liable for the actions of subordinates.²⁵⁹ Sullivan's analysis raises the question of how far tort law can truly be integrated into employment discrimination law, at least without also requiring a duty to prevent discrimination.

Professor Richard Thompson Ford similarly mulled over the question of intent as part of employment discrimination. Ford argues

249. Charles Sullivan, *Tortifying Employment Discrimination*, 92 B.U. L. REV. 1431 (2012) [hereinafter *Tortifying Employment Discrimination*].

250. See *Staub v. Proctor Hosp.*, 562 U.S. 411, 417 (2009).

251. *Tortifying Employment Discrimination*, *supra* note 249, at 1431–32.

252. See *Staub*, 562 U.S. at 411.

253. See *Tortifying Employment Discrimination*, *supra* note 249, at 1435 (citing Pub. L. No. 103-353, 108 Stat. 3153 (codified at 38 U.S.C. §§ 4301–35)).

254. See *id.* at 1435–36 (citing *Staub*, 562 U.S. at 417) (clarifying that both statutes "declare it is unlawful for the specified grounds to be a 'motivating factor' for the challenged employment action," among other similar language).

255. See *id.* at 1436.

256. *Id.* at 1439–40 (quoting *Staub*, 562 U.S. at 422).

257. See *id.* at 1433.

258. See *id.* at 1448.

259. See *id.*

precisely for how to fill the gap that Oppenheimer had described — “abandon[ing] conceptual disputes over ‘discrimination’ in favor of [discussing] the employer’s affirmative duty to avoid decisions and policies that [harm] underrepresented or stigmatized groups.”²⁶⁰ Ford begins his argument with the notion of civil rights as the idea that we should protect individuals from potentially oppressive states.²⁶¹ Over time, he explains, the law has gradually grown to protect individuals not just from oppressive states but also oppressive private institutions.²⁶² By assigning rights to overcome these private actors, he argues that having legal rights does not mean that an individual is specially protected against power.²⁶³ Instead, these rights are a political decision to assign power from one group to another.²⁶⁴ This is the notion that drove change throughout the civil rights era of the American 1960s.²⁶⁵

Today, one of these rights is the right not to be discriminated against in employment based on certain prohibited reasons, including race, sex, religion, etc.²⁶⁶ Yet, while the law states that employers must not discriminate on certain enumerated bases, Ford observes that the law also creates a duty of care, though this duty has been largely undefined.²⁶⁷ Lacking a definition, the bounds of an employer’s duty of care have been debated. Traditionally, the idea has been that employers would only be liable for discrimination that they can prevent as institutions but could not be liable for the discrimination they — the entities themselves — did not cause.²⁶⁸ This means that employers are simply encouraged to avoid decisions that undermine social equality but are not actually encouraged to promote social equality.²⁶⁹

However, even when employers have reasonable anti-harassment or antidiscrimination policies, employees still may face harassment or discrimination.²⁷⁰ That injustice is no different for the individual simply because the employer has an antidiscrimination policy.²⁷¹ As such, Ford argues that the law should address the outcomes openly by defining the employer’s duty of care.²⁷² For example, he suggests a

260. *Rethinking Rights*, *supra* note 25, at 2942.

261. *See id.* at 2946.

262. *See id.* (citing *Marsh v. Alabama*, 326 U.S. 501, 507 (1946) (applying constitutional standards to private entities that serve a “public function”); *Shelley v. Kraemer*, 334 U.S. 1 (1948) (extending constitutional rights to private action)).

263. *See id.*

264. *See id.*

265. *See id.* at 2949.

266. 42 U.S.C. §§ 2000e–2000e-17.

267. *See Rethinking Rights*, *supra* note 25, at 2950–51.

268. *See id.* at 2956.

269. *See Bias in the Air*, *supra* note 25, at 1388.

270. *See Rethinking Rights*, *supra* note 25, at 2957.

271. *See id.* at 2957–58.

272. *See id.* at 2959.

policy change that would reward employers who hire members of underrepresented groups, instead of making it more “risky” to hire such people for desire to protect the company from liability.²⁷³ Similarly, a manager who discriminates in the workplace, where the employer has a reasonable antidiscrimination policy, has acted outside the scope of his authority and should be liable for that action independently.²⁷⁴ In effect, Ford argues for a complete overhaul of the system of antidiscrimination law in favor of policy that hits at the source of the outcomes that employment law actively tries to prevent.

Following in the footsteps of these legal scholars, I argue that in the age of automated decision-making that we now live in, an auditing imperative assigned to the use of automated hiring system is one way to delineate the employer’s affirmative duty of care. This auditing imperative demands certain actions on the part of the employers as well as the designers of automated hiring systems. Below, I detail a hybrid approach to the redress of employment discrimination that, although not doing away entirely with the intent requirement, focuses on alternative means to prevent employment discrimination, by requiring external and internal audits, mandating design elements that allow for record keeping and data retention as the standard mode for automated hiring, and allowing for collective bargaining by workers to set the terms of use of automated hiring in the workplace.

V. A HYBRID APPROACH

As described above, the problems with automated hiring go beyond the scope of issues that could typically be addressed through litigation. Thus, any attempts to remedy those problems must necessarily adopt a hybrid approach. I set forth two proposed hybrid measures: (1) mandated audits (both external and internal, which will enable litigation), and (2) collective bargaining, which could serve three ends: encouraging fairness by design for automated hiring systems by pushing for embedded data-retention mechanisms; including probative criteria in hiring to ensure that criteria is not merely a stand-in for class membership; and negotiating for data control and checks on data portability to prevent the algorithmic blackballing of employees. I also address some potential objections to these proposed measures.²⁷⁵

273. *See id.* at 2960.

274. *See Bias in the Air*, *supra* note 25, at 1417.

275. Note that one scholar advocates for exceptions to copyright law that would allow for scrutiny of decision-making algorithms by third parties without violating the CFAA and also allow for otherwise copyrighted material to be used as part of the training data for algorithmic systems. My approach focuses on the idea of a certified third-party auditor that would alleviate the concerns regarding proprietary information, and does not necessarily require a change in existing framework — a fraught and contentious process.

The auditing of automated decision-making systems is an idea that is gaining ground.²⁷⁶ This is especially true with regard to employment decision-making, as several experts working in the field support the idea of mandated audits for automated hiring systems. One quibble is whether such audits should be internal or external. Meredith Whittaker, co-founder of the AI Now Institute at New York University and founder of Google’s Open Research group, notes that “AI is not impartial or neutral” and suggests that “in the case of systems meant to automate candidate search and hiring, we need to ask ourselves: What assumptions about worth, ability and potential do these systems reflect and reproduce? Who was at the table when these assumptions were encoded?”²⁷⁷ She also observes that because “systems like HireVue are proprietary and not open to review,” there is no way to “validate their claims of fairness and ensure they aren’t simply tech-washing and amplifying longstanding patterns of discrimination[.]”²⁷⁸ Thus, she insists on the need for audits by experts, advocacy groups, and academia.²⁷⁹

In response to this concern, Loren Larsen, Chief Technology Officer of HireVue, admits that it is very important to audit the algorithms used in hiring to identify and correct for any bias but argues

276. See *Auditing Algorithms*, *supra* note 21, at 191 (proposing the retention of audits of automated decision-making to check for discrimination); Julie E. Cohen, *The Regulatory State in the Information Age*, 17 THEORETICAL INQUIRIES L. 369, 372–73 (2016) (“[P]olicymakers must devise ways of enabling regulators to evaluate algorithmically-embedded controls . . .”); Deven R. Desai & Joshua A. Kroll, *Trust but Verify: A Guide to Algorithms and the Law*, 31 HARV. J.L. & TECH. 1, 16–17 (2017) (discussing designing algorithmic systems to enable audits by regulators); Citron & Pasquale, *supra* note 126, at 24–25 (proposing that the Federal Trade Commission (“FTC”) audit consumer scoring systems); Frank Pasquale, *Beyond Innovation and Competition: The Need for Qualified Transparency in Internet Intermediaries*, 104 NW. U. L. REV. 105, 169–71 (2010) (calling for monitoring of search engines and considering the possibility of the FTC playing that role); W. Nicholson Price II, *Regulating Black-Box Medicine*, 116 MICH. L. REV. 421, 464–65 (2017) (calling for greater FDA and third-party scrutiny of medical algorithms); Paul Schwartz, *Data Processing and Government Administration: The Failure of the American Legal Response to the Computer*, 43 HASTINGS L.J. 1321, 1325 (1992) (calling for “independent governmental monitoring of data processing systems”); Rory Van Loo, *Helping Buyers Beware: The Need for Supervision of Big Retail*, 163 U. PA. L. REV. 1311, 1312–16 (2015) (proposing that the FTC monitor Amazon); Shlomit Yanisky-Ravid & Sean K. Hallisey, *Equality and Privacy by Design: A New Model of Artificial Intelligence Data Transparency Via Auditing, Certification, and Safe Harbor Regimes*, 46 FORDHAM URB. L.J. 428, 429 (2019) (proposing “an auditing regime and a certification program, run either by a governmental body or, in the absence of such entity, by private institutions”); see also Kate Crawford & Jason Schultz, *Big Data and Due Process: Toward a Framework to Redress Predictive Privacy Harms*, 55 B.C. L. REV. 93, 121–24 (2014) (considering auditing by public agencies to address predictive privacy).

277. Eric Rosenbaum, *Silicon Valley Is Stumped: Even A.I. Cannot Always Remove Bias from Hiring*, CNBC (May 30, 2018, 5:54 PM), <https://www.cnbc.com/2018/05/30/silicon-valley-is-stumped-even-a-i-cannot-remove-bias-from-hiring.html> [<https://perma.cc/L3TY-TAK9>].

278. See *id.*

279. See *id.*

that “[n]o company doing this kind of work should depend only on a third-party firm to ensure that they are doing this work in a responsible way [I]t is the responsibility of the company itself to audit the algorithms as an ongoing, day-to-day process.”²⁸⁰

Given the example of regulation in other jurisdictions, where for example the GDPR denotes algorithm audits as essential for the public good, particularly for protecting those who are already marginalized citizens,²⁸¹ or the example of the Sarbanes-Oxley Act which mandates auditor independence and also requires that internal officers certify financial reports quarterly,²⁸² I propose that corporations employing automated hiring systems should be mandated to engage in *both* internal *and* external audits of such systems, and I lay out the case for each type of audit in the following sections and also discuss the potential downfalls for each system.

A. Internal Auditing as Corporate Social Responsibility

A federal regime of mandated internal auditing will ensure that companies diligently review the outcomes of automated hiring and correct for any discovered bias. On August 19, 2019, a group of 181 business executives collaboratively working together as the Business Roundtable released a statement in which they recognized a responsibility beyond merely satisfying shareholders.²⁸³ Rather, the group, which included executives from Walmart, Apple, Pepsi, and others, acknowledged that they must also “invest in their employees, protect the environment and deal fairly and ethically with their suppliers.”²⁸⁴ Given this acknowledgement, I argue that internal audits to check automated hiring systems for bias are a key part of the corporate social responsibility (“CSR”) of business firms as this ensures that corporations are taking seriously their responsibility not to unlawfully discriminate against applicants.

280. *Id.*

281. *See id.* (“In recruiting — a space in which sensitive and life-changing decisions are made all the time in which we accordingly have established strong civil rights protections . . . algorithmic bias [is] especially important to detect and act against.”).

282. *See generally* The Sarbanes-Oxley Act of 2002, Pub. L. No. 107-204, 116 Stat. 745.

283. The statement begins: “Americans deserve an economy that allows each person to succeed through hard work and creativity and to lead a life of meaning and dignity. We believe the free-market system is the best means of generating good jobs, a strong and sustainable economy, innovation, a healthy environment and economic opportunity for all.” Statement on the Purpose of a Corporation, *Business Roundtable Redefines the Purpose of a Corporation to Promote ‘An Economy That Serves All Americans’*, BUS. ROUNDTABLE (Aug. 19, 2019), <https://www.businessroundtable.org/business-roundtable-redefines-the-purpose-of-a-corporation-to-promote-an-economy-that-serves-all-americans> [https://perma.cc/Q5PD-RYAY].

284. David Gelles & David Yaffe Bellany, *Shareholder Value Is No Longer Everything*, *Top C.E.O.s Say*, N.Y. TIMES (Apr. 19, 2019), <https://www.nytimes.com/2019/08/19/business/business-roundtable-ceos-corporations.html> [https://perma.cc/4ZWW-5XEE].

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. Such mandated self-audits would be similar to the mandated self-audits of financial institutions. In an internal audit activity,²⁸⁵ or self-auditing, 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.”²⁸⁶ 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.²⁸⁷

I note here that legislation similar to the audit regime I am proposing has been introduced by several members of the New York City Council. The proposed legislation, filed on February 27, 2020, would make it unlawful to sell or offer for sale in New York City an automated employment decision tool that does not comply with the stated provisions, including a requirement that the tool “shall be the subject of a bias audit conducted in the past year prior to selling or offering for sale such tool.”²⁸⁸ “Bias audit” is defined as “an impartial evaluation, including but not limited to testing, of an automated employment decision tool to assess its predicted compliance with the provisions of section 8-107 and any other applicable law relating to discrimination in employment.”²⁸⁹ Section 8-107 prohibits employment discrimination on the basis of “the actual or perceived age, race, creed, color, national origin, gender, disability, marital status, partnership status, caregiver status, sexual and reproductive health decisions, sexual orientation, uniformed service or immigration or citizenship status.”²⁹⁰ However, this is not a federal bill, it does not attach to federal employment antidiscrimination law, and even if passed, it would apply only in New York City.

During the writing of this Article, Senators Cory Booker and Ron Wyden also proposed the Algorithmic Accountability Act of 2019,²⁹¹ with Representative Yvette Clarke sponsoring an equivalent bill in the House, which comports with the auditing proposals I make here, but

285. By internal self-audit, I am referring here to audits that should be conducted by the hiring company, the putative employer.

286. THE INST. OF INTERNAL AUDITORS, INT’L STANDARDS FOR THE PROFESSIONAL PRACTICE OF INTERNAL AUDITING 23 (2016), <https://na.theiia.org/standards-guidance/public%20documents/ippf-standards-2017.pdf> [<https://perma.cc/9AP5-6CMW>].

287. *Id.*

288. Sale of Automated Employment Decision Tools, N.Y. City Counsel Int. No. 1894 (N.Y.C. 2020), <https://legistar.council.nyc.gov/LegislationDetail.aspx?ID=4344524&GUID=B051915D-A9AC-451E-81F8-6596032FA3F9&Options=ID> [<https://perma.cc/RJ9H-GQJK>].

289. *Id.*

290. N.Y. CITY ADMIN. CODE § 8-107 (2021).

291. Algorithmic Accountability Act of 2019, S.1108, 116th Cong. (2019).

which I argue are missing key elements that would allow such audits to be useful. Notably, the proposed bill makes no mention of record-keeping or data retention mandates for automated hiring. An audit that does not include all relevant data will be ineffectual. Furthermore, this proposed bill is lacking a collaborative aspect. My proposal for an “Fair Automated Hiring Mark,” which I explain in more detail below, encourages employers to be actively invested in ensuring that their automated hiring systems are not biased. In the Subsections below, I detail my proposal for electronic “tear-off sheets” that could both protect and embargo the demographic data of job applicants, and I discuss applicant selection and what guidelines should determine the variables deployed by automated hiring systems.

1. Tear-off Sheets: What Information is Needed for Verification?

Professors David Lehr and Paul Ohm note several issues with machine learning algorithms.²⁹² Notably, they observe that many machine learning algorithms suffer from the problem of “over-fitting,” which happens when “a statistical method . . . identif[ies] as legitimate correlations due to randomness, including outliers, in the training data — randomness that will not be the same in the real-world data to which the algorithm is eventually applied.”²⁹³ This presents a problem for making real-world predictions because “if certain variables take on non-randomly extremely high or low values in the training and test data, but not in real-world data, the rules an algorithm learns to make predictions in the former may fail on the latter.”²⁹⁴ Thus, an essential part of the internal audit check is verifying the accuracy of predictions made by the automated hiring system.

Another issue that an internal audit should check for is inherited bias in the automated hiring system that could have a disparate impact on protected categories of applicants. To ask for an employer to audit whether a hiring system has had an adverse impact on applicants who are members of a protected class represents a paradox, as employers are typically not allowed to collect that information at the hiring stage. Professor Ignacio Cofone notes this paradox and argues that the true solution is not just to regulate the “use” of the data, but to regulate the “acquisition” of such information.²⁹⁵

From an auditing standpoint, however, neither the use nor the acquisition of the information is as much a problem as the *lack* of such

292. See David Lehr & Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. DAVIS L. REV. 653, 670 (2017).

293. *Id.* at 684.

294. *Id.* (emphasis omitted).

295. Ignacio N. Cofone, *Algorithmic Discrimination Is an Information Problem*, 70 HASTINGS L.J. 1389, 1392 (2019) (emphasis omitted).

data. Thus, my proposal is a redesign of automated hiring system to have a “tear-off sheet” like traditional paper hiring used to have.²⁹⁶ This was an additional sheet that could be torn away from all paper applications before those applications were passed to the decision-maker. In the case of an automated hiring system, it is a simple method of writing code wherein demographic information (such as age, race, gender) is solicited from the job applicant but such protected information is segregated from the rest of the electronic application, and is embargoed, meaning decision-makers cannot access that information, until after a hiring decision has been made. Currently, many applications do solicit these types of demographic information, but only on a voluntary basis. This means that many applicants may choose not to share the information. Thus, my proposal is that provision of demographic information would be mandatory for automated hiring, and that a notice regarding the initial sequestration of said demographic information should be provided to applicants.

2. Enhancing Applicant Selection: What Standards Should Apply?

Standards and best practices already exist for conducting an effective internal audit.²⁹⁷ As an international professional association, the Institute of Internal Auditors (“IIA”) gives guidance on internal auditing.²⁹⁸ For an internal audit to be considered effective, it should achieve ten core principles, which include “[d]emonstrat[ing] competence and due professional care” and “[being] insightful, proactive, and future-focused.”²⁹⁹ Also, as listed in the Institute’s Code of Ethics, internal auditors are expected to uphold the following principles: integrity, objectivity, confidentiality, and competency.³⁰⁰ 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

296. The EEOC noted in an informal discussion letter that “tear-off sheets” are lawful under Title VII because of a legitimate need for the information for affirmative action purposes or to track applicant flow. *The EEOC Informal Discussion Letter*, U.S. EQUAL EMP. OPPORTUNITY COMM’N (Aug. 5, 2002), <https://www.eeoc.gov/foia/eeoc-informal-discussion-letter-78> [<https://perma.cc/58M2-BUND>].

297. *See, e.g., id.* at 1–3.

298. *See Core Principles for the Professional Practice of Internal Auditing*, INST. INTERNAL AUDITORS, <https://na.theiia.org/standards-guidance/mandatory-guidance/Pages/Core-Principles-for-the-Professional-Practice-of-Internal-Auditing.aspx> [<https://perma.cc/7GT6-AHGY>].

299. *Id.*

300. *See Code of Ethics*, INST. INTERNAL AUDITORS (Jan. 2009), https://na.theiia.org/standards-guidance/Public%20Documents/IPPF_Code_of_Ethics_01-09.pdf [<https://perma.cc/D6YK-JYE2>].

assessment by an independent reviewer from outside of the organization, respectively.³⁰¹

Internal audits are already commonplace in some industries. One genre of organizations that follow the IIA standards comprises bank and financial service companies.³⁰² I have previously compared the fiduciary duties of banks to the fiduciary duties of platforms who serve as information fiduciaries to the job applicants, who entrust such platforms with their personal data.³⁰³ In banks, internal audits are required not only in terms of financial reporting, but also regarding legal compliance and general effectiveness.³⁰⁴ Relevant institutions have constantly emphasized the independence of these audits. The 2001 guidelines of the Basel Committee on Banking Supervision, the principal agency establishing international banking standards, states that “[a] bank’s internal audit function must be . . . independent from the everyday internal control process.”³⁰⁵ Further, the guidance issued by a subcommittee of the Federal Reserve System emphasizes that such internal audit must “[be] independent from the day-to-day functioning of the bank and [have] access to all activities conducted by the banking organization.”³⁰⁶ In support of this, the manuals of the Federal Deposit Insurance Corporation, Officer of the Comptroller of the Currency, and Federal Financial Institutions Examination Council advocate that internal auditors report “solely and directly” to the audit committee.³⁰⁷ Given the risk of management interference, an audit committee should consist of outside directors, without reporting to their supervisors.³⁰⁸

Self-auditing is also conducted and recommended in other 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 self-audit is an “assessment of workplace hazards, controls, programs, and documents performed by a business owner or employee” in compliance with the Occupational

301. THE INST. OF INTERNAL AUDITORS, *supra* note 286; Matthew Bender, BANKS & THRIFTS: GOV’T ENFORCEMENT & RECEIVERSHIP § 5.04, 5–39 (2018).

302. Federal banking regulators suggest that the internal audit function be conducted according to professional standards. See Michael E. Murphy, *Assuring Responsible Risk Management in Banking: The Corporate Governance Dimension*, 36 DEL. J. CORP. L. 121, 136–37 (2011).

303. See Ifeoma Ajunwa, *Genetic Testing Meets Big Data: Torts and Contract Law Issues*, 75 OHIO ST. L.J. 1225 (2014).

304. See Murphy, *supra* note 302, at 136.

305. *Id.* at 137 (citing BASEL COMM. ON BANKING SUPERVISION, INTERNAL AUDIT IN BANKS AND THE SUPERVISOR’S RELATIONSHIP WITH AUDITORS 3 (2001)).

306. *Id.* at 138 (citing BASEL COMM. ON BANKING SUPERVISION, FRAMEWORK FOR INTERNAL CONTROL SYSTEMS IN BANKING ORGANISATIONS 20–21 (1998)).

307. See *id.* at 139; GARY M. DEUTSCH, RISK ASSESSMENTS FOR FINANCIAL INSTITUTIONS § 27A.03[11][c], 27A-47 (2017).

308. See Murphy, *supra* note 302, at 139.

Safety and Health Administration (“OSHA”) regulations.³⁰⁹ Occupational safety and health self-audits are already standard in the manufacturing sector, and there are suggestions to improve inter-rater reliability and accuracy in the process.³¹⁰ Furthermore, OSHA allows hiring a consultant within the company to perform self-audits when OSHA is not able to do an inspection immediately.³¹¹

3. The Benefits of Internal Audits

Others have noted that self-audits can enhance CSR.³¹² The four levels of CSR self-audit allow companies to examine their performance in relation to ad hoc policy, standard policy, planned policy, and evaluated and reviewed policy.³¹³ Furthermore, self-audits allow for strategic and operational business planning through identification of strengths and prevention of problems.³¹⁴ This genre of CSR 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.”³¹⁵

Safe harbor from antidiscrimination laws, which other scholars have considered,³¹⁶ can be another incentive for internal auditing. Yet, there is a question of whether internal audits alone (or even in conjunction with external audits) are adequate for ensuring safe harbor from antidiscrimination laws which other scholars have addressed. I, however, maintain that internal audits can confer other benefits besides safe harbor. I argue that rather than merely serving as a protectionist tool against employment discrimination lawsuits, internal audits would benefit 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.³¹⁷

309. Samuel C. Yamin, David L. Parker, Min Xi & Rodney Stanley, *Self-Audit of Lockout/Tagout in Manufacturing Workplaces: A Pilot Study*, 60 AM. J. IND. MED. 504, 504 (2017).

310. *Id.* at 504–06.

311. See *Martin v. Bally’s Park Place Hotel & Casino*, 983 F.2d 1252, 1252 (1993); Olivia K. LaBoda, *Dueling Approaches to Dual Purpose Documents: The Reaches of the Work Product Doctrine After Textron*, 44 SUFFOLK U. L. REV. 727, 737 (2011).

312. See Peter Kok, Ton van der Wiele, Richard McKenna & Alan Brown, *A Corporate Social Responsibility Audit within a Quality Management Framework*, 31 J. BUS. ETHICS 285, 291–93 (2001).

313. See *id.*

314. See *Self-Audit for Quality Improvement*, 18 STRATEGIC DIRECTION 5, 18 (2002).

315. *Id.*

316. See, e.g., Pauline Kim, *Safe Harbors for Algorithms?* (unpublished manuscript) (on file with author).

317. See Katherine W. Phillips, *Commentary* to EARL LEWIS, NANCY CANTOR, KATHERINE PHILLIPS & SCOTT E. PAGE, *THE DIVERSITY BONUS: HOW GREAT TEAMS PAY OFF IN THE KNOWLEDGE ECONOMY* 223, 238 (2019) (showing that diverse groups outperform homogenous groups because of both an influx of new ideas and more careful information

Thus, the internal audits could provide corporations with a tool to discover their blind spots in regard 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, indicating either 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. External Auditing: The Fair Automated Hiring Mark

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. I take as inspiration for this proposed certification system Professors Ian Ayres and Jennifer Brown's framework for corporations to certify discrimination-free workplaces that comply with the Employment Non-Discrimination Act ("ENDA").³¹⁸ The authors propose:

[B]y entering into 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.³¹⁹

Other legal scholars have also proposed certification systems for algorithms. Notably, Andrew Tutt has proposed an "FDA for algorithms," in which the federal government 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

processing); see also Sheen S. Levine et al., *Ethnic Diversity Deflates Price Bubbles*, 111 PROC. NAT'L ACAD. SCI. 18524 (2014).

318. ENDA is legislation proposed in the United States Congress that would prohibit discrimination in hiring and employment on the basis of sexual orientation or gender identity by employers with at least 15 employees. See generally Ian Ayres & Jennifer Gerarda Brown, *Mark(et)ing Nondiscrimination: Privatizing ENDA with a Certification Mark*, 104 MICH. L. REV. 1639 (2006).

319. *Id.* at 1641.

decision-making power.³²⁰ And Professor Rory Van Loo makes a compelling case for regulatory monitoring of platforms that employ automated decision-making.³²¹ He defines regulatory monitoring as “the collection of information that the [government] agency can force a business to provide even without suspecting a particular act of wrongdoing.”³²² Van Loo notes that key factors indicating a need for regulatory monitoring include a public interest in preventing harm, information asymmetries, and a lack of faith in self-regulation.³²³

Given that these factors are undeniably present for automated hiring, I argue for either a government agency or a third-party non-governmental agency as auditing and certifying authority. The governmental agency could be under the aegis of the EEOC. Thus, the EEOC would audit and certify automated hiring platforms before those platforms could lawfully be deployed in the hiring process. However, given the financial and time burden such a certifying process could exact on governmental resources, a non-governmental entity, much like the Leadership in Energy and Environmental Design (“LEED”) certification system, is a good alternative. LEED was established in 1993 “with a mission to promote sustainability-focused practices in the building industry.”³²⁴ Thus, LEED serves as a “green certification program for building design, construction, operations, and maintenance.”³²⁵ The LEED certification involves a formal certification letter, as well as plaques, signage for buildings, and an electronic badge that may be displayed on a website.³²⁶

This third-party certification would not comprise of a one-time audit, but rather involve periodic audits of the hiring algorithms to check for disparate impact on vulnerable populations. Thus, this ongoing process would ensure that the audited corporations and organizations 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 (“FAHM”; see illustration of a potential mark below) for its online presence, for communication materials, and for display on hiring advertisements to attract a more diverse pool of applicants.

320. See Tutt, *supra* note 4, at 83.

321. Rory Van Loo, *The Missing Regulatory State: Monitoring Businesses in an Age of Surveillance*, 72 VAND. L. REV. 1563 (2019).

322. *Id.* at 1574.

323. *Id.* at 1573.

324. *Impact Conference*, U.S. GREEN BUILDING COUNCIL, <https://impact.usgbc.org/#about> [https://perma.cc/VSM4-JNF3].

325. *Global Dow Center Earns LEED Silver Certification*, FACILITY EXECUTIVE, <https://facilityexecutive.com/2020/01/global-dow-center-earns-leed-silver-certification> [https://perma.cc/B7PQ-PKCT].

326. See *Congrats! You've Earned LEED Certification.*, U.S. GREEN BUILDING COUNCIL, <https://new.usgbc.org/post-certification> [https://perma.cc/2RE3-HWUA].



Figure 1: The Proposed Fair Automated Hiring Mark

I envision that such a third-party certification entity would be composed of multi-disciplinary teams of auditors comprising both lawyers and either software engineers or data scientists who would audit the hiring algorithms employed by corporations and organizations. This strategy would prevent some of the tunnel-vision problems associated with technology created without consideration for legal frameworks and broader societal goals. Furthermore, such a certification system could serve as a feedback mechanism and thus enable better design and best practices for automated hiring systems.

1. The Pros and Cons of a Governmental Certifying System

A governmental certification that is federally mandated would provide uniformity in the practice of automated hiring and would also ensure compliance in regard to auditing.³²⁷ However, the issues of regulatory capture³²⁸ and political wind shifts weigh against the adoption of a governmental certifying system. As history has shown, governmental agencies are vulnerable to regulatory capture,³²⁹ meaning that private influence on the workings of such agencies, as well as political wind shifts, can render such agencies toothless or ineffectual. While there are varying definitions of regulatory capture, “[w]hat is true, however, is that because the top officials of federal regulatory agencies are presidential appointees, interest groups,

327. Some legal scholars have previously argued for governmental oversight based on a taxonomy of the distinct operations of algorithmic systems in a wide range of spheres. See Desai & Kroll, *supra* note 276, at 42–55. My proposed interventions in this Article focus solely on the employment sphere.

328. Daniel Carpenter and David Moss define “regulatory capture” as “the result or process by which regulation, in law or application, is consistently or repeatedly directed away from the public interest and toward the interests of the regulated industry, by the intent and action of the industry itself.” DANIEL CARPENTER & DAVID A. MOSS, PREVENTING REGULATORY CAPTURE: SPECIAL INTEREST INFLUENCE AND HOW TO LIMIT IT 13 (2014).

329. See, e.g., Stavros Gadinis, *The SEC and the Financial Industry: Evidence from Enforcement Against Broker-Dealers*, 67 BUS. LAW. 679 (2012) (highlighting the inherent connection between the public and private enforcement of securities laws); see also David Freeman Engstrom, *Corralling Capture*, 36 HARV. J.L. & PUB. POL’Y 1, 35–37 (2013) (detailing the presumed problem of regulatory capture).

whether they are industries, unions, or consumer or environmental groups, influence the regulatory agencies, and one can think of this influence as a kind of capture.”³³⁰

Examples of regulatory capture abound in American government, including that of the U.S. Securities and Exchange Commission (“SEC”),³³¹ the Food and Drug Administration (“FDA”),³³² and most importantly the EEOC.³³³ In the employment context specifically, the EEOC, which is charged with employment regulation, has been susceptible to administration change. Consider, for example, that in 2014 President Obama issued a presidential memorandum on pay data transparency³³⁴ instructing the Secretary of Labor to propose a regulation mandating that federal contractors must disclose pay data broken down by race and gender to the EEOC.³³⁵ This presidential memorandum meant to combat gender gaps in pay.³³⁶ However, in 2017, the Acting Chair of the EEOC, appointed by President Trump,

330. CARPENTER & MOSS, *supra* note 328, at 54 (2014). 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. 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. The FDA, without corroborating evidence from clinical trials, approved a package insert for OxyContin that stated 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. See Patrick Radden Keefe, *The Family That Built an Empire of Pain*, *NEW YORKER* (Oct. 23, 2017), <https://www.newyorker.com/magazine/2017/10/30/the-family-that-built-an-empire-of-pain> [<https://perma.cc/5W8K-UPK2>].

331. Other scholars have detailed a revolving door of SEC employees to and from the financial sector and how it has contributed to regulatory capture of the SEC. See, e.g., Stewart L. Brown, *Mutual Funds and the Regulatory Capture of the SEC*, 19 U. PA. J. BUS. L. 701, 707 (2017).

332. See Patrick Radden Keefe, *The Family That Built an Empire of Pain*, *NEW YORKER* (Oct. 23, 2017), <https://www.newyorker.com/magazine/2017/10/30/the-family-that-built-an-empire-of-pain> [<https://perma.cc/5W8K-UPK2>] (discussing how a family-owned business co-opted the FDA drug certification system through fraud and corruption).

333. Consider that the Trump administration attempted to suspend a pay data collection rule that had been promulgated by the Obama administration to combat the gender pay gap through encouraging transparency in pay. See Alexia Fernández Campbell, *Trump Tried to Sabotage a Plan to Close the Gender Pay Gap. A Judge Wouldn't Have It.*, *VOX* (Apr. 26, 2019, 10:10 AM), <https://www.vox.com/2019/4/26/18515920/gender-pay-gap-rule-eoc> [<https://perma.cc/6PSR-JTGV>].

334. See Memorandum on Advancing Pay Equality Through Compensation Data Collection, 2014 DAILY COMP. PRES. DOC. 251 (Apr. 8, 2014); see also Press Release, The White House, Office of the Press Sec’y, Fact Sheet: New Steps to Advance Equal Pay on the Seventh Anniversary of the Lilly Ledbetter Fair Pay Act (Jan. 29, 2016), <https://obamawhitehouse.archives.gov/the-press-office/2016/01/29/fact-sheet-new-steps-advance-equal-pay-seventh-anniversary-lilly> [<https://perma.cc/29TM-V87Y>].

335. See Memorandum on Advancing Pay Equality, *supra* note 334.

336. See Press Release, The White House, *supra* note 334.

issued a press release announcing an immediate stay of the EEOC regulation.³³⁷

2. The Pros and Cons of a Third-Party Non-Governmental Certifying System

A commercial third-party certifying entity with a business reputation to protect would be much less susceptible to regulatory capture. For one, given the voluntary nature of the relationship between the certifying entity and the employer using automated hiring systems, 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. Notably, a non-governmental entity would better withstand the vagaries of political wind shifts like those that influenced the Federal Communications Commission³³⁸ and the Federal Trade Commission (“FTC”) regarding net neutrality³³⁹ or the Environmental Protection Agency regarding climate change.³⁴⁰

One argument, however, is that even independent third-party certifying agencies are not immune to capture. As such entities will derive an economic benefit from certifications, there is the danger that such an agency could become a mere rubber-stamping entity without adequate legal teeth to enforce any sanctions against the entities it is certifying. However, said agency would operate on the trust of job

337. See Danielle Paquette, *The Trump Administration Just Halted This Obama-Era Rule to Shrink the Gender Wage Gap*, WASH. POST (Aug. 30, 2017, 2:37 PM), <https://www.washingtonpost.com/news/wonk/wp/2017/08/30/the-trump-administration-just-halted-this-obama-era-rule-to-shrink-the-gender-wage-gap/> [https://perma.cc/EMU9-YA73].

338. See Brian Fung, *The House Just Voted to Wipe Away the FCC’s Landmark Internet Privacy Protections*, WASH. POST (Mar. 28, 2017, 7:37 PM), <https://www.washingtonpost.com/news/the-switch/wp/2017/03/28/the-house-just-voted-to-wipe-out-the-fccs-landmark-internet-privacy-protections/> [https://perma.cc/LAV4-LLTE]; see also Jeff Dunn, *Trump Just Killed Obama’s Internet-Privacy Rules — Here’s What That Means for You*, BUSINESS INSIDER (Apr. 4, 2017, 10:55 AM), <http://www.businessinsider.com/trump-fcc-privacy-rules-repeal-explained-2017-4> [https://perma.cc/VE5S-WD5N].

339. See Michael Santorelli, *After Net Neutrality: The FTC Is the Sheriff of Tech Again. Is It Up to the Task?*, FORBES (Dec. 15, 2017, 11:44 AM), <https://www.forbes.com/sites/washingtonbytes/2017/12/15/the-game-is-on-the-ftc-tech-regulation-post-net-neutrality/> [https://perma.cc/Q4MF-DZ3C] (discussing the FTC’s stance against net neutrality).

340. See Brady Dennis & Juliet Eilperin, *How Scott Pruitt Turned the EPA into One of Trump’s Most Powerful Tools*, WASH. POST (Dec. 31, 2017), https://www.washingtonpost.com/national/health-science/under-scott-pruitt-a-year-of-tumult-and-transformation-at-epa/2017/12/26/f93d1262-e017-11e7-8679-a9728984779c_story.html [https://perma.cc/M7YM-UM5H]; see also Eric Lipton & Danielle Ivory, *Under Trump, EPA Has Slowed Actions Against Polluters, and Put Limits on Enforcement Officers*, N.Y. TIMES (Dec. 10, 2017), <https://www.nytimes.com/2017/12/10/us/politics/pollution-epa-regulations.html> [https://perma.cc/M4FD-SUUL].

applicants as consumers, and the internet also affords greater information dissemination. Thus, consumers in the form of job applicants can now more forcefully make their voices heard regarding algorithmic bias and could still blow the whistle³⁴¹ on any misconduct, in turn undermining any certifying mark that does not hold true.

Another valid concern regarding external auditing agencies is the privacy of applicant data. In particular, there is a need for regulation regarding the end uses of applicant data derived from third-party audits of automated hiring. For one, there should be regulations prohibiting third-party vendors from selling data derived from applicant information. In the absence of such regulation, companies undertaking a third-party audit could enter into contractual agreements barring the use of applicant data beyond the purposes of the audit, including the sale or transfer of that data to other parties.

A recent audit by HireVue may yet provide the best argument against third party auditing. In 2019, the nonprofit Electronic Privacy Information Center lodged a complaint with the FTC alleging that HireVue's use of AI to assess job candidate's video interviews constituted "unfair and deceptive trade practices."³⁴² While HireVue denied any wrongdoing, in 2020, HireVue announced it would cease to include a candidate's facial expressions in video interviews as a factor its algorithms considered.³⁴³ On January 11, 2021, HireVue announced that it had brought in the auditing entity, O'Neil Risk Consulting and Algorithmic Auditing ("ORCAA"), to conduct an audit of its video interviewing system.³⁴⁴ The report of the audit, however, left many questions unanswered. For one, ORCAA limited the audit to "pre-built assessments used in hiring early career candidates, including from college campuses."³⁴⁵ This audit does not assess what HireVue calls "custom assessments," special algorithms which companies may

341. See Katyal, *supra* note 4, at 107–08 (making a powerful argument for the importance of whistleblowers in rectifying algorithmic bias). Other legal scholars have also made the same argument while noting how trade secret laws might interfere with whistleblowing. See Desai & Kroll, *supra* note 276, at 56–64 (2017).

342. Complaint and Request for Investigation, Injunction, and Other Relief Submitted by The Electronic Privacy Information Center (EPIC) at 1, HireVue Inc. (F.T.C. Nov. 6, 2019), https://epic.org/privacy/ftc/hirevue/EPIC_FTC_HireVue_Complaint.pdf [<https://perma.cc/G36P-2W9E>].

343. Jeremy Kahn, *HireVue Drops Facial Monitoring Amid A.I. Algorithm Audit*, FORTUNE (Jan. 19, 2021), <https://fortune.com/2021/01/19/hirevue-drops-facial-monitoring-amid-a-i-algorithm-audit/> [<https://perma.cc/APC2-6B5S>].

344. See Lindsey Zuloaga, *Industry Leadership: New Audit Results and Decision on Visual Analysis*, HIREVUE (Jan. 11, 2021), <https://www.hirevue.com/blog/hiring/industry-leadership-new-audit-results-and-decision-on-visual-analysis> [<https://perma.cc/3LZE-QHTB>].

345. O'NEIL RISK CONSULTING AND ALGORITHMIC AUDITING, DESCRIPTION OF ALGORITHMIC AUDIT: PRE-BUILT ASSESSMENTS 1 (2020), <https://webapi.hirevue.com/wp-content/uploads/2021/01/oneil-risk-consulting-and-algorithmic-auditing-01-2021.pdf> [<https://perma.cc/6LME-BVVFV>].

commission that “are designed around job-related outcomes specified by the client” with the potential purpose to “predict what a candidate’s job performance would be, were that candidate hired.”³⁴⁶

Limiting the scope of the audit to “pre-built” assessments means a potentially damning majority of HireVue use cases may have been excluded from the purview of the audit.³⁴⁷ ORCAA acknowledges this reality in the audit report, claiming “the use case we audited is not necessarily common or representative of HireVue’s business overall” but rather supposedly reflects what HireVue believes is a use case that “would prompt hard fairness questions.”³⁴⁸ Even though an audit of custom assessments algorithms may be more difficult to conduct because those algorithms vary in nature, many concerns raised about HireVue center around bias replication by algorithms that rely on job performance and hiring data from existing companies.³⁴⁹ This audit did not consider such concerns. Further, the applicability of the results of this audit to decisions about the suitability of HireVue technology as a whole heavily depends on the significance of the pre-built assessment use case, data on which is currently unavailable to the general public. If the pre-built assessment use case is a minor part of HireVue’s business model, then this audit is practically insignificant. A more meaningful audit would require examining multiple use-case scenarios for fairness to understand the potential discriminatory effects of the most common ways that HireVue’s product is deployed. The auditing report should include demographic information about *total applicants screened* under each use case and any disproportionate impact on protected categories. Despite these inadequacies, the fact that HireVue voluntarily undertook this independent third-party audit is welcome development in the oversight of automated hiring systems. HireVue did also identify further investigation as to potential bias arising from the AI evaluation of different accents and also length of responses.³⁵⁰ In

346. *Id.* at 2.

347. While HireVue does not share details on the type and frequency of their use cases, evidence suggests that the company is commissioned to create custom assessments by some major clients. See *Unilever + HireVue*, HIREVUE, <https://www.hirevue.com/case-studies/global-talent-acquisition-unilever-case-study> [https://perma.cc/3N5M-5HCF] (describing that HireVue claims its algorithms assessed “those candidates that are most likely to be successful at Unilever,” implying that the Unilever algorithm was a custom assessment designed to predict potential job performance at Unilever).

348. O’NEILL RISK CONSULTING AND ALGORITHMIC AUDITING, *supra* note 345, at 2.

349. See Rachel Winters, *Should Robots Be Conducting Job Interviews?*, SLATE (Oct. 5, 2020, 9:00 AM), <https://slate.com/technology/2020/10/artificial-intelligence-job-interviews.html> [https://perma.cc/V8CW-9NJA]; Andrew Jack, *Will Recruitment ‘Gamification’ Drive Diversity or Replicate Biases?*, FIN. TIMES (June 3, 2020), <https://www.ft.com/content/b24a7e9e-a1c1-11ea-b65d-489c67b0d85d> [https://perma.cc/4UPU-BFFA]; Sarah Fister Gale, *Could Video Interviewing Land You in Court?*, WORKFORCE (July 1, 2019), <https://www.workforce.com/news/video-interviewing-land-you-in-court> [https://perma.cc/ZV2X-MPFP].

350. O’NEILL RISK CONSULTING AND ALGORITHMIC AUDITING, *supra* note 345, at 4–5.

all, I argue that the HireVue audit, as the first of its kind, underscores the need to create industry standards or guidelines for third-party independent audits and, perhaps, for governmental mandated audits conducted by a governmental agency with standardized procedures.

This last point especially rises from the skepticism of experts regarding internal audits. Dipayan Ghosh, a Harvard fellow and former Facebook privacy and public policy official, has no confidence in any internal review process given past cases of self-certifying companies revealed to be engaging in practices that were harmful to society and certain populations.³⁵¹ According to Ghosh: “The public will have little knowledge as to whether or not the firm really is making biased decisions if it’s only the firm itself that has access to its decision-making algorithms to test them for discriminatory outcomes.”³⁵² Ghosh notes that start-ups do not face enough pressure to use third-party audit firms because it is “not required by law,” “costs money,” and would “require ‘tremendous levels’ of compliance beyond what internal audits likely require.”³⁵³

C. Collective Bargaining

While internal and external audits could both enable litigation by generating data to serve as statistical evidence of disparate impact or by uncovering practices that could be considered *discrimination per se*, collective bargaining as a collaborative exercise between employers and worker unions could also set fair standards for automated hiring and securing applicant data. In this section, I argue that collective bargaining provides another avenue to check some of the deleterious effects of automated hiring. Notably, collective bargaining could focus on the role of data collection and usage. The target of such bargaining would be trifold: (1) agreements as to what data will be *digested* by automated hiring systems; that is, setting the standards for probative applicant assessment criteria; (2) agreements as to the *end uses* of such data; that is, contractual agreements as to what the data collected will be used for, as well as data-retention agreements; and (3) agreements as to the control and portability of the data *created* by automated hiring systems.

While there has been much focus on the data input required for automated decision-making, the data generated by this decision-making process is equally consequential, if not more so. This is because automated hiring systems hold the potential to create indelible portraits

351. See Rosenbaum, *supra* note 277.

352. *Id.*

353. *Id.*

of applicants, which may be used to classify those individuals.³⁵⁴ As a result, data submitted by an applicant is deployed not just for one job classification or even presented to just one employer. Rather, an applicant-data-generated worker profile may live on past the snapshot in time when the worker applied for a specific position and may come to haunt them during an entirely different bid for employment.³⁵⁵ In the following sections, I detail the important role of collective bargaining in achieving fair standards not only for the curation of input data, but also for the portability of output data.

1. Data Digested and Determining Probative Evaluation Criteria

Arguments over standards of fairness and other approaches to algorithmic accountability tend to neglect the role of data in perpetuating discrimination. Yet, as several legal scholars have observed, data is not neutral; rather, it is tainted by structural and institutional bias.³⁵⁶ Collective bargaining regarding what data may be used for assessment as part of algorithmic hiring systems is one necessary approach to curbing employment discrimination. While the content of hiring criteria is typically not a topic of collective bargaining — collective bargaining tends to focus on the conditions of employment for workers who have already been hired — I argue that union leaders should not overlook the importance of securing fair data collection and evaluation standards for their members. There is also the argument that unions may tend to prioritize a focus on securing good working conditions for current employees. Yet, with the decline in union membership, securing good hiring conditions could be a boon for unions.

The first task for unions to tackle is negotiating what data may be digested by hiring algorithms. A crucial issue for this negotiation will be determining what data is probative of “job fitness” or what data may even be considered job-related. Professor Sullivan notes: “The employer’s reliance on the algorithm may be job-related, but the algorithm itself is measuring and tracking behavior that has no direct relationship to job performance.”³⁵⁷ And while some of the information

354. Professors Rick Bales and Katherine Stone have argued: “The data collected are transformed by means of artificial intelligence (AI) algorithms into a permanent electronic resume that companies are using to track and assess current workers, and it could potentially be shared among companies as workers move around the boundaryless workplace from job to job.” Bales & Stone, *supra* note 60, at 3.

355. *Id.* at 3–4 (“This invisible electronic web threatens to invade worker privacy, deter unionization, enable subtle forms of employer blackballing, exacerbate employment discrimination, render unions ineffective, and obliterate the protections of the labor laws.”).

356. See Mike Ananny & Kate Crawford, *Seeing Without Knowing: Limitations of the Transparency Ideal and Its Application to Algorithmic Accountability*, 20 *NEW MEDIA & SOC’Y* 973, 982 (2016); see also Chander, *supra* note 140, at 1039.

357. See Sullivan, *supra* note 14, at 421.

digested by hiring algorithms may be correlated with job success, as other scholars have noted: “If a statistical correlation were sufficient to satisfy the defense of job-relatedness, the standard would be a tautology rather than a meaningful legal test.”³⁵⁸

Rather than rely on flimsy and often irrelevant correlations excavated by the algorithms, I concur with legal scholars who have argued that the Uniform Guidelines on Employee Selection Procedures³⁵⁹ should apply in negotiating what data will be digested by automated hiring systems.³⁶⁰ Although these Uniform Guidelines do not amount to law,³⁶¹ they have been accorded deference in case law³⁶² and have been viewed as authoritative in deciding employment discrimination cases.³⁶³ As Professor Sullivan notes: “While [the Uniform Guidelines] have been used mainly for the validation of traditional paper-and-pencil tests with a disparate impact, the Guidelines broadly apply to any ‘selection procedure.’”³⁶⁴

The Uniform Guidelines are useful because they set standards for when selection criteria could be considered valid. The Uniform

358. See *Data-Driven Discrimination at Work*, *supra* note 5, at 920.

359. Uniform Guidelines on Employee Selection Procedures, 29 C.F.R. § 1607 (2021).

360. See Sullivan, *supra* note 14, at 420–22; King & Mrkonich, *supra* note 96, at 574. (supporting the use of the Guidelines in candidate selection generally)

361. See Sullivan, *supra* note 14, at 422.

362. The Court in *Griggs* concluded that the EEOC’s interpretation of the guidelines should be given “great deference.” See *Griggs v. Duke Power Co.*, 401 U.S. 424, 433–34 (1971). Later in *Moody*, the Court further observed that the “[g]uidelines draw upon and make reference to professional standards of test validation established by the American Psychological Association” and that while the guidelines were “not administrative ‘regulations’ promulgated pursuant to formal procedures established by the Congress . . . they do constitute ‘[t]he administrative interpretation of the Act by the enforcing agency.’” *Albemarle Paper Co. v. Moody*, 422 U.S. 405, 430–31 (1975) (quoting *Griggs*, 401 U.S. at 433–34). The Uniform Guidelines replaced the original EEOC guidelines in 1978 and it enjoys broader consensus than the EEOC guidelines as it represents the collective view of the EEOC and other federal agencies such as the Department of Labor, the Civil Service Commission, and the Department of Justice. Thus, courts have similarly viewed the Guidelines as authoritative. The court in *Gulino* noted: “[T]hirty-five years of using these Guidelines makes them the primary yardstick by which we measure defendants’ attempt to validate [a standardized certification test].” *Gulino v. N.Y. State Educ. Dep’t*, 460 F.3d 361, 384 (2d Cir. 2006).

363. Sullivan, *supra* note 14, at 422 n.106 (noting that per the results of a Lexis Advance search on Dec. 10, 2017, “[t]he Guidelines have been cited in more than 300 cases, including a number of Supreme Court decisions”).

364. *Id.* at 422 nn.107–08 (citations omitted); see also *id.* at 422 n.108 (discussing 29 C.F.R. § 1607.3(A) (2018), which explains that “the hiring, promotion, or other employment or membership opportunities of members of any race, sex, or ethnic group will be considered to be discriminatory and inconsistent with these guidelines, unless the procedure has been validated in accordance with these guidelines . . .”). Sullivan explains that “[s]election procedure” is in turn defined broadly to include “[a]ny measure, combination of measures, or procedure used as a basis for any employment decision,” and includes “the full range of assessment techniques from traditional paper and pencil tests, performance tests, training programs, or probationary periods and physical, educational, and work experience requirements through informal or casual interviews and unscored application forms.” *Id.* (citing 29 C.F.R. § 1607.16(Q) (2018)).

Guidelines provide for “three kinds of validation: criterion, content, and construct.”³⁶⁵ The aim of all three types of validation is to prompt the employer to provide evidence of a predictive causal relationship between the selection method and the job performance:

Evidence of the validity of a test or other selection procedure by a criterion-related validity study should consist of empirical data demonstrating that the selection procedure is predictive of or significantly correlated with important elements of job performance. Evidence of the validity of a test or other selection procedure by a content validity study should consist of data showing that the content of the selection procedure is representative of important aspects of performance on the job for which the candidates are to be evaluated. Evidence of the validity of a test or other selection procedure through a construct validity study should consist of data showing that the procedure measures the degree to which candidates have identifiable characteristics which have been determined to be important in successful performance in the job for which the candidates are to be evaluated.³⁶⁶

As validation generally requires a job analysis, unions can be actively involved in conducting the job analysis and in thus setting the standards to demonstrate that: (1) the selection criteria for the hiring algorithm relate to important aspects of the job, (2) the data used actually allows for a prediction of future job performance based on the selection, and (3) the candidate selections are not the result of some nebulous correlation but rather indicate identifiable characteristics that are causally related to better job performance. A question arises here as to whether unions will have the requisite technical savvy to understand and implement these measures. This dilemma underscores the need for greater attention to law and technology courses in law school to train the next generation of union leaders, ensuring they remain competent to address the next generation of workplace technologies.

But even after the determination of probative data for job fitness, there still remains the problem of biased data. For example, data that may be probative for job fitness, such as test scores, may still bear the taint of past biased decisions. Consider for example that racial housing segregation has resulted in a concentration of better-resourced schools

365. *Id.* at 423 (citing RAMONA L. PAETZOLD & STEVEN L. WILLBORN, *THE STATISTICS OF DISCRIMINATION* §§ 5.13–.17 (2d ed. 2017–2018)).

366. *Id.* (quoting 29 C.F.R. § 1607.5B (2018)) (alterations in original).

in majority-white neighborhoods where students who attend receive better preparation for standardized tests. Although performance on standardized tests may be considered probative of job fitness, the use of such a criterion could result in disparate impact. In recognition of the historical taint of structural bias on data that could otherwise be probative, some scholars have called for “algorithmic affirmative action,” which focuses not merely on the design of algorithms, but also on transparency about the biases encoded in the data and the correction of the data used.³⁶⁷

Alternatively, employers could outright reject the use of such biased data. For example, rather than depend on standardized testing, employers might design video games to assess job performance qualities of applicants, such as “social intelligence, ‘goal-orientation fluency,’ implicit learning, task-switching ability, and conscientiousness.”³⁶⁸ According to David Savage and Professor Richard Bales, these algorithms, which only identify individual personal qualities, can reduce discrimination in evaluating job applicants.³⁶⁹ Administering video games based on such algorithm in the initial hiring process not only will 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.³⁷⁰

2. Data End Uses and Fairness by Design

One common retort to addressing bias in algorithms is that machine learning algorithms are ungovernable,³⁷¹ however, like other legal scholars, I argue that adjusting the design features of hiring platforms, coupled with auditing mandates, facilitate antidiscrimination ends by bringing automated hiring systems under the rule of law. More specifically, I argue that fairness can be part of the design of these algorithmic systems from the outset, especially for establishing data-retention features as a standard. These machine learning algorithms, which have the capacity to derive new models as they learn from large datasets, are constantly reevaluating the variable inputs of calculations.

367. See Chander, *supra* note 140, at 1039.

368. See David D. Savage & Richard Bales, *Video Games in Job Interviews: Using Algorithms to Minimize Discrimination and Unconscious Bias*, 32 A.B.A. J. LAB. & EMP. L. 211, 222 (2017) (quoting Don Peck, *They're Watching You at Work*, ATLANTIC (Dec. 2013), <http://www.theatlantic.com/magazine/archive/2013/12/theyre-watching-you-at-work/354681> [<https://perma.cc/9792-WSKK>]).

369. *Id.* at 224–26.

370. *Id.*

371. See, e.g., Kroll et al., *supra* note 21 (noting that some existing algorithmic systems are largely ungovernable because they were not built with auditing in mind. They note also that there are ways to build for auditing, but that this design logic should exist at the onset).

Some researchers have argued that humans could lose their agency over algorithms given the extensive potential of algorithms for calculations and the amount of data they use.³⁷² To limit this reduction in choice-making power, some have exhorted that humans need to set “checks” on algorithms, ensuring that humans can inspect both the data that enters the system and the results that exit.³⁷³ By doing so, humans might reduce the chance that algorithms would 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.³⁷⁴

By complying with key standards of legal fairness when determining design features, programmers can reduce discriminatory effects of hiring algorithms, such that the algorithms avoid disparate impact for protected classes and comply with the principles of employment antidiscrimination laws.³⁷⁵ Professor MacCarthy notes that 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.”³⁷⁶ Those that support group fairness measures, such as statistical parity³⁷⁷ and equal group error rates, try to reduce the subordination of disadvantaged groups by allowing for some sacrifice of accuracy.³⁷⁸ 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.³⁷⁹

I argue that to achieve fairness by design for automated hiring systems, it is also important to incorporate record-keeping and data-

372. See, e.g., Katherine J. Strandburg, *Rulemaking and Inscrutable Automated Decision Tools*, 119 COLUM. L. REV. 1851, 1852 (2019).

373. See Madalina Busuioc, *Accountable Artificial Intelligence: Holding Algorithms to Account*, PUB. ADMIN. REV. (manuscript at 2) (forthcoming).

374. See Ruchir Puri, *It’s Time to Start Breaking Open the Black Box of AI*, IBM WATSON BLOG (Sept. 19, 2018), <https://www.ibm.com/blogs/watson/2018/09/trust-transparency-ai/> [<https://perma.cc/P97S-K7VD>].

375. See Mark MacCarthy, *Standards of Fairness for Disparate Impact Assessment of Big Data Algorithms*, 48 CUMB. L. REV. 67, 77–78 (2018).

376. *Id.* at 68. See generally Reva B. Siegel, *Equality Talk: Antisubordination and Anticlassification Values in Constitutional Struggles over Brown*, 117 HARV. L. REV. 1470 (2004) (providing background for the development of competing theories on equal protection law); Jack M. Balkin & Reva B. Siegel, *The American Civil Rights Tradition: Anticlassification or Antisubordination?*, 58 U. MIA. L. REV. 9 (2003) (relating the history of the development and application of two distinct antidiscrimination principles in American law).

377. Proponents of statistical parity argue that it is more desirable because it “equalizes outcomes across protected and non-protected groups.” See Cynthia Dwork, Moritz Hardt, Toniann Pitassi, Omer Reingold & Richard Zemel, *Fairness Through Awareness*, 3 INNOVATIONS IN THEORETICAL COMPUT. SCI. CONF. 214, 215 (2012).

378. See MacCarthy, *supra* note 375, at 68.

379. See *id.* at 71.

retention mechanisms as part of the standard design. Determining disparate impact in hiring algorithms is a relatively simple matter of evaluating the outcomes using the EEOC rule.³⁸⁰ This rule mandates that “[a] selection rate for any race, sex, or ethnic group which is less than four-fifths . . . of the rate for the group with the highest rate will generally be regarded by the Federal enforcement agencies as evidence of adverse impact.”³⁸¹ Currently, however, job applicants who do not make it past the hiring algorithms are typically lost to the ether.³⁸² Thus, there is no sure way for plaintiffs to compare relative percentages of job applicants who were hired from protected categories against the number who applied as required by the EEOC rule,³⁸³ and there is still no clear method to confirm best hiring outcomes against the actual pool of qualified applicants. As the data from automated hiring systems remains solely in the control of the employer, appropriate record-keeping and data-retention procedures are necessary to enable disparate impact claims.

It thwarts the purpose of the EEOC rule if automated hiring systems do not retain data when an applicant from a protected category is prevented from completing an application or do not even retain the data of complete but unsuccessful applications. My proposal for a legal requirement for corporations to deploy only automated hiring systems with data-retention mechanisms would ensure that data from failed job applicants is preserved so that it can later be compared against that of the successful applicants, with the aim of discovering whether the data evinces disparate impact regarding the population of failed applicants. Although there are valid privacy concerns with the retention of applicant data, I believe they can be addressed by embargoing the data at the initial stage, and by a hard deletion of the data after a specified time. There would also be steep penalties attached to re-selling the data or co-opting it for end uses besides those expressly assented to by the applicants.

Responsible record-keeping and data-retention are also necessary for conducting both internal and external audits. The data for internal audits serves two purposes: (1) it will alert employers to any disparate impact created by the automated hiring system, thus allowing them to preemptively correct any imbalances and avoid costly lawsuits; and (2) it might also alert employers to more structural issues present in their hiring. Such structural issues might include: (1) mismatched or non-probative selection criteria; (2) a shallow hiring pool for applicants from protected categories; and (3) technical or accessibility problems present in the automated hiring platform. Thus, the data from internal

380. *See* 29 C.F.R. § 1607.4(D) (2020).

381. *Id.*

382. *See* O’NEIL, *supra* note 1, ch. 4.

383. *See* 29 C.F.R. § 1607.4(D) (2020).

audits may offer a direct benefit to employers that is separate from their duty not to discriminate.³⁸⁴ Such a boon should be counted in any cost-benefit analysis³⁸⁵ of my proposed record-keeping and data-retention measures.

3. Data Control and Portability

Earlier in the Article, I noted the vast expanse of information collected by hiring platforms; for this section I note how the indelibility of the data profiles created by automated hiring systems could also enable employment discrimination. Moreover, these data profiles, some of which are created by third-party automated hiring vendors, contain not just information provided by the job applicant, but also data gleaned from online sources (such as social media profiles) and peddled by gray market data brokers.³⁸⁶ Therefore, such information may include errors or could provide an inaccurate portrait of the applicant as construed from the erroneous data.³⁸⁷ Even if the information contained in the profile is accurate, there is also the issue of “context

384. See, e.g., *Bias in the Air*, *supra* note 25, at 1384 (2014) (arguing that employment law should impose a duty of care on employers to refrain from practices that go against equal opportunity in employment); see also Robert Post, Lecture, *Prejudicial Appearances: The Logic of American Antidiscrimination Law*, 88 CALIF. L. REV. 1, 40 (2000) (arguing that antidiscrimination law aims to achieve positive intervention and change in social practices as opposed to solely dictating prohibitions). Other professors have also used a “duty of care” framework to propose remedial measures for employment discrimination. See *Negligent Discrimination*, *supra* note 28, at 933; see also *Managing the Macaw*, *supra* note 29, at 1364. I later discuss why the duty not to engage in practices that negate equal opportunity supports my external audit proposal.

385. Cf. Laurence H. Tribe, Lecture, *Seven Deadly Sins of Straining the Constitution Through a Pseudo-Scientific Sieve*, 36 HASTINGS L.J. 155, 161 (1984) (arguing that there is a “pernicious tendency” for cost-benefit analysis to “dwarf soft variables” in constitutional law).

386. See, e.g., *Web Scraping as a Valuable Instrument for Proactive Hiring*, DATAHEN (Apr. 5, 2017), <https://www.datahen.com/web-scraping-valuable-instrument-proactive-hiring/> [<https://perma.cc/2DQY-QQAY>] (“What can recruiters do to use this huge advantage to their benefit? They can scrape or crawl data off of those kind [sic] of job portals and run analytics through it. By doing so they are able to determine the likelihood of filling a particular position in a specified location based on historical data patterns.”). The article further notes that “[e]verything is relevant and important here and can impact the results of the research. Every little nuance, like the day of the week, [sic] certain types of jobs should be posted or other kinds of factors that will influence the decision making of the prospective candidate.” *Id.*

387. Consider *Thompson v. San Antonio Retail Merchants Association*, where the Fifth Circuit affirmed the district court’s finding that defendant SARMA had created an erroneous profile for Thompson by 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. 682 F.2d 509, 509 (5th Cir. 1982). See also *Spokeo v. Robins, Inc.*, 136 S. Ct. 1540, 1550 (2016) (holding that a “people search engine” provided incorrect personal information about a consumer to employers, and further that the consumer may not be able to show concrete injury).

collapse,”³⁸⁸ wherein information the applicant provided in the context of applying for one specific job position may inappropriately be revived to evaluate the candidate for another job position.

Given these problems, applicant control and agency over both data collection and the portability of any created applicant profiles are crucial matters. Thus, as part of collective bargaining, unions should negotiate with employers regarding how applicant data will be handled. There is some tension here between data retention for the purpose of facilitating audits and applicants’ control of their data. But that tension is easily resolved by data anonymization and aggregation. The relevant data for audits here is demographic data that reveal protected characteristics. Unions can negotiate with firms not to retain or trade in applicant profiles that contain not just demographic data but sensitive personal information and evaluations about applicant fitness.

4. Preventing “Algorithmic Blackballing”

Negotiations regarding the retention of subjective applicant profiles or evaluations are necessary to avoid what I term “algorithmic blackballing.” When applicant profiles are allowed to live on past their shelf life, such profiles may come to haunt the applicant in a different bid for work, whether with the same employer or, if traded, with another employer.³⁸⁹ Absent any quick federal action to regulate this, unions could have a role to play.

Consider this scenario: John applies for work through the hiring platform of a major corporation. This platform creates profiles of all applicants. From those profiles, the employer chooses a subset of applicants to invite for interviews and rejects the rest. However, the hiring platform retains the profiles of all job applicants and uses that data internally; whenever the applicant applies again for a job, even if it is a different job from the initial attempt, this applicant profile is revived and data from it once again becomes the basis for a rejection. This result is unfair for various reasons. First, the continued retention and use of applicant profiles misappropriates applicant data — when applicants submit an application, they intend for the information they provide to be used solely for establishing their fitness for the target job position. It is not commonly understood that applicant data submitted at one moment in time could once again, potentially many years later,

388. Scholars have used the term “context collapse” to describe the phenomenon when communication that is meant for one particular audience is transported to another (dissimilar) audience without context or translation, resulting in misunderstanding or acrimony. *See, e.g.*, Alice E. Marwick & danah boyd, *I Tweet Honestly, I Tweet Passionately: Twitter Users, Context Collapse, and the Imagined Audience*, 13 *NEW MEDIA & SOC’Y* 114, 122 (2010).

389. Professors Rick Bales and Katherine Stone have argued: “The electronic resume produced by AI will accompany workers from job to job as they move around the boundaryless workplace.” Bales & Stone, *supra* note 60, at 3.

be used as evidence of whether an applicant is fit for another job. Second, retention and re-use of an applicant profile deny the applicant a chance to present himself in a manner that is more competitive for the job. For example, the applicant could have achieved tangible assets like a new credential or have attained less quantifiable attributes such as better communication skills.

Further exacerbating the problem is that there are no laws prohibiting automated hiring platforms from selling applicant data. This means that applicant data created for one specific employer could be transported for the use of a completely different employer. Consequently, an applicant rejected by one employer could also, without leave to submit amendments to their profile, continue to be rejected by multiple employers.

I term this type of exclusion “algorithmic blackballing.” The algorithmic blackballing of applicants thwarts the goals of antidiscrimination law. While an applicant may not be right for a specific job at a specific point in time, using the same information that underlies that determination and applying it to a different job, even if at the same company, is antithetical to the bedrock legal doctrine of equal opportunity for all job applicants.

D. The Employer’s Burden

Any opposition to my proposals will largely entail economic critiques centered on the cost to employers; however, those arguments ignore that the overarching aim of employment antidiscrimination law is to preserve equal opportunity for all job applicants and that antidiscrimination imposes a duty on employers to work towards that end.³⁹⁰ It is true that audits cost both time and money, so employers could argue that mandated audits pose an undue economic burden and would negate the cost-saving benefits of automated hiring. However, as legal scholars like Professor Charles Sullivan have recognized: “antidiscrimination laws do not require shareholder value maximization The statutes do accommodate productivity concerns by allowing neutral practices with a disparate impact to be justified by business necessity.”³⁹¹

Professor Richard Thompson Ford’s position³⁹² even more forcefully supports the argument for employers to shoulder the burden

390. Cf. SOLON BAROCAS & HELEN NISSENBAUM, *Big Data’s End Run Around Anonymity and Consent*, in PRIVACY, BIG DATA, AND THE PUBLIC GOOD: FRAMEWORKS FOR ENGAGEMENT 44, 44 (Julia Lane et al. eds., 2014) (noting that “where these data commit to record details about human behavior, they have been perceived as a threat to fundamental values, including everything from autonomy, to fairness, justice, due process, property, solidarity, and, perhaps most of all, privacy”).

391. Sullivan, *supra* note 14, at 398 n.12.

392. See *Bias in the Air*, *supra* note 25.

of checking for bias in algorithmic hiring systems. Ford argues that employment discrimination law:

imposes a duty of care on employers to avoid decisions that undermine social equality [W]e could better improve employment discrimination law—making it more successful as an egalitarian intervention and less intrusive on legitimate employer prerogatives—if we abandoned attempts to precisely define concepts such as “objective causation” and “discriminatory intent” and instead *focused on refining the employer’s duty of care to avoid antiegalitarian employment decisions*.³⁹³

If, as Ford argues, employment discrimination law already imposes a duty of care on employers to ensure that their employment decisions are not discriminatory, then calling for mandated audits of algorithmic hiring systems does not impose a new burden; rather, it merely delineates exactly how that duty of care should be fulfilled. Mandated audits are in line with the duty of care to verify that employment decisions are not unlawfully discriminatory. Moreover, self-audits need not be prohibitively costly. If, as I detail in Section V.C.2, the automated hiring system has already been designed in such a way to retain and easily produce the information needed for the audits, the process of conducting self-audits should in reality pose no added economic burden. I will also note here that given that there is already a legal obligation for employers to engage in collective bargaining, the proposals discussed here could be part of that process and thus should not incur additional expense.

VI. CONCLUSION

In a previous article, I detailed how automated hiring has been perceived as a panacea for human bias in employment decision-making.³⁹⁴ However, as I argued in this article, automated hiring may in actuality represent a misguided Gordian knot approach to the systemic problem of employment discrimination. As automated decision-making cannot be fully disentangled from human decision-making, the former action cannot then be an antidote for the noxious effects of the latter. The human hand, and its attendant bias, remains present in automated decision-making. One concern then is that

393. *Id.* (emphasis added).

394. See Ajunwa, *supra* note 6.

automated hiring represents a Trojan horse;³⁹⁵ although it appears as a time- and money-saving gift to corporations inundated by a deluge of job applications, in reality, it may conceal amplified bias and replicate unlawful discrimination, all disguised as artificial intelligence. The problems with automated hiring as identified elude the parameters of litigation redress mechanisms. This is true especially when considering the onerous proof requirements of antidiscrimination law. Thus, to enjoy any benefits of automated hiring systems, without further exacerbating the existing problem of bias, I advocate for a hybrid approach that deploys mechanisms from labor law and administrative law. This necessitates the recognition of an auditing imperative as part of an employer's affirmative duty of care. To fulfill such an auditing imperative demands record-keeping and data-retention mandates, including ex ante non-adversarial interventions such as collective bargaining, to set the standards for data collection. Working in tandem, these proposed measures will get us closer as a society to the American ideal of equal opportunity in employment.

395. My thanks to Professor Ryan Calo for noting this particular analogy during my paper workshop at the Privacy Law Scholars Conference.

APPENDIX

Table 1: An Evaluation of Extant Hiring Algorithms³⁹⁶

Automated Hiring Platform or Software Program	Year Created	Companies Using Them	Features
ADP Workforce Now	2009	<ul style="list-style-type: none"> • More than 20,000 clients by 2011 	<ul style="list-style-type: none"> • Presents candidate data in proprietary dashboard • “Benchmarking” insights used to determine compensation etc.; bills data as “decision-quality”
ApplicantPro	2007	<ul style="list-style-type: none"> • Goodwill • JC Resorts • New York State Psychiatric Institute 	<ul style="list-style-type: none"> • Automated screening • Integrated behavioral assessments • Integrated background checks • Automated tracking of compliance data
Arya (LeoForce)	2013	Unknown	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Bel Brands USA • BevMo! • Calibre • Cancún Resort Las Vegas • Ghirardelli • Level 3 Communications • LaForce • Proficio Bank 	<ul style="list-style-type: none"> • Advertises itself as defense to discrimination lawsuits and seeks to automate EEO/OFCCP compliance • Social media integration

396. My thanks to my research assistants, Eric Liberatore, Jane Kim, and Kayleigh Yerdon who all contributed to this table. For brevity, this table only displays up to ten company names.

		<ul style="list-style-type: none"> • Voxellab • Visit Philadelphia 	<ul style="list-style-type: none"> • Can track demographic trends in applicant sourcing
AssessFirst	2003	<ul style="list-style-type: none"> • Air France • Burger King • Olympus • Ingenico Group • AXA • BNP Paribas • SMCP 	<ul style="list-style-type: none"> • Predicts recruiting success with psychometrics • Can pre-select candidates • Algorithm compares job profile to candidate profiles to source applicants
BALANCEtrak (Berkshire Associates)	2010	<ul style="list-style-type: none"> • Sodexo • FCS Financial • 84 Lumber • And five others 	<ul style="list-style-type: none"> • Screening and scoring features • Tracks jobseeker activity • Background check integration
BirdDogHR	2010	<ul style="list-style-type: none"> • Utz • CF Evans Construction • Iowa DOT • Martin Marietta Materials • Optima Tax Relief • Surgical Specialties Corporation 	<ul style="list-style-type: none"> • Automated screening and scoring • Integrated drug testing and background check results
Breezy HR	2014	<ul style="list-style-type: none"> • Shipt • Linium • Microsoft • Personnel • Docebo • Appcues • Telus • Piksel • Zapier • Freshii • And five others 	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Vet2Tech • The Chatham Group • Perma-Seal • BVS Trans Tech • Ecotech 	<ul style="list-style-type: none"> • Predictive intelligence suggests who to contact, when to contact them, and how to take action • Captures info from the Web to source candidates

		<ul style="list-style-type: none"> • EXILANT Technologies • Medsys Group • Adams Consulting Group • Apex Systems • ALKU • And two others 	<ul style="list-style-type: none"> • Encourages “run[ning] your business by the numbers”
ClearCompany	2004	<ul style="list-style-type: none"> • Borden • MetaBank • Goodwill • Jackson Hospital • Arizona Supreme Court • Sandhills Community College • PSCU Financial Services • Philips • Edible Arrangements • Applied Technical Systems 	<ul style="list-style-type: none"> • Predictive performance data and quality of hire reports • Pre-recorded video interviewing • Enables text messaging with candidates, then attaches those conversations to profile • Automates background and reference checks; can make authorizations less explicit • Passive candidate sourcing • Gives current employees referral tools • Lets users organize applicants by any metric • Comes with automatic “interview guides” to suggest what should be asked • One-click background check
CleverStaff	2014	<ul style="list-style-type: none"> • Kama Games • Conscencia • Verta Media • Svitla Systems • Avon • RSM 	<ul style="list-style-type: none"> • Suggests “appropriate” candidates • Resume parsing
Comeet	2012	<ul style="list-style-type: none"> • Gartner • Gett • Fiverr • SodaStream • SironSource • AppsFlyer • Zoom • Chegg • Matomy Media Group • Playbuzz 	<ul style="list-style-type: none"> • Assessment analytics • App guides interviewers • Sourcing includes social media profiles

		<ul style="list-style-type: none"> • And two others 	
COMPAS for Staffing	2008	<ul style="list-style-type: none"> • TEEMA • Cypress • Talener • David Aplin Group 	<ul style="list-style-type: none"> • Assessments • Recruiting intelligence analytics • Social integration • Automated sourcing
Crelate Talent	2012	Unknown	<ul style="list-style-type: none"> • Detailed candidate profiles • Candidate analytics in reports • Generates EEO/OFCCP compliance report, which could be problematic • Prescreening questions
Entelo	2010	<ul style="list-style-type: none"> • Hubspot • Splunk • Intel • Wayfair • Lyft • PG&E • Cisco • United Airlines • Netflix • EA • And ten others 	<ul style="list-style-type: none"> • Predicts best candidates using hundreds of variables • Candidate social media automatically available • Predicts whether currently employed candidates are likely to move • While it allows users to sort candidates from underrepresented groups to the top, that also implies a user could sort those candidates out
Exelare	1999	<ul style="list-style-type: none"> • Arrow International • Global Rhymes • ERIMAX • Teachers R Us • BlueSky Technology Partners • Operation Homefront 	<ul style="list-style-type: none"> • Resume harvesting
Firefish	2010	<ul style="list-style-type: none"> • Nine Twenty • Lancaster & Duke • Purcon • Revoco • Avantus • T-Impact • Baobab Sales 	<ul style="list-style-type: none"> • Color-codes candidates to rank them • Records all communication with candidates, from text to VOIP, for everyone in company to use

Glider	2015	<ul style="list-style-type: none"> • Tavant Technologies • DataRPM • Inmobi • TATA Consultancy Services • TATA Power • KPMG • Facebook • Nutanix • Novopay • Fortinet • And seven others 	<ul style="list-style-type: none"> • AI “stack ranks” candidates and sends personalized messages • Auto-scores screening, allowing people with no technical knowledge to evaluate performance on technical tasks • One-way video interviewing • Tracks if candidates opened emails
Greenhouse	2012	<ul style="list-style-type: none"> • Airbnb • Evernote • Pinterest • Red Ventures • Twilio • Vimeo • Survey Monkey • DocuSign • Golden State Warriors • Lyft • J.D. Power 	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Kreig Devault • Endeavor Robotics • Navy Army Community Credit Union • Wabash Valley Power • Bluestone Properties • Central Restaurant Products 	<ul style="list-style-type: none"> • Social media integration • Screening and scoring • Integrated background checks • Touts compliance
HireVue	2004	<ul style="list-style-type: none"> • Singapore Airlines • TJX • Honeywell • Intel • Mount Sinai • IBM • Vodafone • Urban Outfitters • Under Armour • Hilton • And 46 others 	<ul style="list-style-type: none"> • Predictive people analytics • 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 • Micro-facial analysis for traits such as

			<p>veracity and trustworthiness</p> <ul style="list-style-type: none"> • Acquired MindX (psychometric games) to further develop assessment capabilities • Structured interviews
Hyrell	2007	<ul style="list-style-type: none"> • City of Pittsfield (MA) • NFSTC • D.L. Evans Bank • FASTSIGNS • Primrose Schools • National Cattlemen's Beef Association 	<ul style="list-style-type: none"> • Pre-scores applicants • Provides analytics on applicants
iCIMS	1999	<ul style="list-style-type: none"> • Foot Locker • Dentsu Aegis • Dish Network • Ketchum • AmTrust • Trilogy • Gannett Fleming • NorthStar • Mohawk • Southeastern Grocers • And 12 others 	<ul style="list-style-type: none"> • Automated communication with candidates • Recruits through social media; applying via Facebook means they can access candidate's Facebook • Facilitates employee referrals, reinforcing historical hiring patterns • Screening and assessment results
JazzHR	2016	<ul style="list-style-type: none"> • Mashable • Speck • Red Bull • GoGo Squeez • Wedding Wire • R/GA 	<ul style="list-style-type: none"> • Like many, automates some communication • Guided interviews • Evaluation templates with automated scoring
JobDiva	2003	<ul style="list-style-type: none"> • Telesis Corporation • Tech Firefly • Trantor Software • FEV Inc. • Essnova Solutions 	<ul style="list-style-type: none"> • Pre-screening and sorting based on answers • Can refine by geography, education, and "other" • Automates resume sorting
Jobjet	2016	<ul style="list-style-type: none"> • Cisco • Amazon • Korn Ferry • Synechron • Zoom • Parsons • AMN Healthcare 	<ul style="list-style-type: none"> • 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

		<ul style="list-style-type: none"> • Kaiser Permanente 	<ul style="list-style-type: none"> • Uses “Big Data” to source and qualify candidates • Brands on speed — “20x faster”
JobScore	2006	<ul style="list-style-type: none"> • Dialpad • Bleacher Report • Parc • Gracenote • Edmunds • Hearst • Sesame Workshop 	<ul style="list-style-type: none"> • Return on Investment (ROI) analytics on applicant sources • Employee referral integration • Social media integration • Automated compliance • Standardized interviewing/templates • Turns resumes 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	<ul style="list-style-type: none"> • Shift Technology • Destinations of the World • The Fern Hotels & Resorts • VIB • PBS Worldwide BVBA • Voglis Co. Ltd. • English Lakes Hotels, Resorts and Venues • BiOZEEN • Waman Hari Pethe Jewelers • Axtrum Solutions • Keley Consulting 	<ul style="list-style-type: none"> • Social integration • Sourcing with “advanced intelligence” • Interview scoring • Video screening
Jobvite	2006	<ul style="list-style-type: none"> • Weight Watchers • JCPenney • LinkedIn • Blizzard Entertainment • Education First • Havas Group • Universal Music Group • Partners in Health 	<ul style="list-style-type: none"> • Referral emphasis • Filters out candidates • Emphasizes time and costs saved • One-way video for recorded assessments

		<ul style="list-style-type: none"> • Seneca • Trek • Wayfair 	
Lever	2012	<ul style="list-style-type: none"> • Quora • Reddit • Lyft • Hot Topic • KPMG • Wieden + Kennedy • Netflix • Success Academy Charter Schools • Eventbrite • Soylent • And five others 	<ul style="list-style-type: none"> • Automated sourcing • Assessments built-in • Predictions and recommendations • Encourages fast decisions as “data-driven” • Features to automate nurturing top talent
LinkedIn Talent Insights	2017	<ul style="list-style-type: none"> • Nestlé • Amazon • Dropbox • Siemens 	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Valor Partners • Ingenium • Contract Recruiter • Robinson Resource Group • The Carolan Group • Indigo Partners • Dental Team Finder 	<ul style="list-style-type: none"> • Finds personal contact info on candidates • Automates sourcing
Mya	2017	<ul style="list-style-type: none"> • Adecco Group 	<ul style="list-style-type: none"> • Automates sourcing, screening, and scheduling • Sends data from “conversations” directly to ATS • Machine learning means her interactions

			<p>are based on past candidates</p> <ul style="list-style-type: none"> • Can only interact with candidates who apply online; thus, candidates who apply in-person cannot be hired
Newton	2009	Unknown	<ul style="list-style-type: none"> • Built-in EEO/OFCCP compliance could raise concerns
Oleeo	2018 ³⁹⁷	<ul style="list-style-type: none"> • Bank of America • Morgan Stanley • NBC Universal • WPP • Marks & Spencer • UK Civil Service 	<ul style="list-style-type: none"> • Claims to eliminate bias by automating every step • Prescriptive hiring recommendations • Clients can apply via social profiles • Sorting in/out based on skills • Auto-scoring of applicants
Olivia (Paradox)	2017	<ul style="list-style-type: none"> • CVS Health • Staples • Sprint • Delta Air Lines • DXC Technology • Alorica • Pilot Flying J 	<ul style="list-style-type: none"> • Assistive intelligence recruiting assistant that “talks” to interested candidates and creates data on them • Machine learning means her interactions are based on past candidates
Oracle Taleo	2012 ³⁹⁸	<ul style="list-style-type: none"> • Western Union • Hitachi Consulting • Hill International • NMDP • Chubb • Chicago Public Schools • JPMorgan Chase • Wegmans • Honda 	<ul style="list-style-type: none"> • Social media and referral sourcing
PeopleFluent	1997	<ul style="list-style-type: none"> • Altair • American Cancer Society • Aon • Avaya • Blue Cross Blue Shield • Citrix 	<ul style="list-style-type: none"> • Integrates recruiting software with other talent management platforms (learning, compensation, collaboration, etc.) • Vendor Management Software gives control

397. Oleeo was originally formed in 1995 as WCN.

398. Taleo existed prior to this, but in 2012 was acquired by Oracle.

		<ul style="list-style-type: none"> • Family Dollar • Hertz • McDonald's • Nationwide 	over contingent/contract labor
QJumpers	2006	<ul style="list-style-type: none"> • Toyota • Avis/Budget • Briscoe Group • Bupa • Calder Stewart • Skyline • New Zealand Avocado • Marra Building Solutions • Elms Hotel 	<ul style="list-style-type: none"> • Automatically ranks candidates • Will soon automate searching for top talent
Recruitee	2015	<ul style="list-style-type: none"> • Greenpeace • Vice • Taco Bell • Hotjar • Hudson's Bay • Sky • Zomato • QWILR • Scotch & Soda • Lacoste • And two others 	<ul style="list-style-type: none"> • Imports passive candidates from social media sites • Can set default reasons for disqualification
Recruiterbox	2009	<ul style="list-style-type: none"> • Wolfram • The Onion • Makita • Swift Capital • Olark 	<ul style="list-style-type: none"> • Prospecting of candidates • Assessment templates
Recruiterflow	2017	<ul style="list-style-type: none"> • FusionCharts • Ixigo • Canvas Search Group • Khosla Labs • ParallelDots • E2X 	<ul style="list-style-type: none"> • Structured interviewing and scoring • Automated sourcing
SkillSurvey	2001	<ul style="list-style-type: none"> • Clemson University • DocuSign • Penn Medicine • Talbots • L.L. Bean • Burlington Coat Factory • Brown-Forman • Adidas • Keurig • MedOptions • And four others 	<ul style="list-style-type: none"> • Online reference-checking • Claims predictive technology reduces bias • Physician peer-referencing online (unique service) • Automates tracking of pipeline candidates

SmartRecruiters	2010	<ul style="list-style-type: none"> • Optimizely • Colliers International • Berkshire Healthcare • Associa • Atlassian • Foster Farms • FishNet Security • Smaato • Equinox 	<ul style="list-style-type: none"> • Metrics aim to focus recruiting to historically effective sources • Assessment tools • Measures performance and fit • Aims to make interviewing “objective” with scorecards (yet this merely quantifies subjective assessments)
Talenthire (CEIPAL)	2013	Unknown	<ul style="list-style-type: none"> • Social media integration • Vendor management integration for contingent labor • Target sourcing
Teamtailor	2012	<ul style="list-style-type: none"> • Tenant & Partner • Arken Zoo • Notified • SATS • Vårdkraft • Ingenjörer utan gränser • Paradox Interactive • Servicefinder 	<ul style="list-style-type: none"> • Screening questions for applicants, sortable by candidate answers • ROI-driven analytics discourage innovative recruiting
TextRecruit	2014	<ul style="list-style-type: none"> • UPS • Six Flags • Ford • Whole Foods • USAA • The Cheesecake Factory • Amazon • Kindred Healthcare • Supercuts • VMware • Con-way Freight 	<ul style="list-style-type: none"> • AI texting/online messaging chatbot performs “sentiment analysis” to determine candidate satisfaction during conversations (also does this for current employees) • Integrates with ATS
VidCruiter	2009	<ul style="list-style-type: none"> • Liberty Mutual • Axiom Law • KIPP • University of Hawaii at Mānoa • IT Convergence • Miratel Solutions • Olameter • Wondersitter 	<ul style="list-style-type: none"> • Automates interviewing with one-way video using predetermined questions • Automatically ranks candidates based on pre-recorded interviews • Website advertises that it “protect[s]” from

		<ul style="list-style-type: none"> • UBC Sauder School of Business • iPacesetters • And four others 	<p>discrimination lawsuits by using structured interviews</p> <ul style="list-style-type: none"> • 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
Whozwho	2017	<ul style="list-style-type: none"> • Kids Village • Nightowl • Sales Coaching International • Simple 	<ul style="list-style-type: none"> • Attempts to use behavioral science to determine cultural fit • Ranks on personality, in addition to assessments of skills, experience, and education
Workable	2012	<ul style="list-style-type: none"> • Cognizant • Porsche • Ryanair • Sears • Sephora • Wyndham Hotel Group • Upwork • Basecamp • Zapier • Merrill Corporation • And three others 	<ul style="list-style-type: none"> • Sourcing tool aggregates social profile data to create candidate profiles • Facilitates employee referrals • Structured interviews and scorecards
Workday	2005	Unknown ³⁹⁹	<ul style="list-style-type: none"> • Import social media profiles • Encourages shifting of talent spending to what software determines is working • Top-talent focus
Workpop	2014	<ul style="list-style-type: none"> • Fresh Brothers • The Melting Pot • Giant Eagle • Sprinkles • Ashley Homestore • WCG Hotels 	<ul style="list-style-type: none"> • Automated sourcing • Algorithm based on millions of applications sets starting bids for each position on job boards

399. We are unable to determine which companies specifically use the recruiting module of Workday, just companies that use any Workday module.

			<ul style="list-style-type: none"> • Grows applicant pool by having applicants add co-workers as references; the references themselves are then in the pool • Automates rankings of candidates with Smart Rank
Zoho Recruit	1996	<ul style="list-style-type: none"> • DreamWorks • Manning Global • Columbia University School of Professional Studies • Tata Projects • Urban Eats • RBL Bank • Sterlite Power • GEP • Scientific Games • International School of London Qatar 	<ul style="list-style-type: none"> • Social media candidate sourcing • Allows reformatting of parsed resumes; can delete candidate resume information before sharing with rest of company

Table 2: Strategies for Beating Automated Hiring Platforms

Method	Description
“Key Word” Usage	Look at employer’s job description and try to include in your resume as many of the exact buzz words it uses. Avoid synonyms — use exact language. ⁴⁰⁰
Avoid Over-Complication	These systems can get confused by over-complication (including fancy fonts, colors, and graphics), so they will not select a resume if it contains these elements. ⁴⁰¹
Follow-Up	People are sorted out of AHPs so often that recruiters may not know which candidates are genuinely interested and which simply “dropped” their resumes there. If you are genuinely interested, one of the best ways to beat the AHP is to follow up with a recruiter via LinkedIn or other sites. ⁴⁰²
Relevant Keywords	Keywords are rated higher by algorithms when they appear in a relevant paragraph (with related text), so if you can add

400. See Trudy Steinfeld, *Decoding the Job Search: How to Beat the ATS (Applicant Tracking System)*, FORBES (May 31, 2016), <https://www.forbes.com/sites/trudysteinfeld/2016/05/31/decoding-the-job-search-how-to-beat-the-ats-applicant-tracking-system> [https://perma.cc/98L9-LQPW].

401. *See id.*

402. *See id.*

	this to your resume in a section about your accomplishments, you should. ⁴⁰³
Use Free Screening Tools	Applicants can check to see how well their resume will scan by using free sites like jobscan.com. ⁴⁰⁴
Full Titles and Acronyms	Some AHPs will look for the acronym of a title/certification (CPA, for example), while others will look for the spelled-out form of the title (Certified Public Accountant). Be sure to include both on your resume. ⁴⁰⁵
Avoid Spelling Mistakes	Many AHPs will terminate your application immediately if you have spelling mistakes, because they will not understand what you're trying to say. ⁴⁰⁶
Avoid Headers and Footers	Headers and footers will “jam” algorithms, meaning that the algorithm will not be able to process your resume further. Avoid these! ⁴⁰⁷
Submit Resume in Text Format	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. ⁴⁰⁸
Include Postal Address	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! ⁴⁰⁹
Pay Attention to Font	Avoid serif fonts (such as Times New Roman), because some screeners reject resumes with these fonts. ⁴¹⁰
Stick to “Orthodox” Sections	Name your sections “Work Experience” and “Education” instead of “Career Achievements” or “Training,” because AHPs are trained to search for specific information under

403. See *How to Beat Automated Resume Screening*, WORKOPOLIS (June 28, 2017), <https://careers.workopolis.com/advice/beat-automated-resume-screening> [https://perma.cc/H28G-VH5R].

404. See *id.*

405. See Regina Borsellino, *Beat the Robots: How to Get Your Resume Past the System & Into Human Hands*, MUSE, <https://www.themuse.com/advice/beat-the-robots-how-to-get-your-resume-past-the-system-into-human-hands> [https://perma.cc/NG3L-J7FC].

406. See *id.*

407. See Peter Cappelli, *How to Get a Job? Beat the Machines*, TIME (June 11, 2012), <http://business.time.com/2012/06/11/how-to-get-a-job-beat-the-machines> [https://perma.cc/U8VK-XHFT].

408. See *id.*

409. See Pamela Skillings, *How to Get the Applicant Tracking System to Pick Your Resume*, BIG INTERVIEW (Mar. 2015), <https://biginterview.com/blog/2015/03/applicant-tracking-system.html> [https://perma.cc/YB9D-MWDW].

410. See Melanie Pinola, *Format Your Resume So It Gets Past Applicant Screening Software*, LIFEHACKER (Feb. 26, 2013, 2:00 PM), <https://lifehacker.com/5987055/format-your-resume-so-its-compatible-with-applicant-screening-software> [https://perma.cc/4VBA-YQCJ].

	specific sections (usually, Education, Work Experience, Skills and Contact Information). ⁴¹¹
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. ⁴¹²
Be Average on Personality Tests	"Score somewhere between the 40 th and 60 th percentiles" and "try to answer as if you were like everybody else is supposed to be." Basically, try to answer questions in the most average way possible. ⁴¹³
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." ⁴¹⁴
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. ⁴¹⁵
When it Comes to Hypothetical Judgment Questions, Don't Reflect	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. ⁴¹⁶
Add Buzz Words in White Ink	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. ⁴¹⁷

411. See Richard Poulin, *Is Your Resume Ready for Automated Screening?*, LINKEDIN (Mar. 10, 2016), <https://www.linkedin.com/pulse/your-resume-ready-automated-screening-richard-poulin/> [<https://perma.cc/NWV9-FD2Y>].

412. *See id.*

413. See WILLIAM H. WHYTE, *THE ORGANIZATION MAN* 405 (2002).

414. *See id.*

415. *See id.* at 408.

416. *See id.* at 409.

417. See Osas Obaiza, *Hack Your Resume to Fool Keyword-Hunting Robots & Land Yourself More Interviews (The Evil Way)*, WONDER HOW TO (May 16, 2013, 2:16 PM), <https://jobs-resumes.wonderhowto.com/how-to/hack-your-resume-fool-keyword-hunting-robots-land-yourself-more-interviews-the-evil-way-0146824/> [<https://perma.cc/G994-AA6C>].