
1-1-2023

Automated Governance

Ifeoma Ajunwa

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Recommended Citation

Ifeoma Ajunwa, *Automated Governance*, 101 N.C. L. REV. 355 ().

Available at: <https://scholarship.law.unc.edu/nclr/vol101/iss2/4>

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AUTOMATED GOVERNANCE*

IFEOMA AJUNWA**

Although one might contend that acquiescing to algorithmic decisions as a consumer is a personal and private choice, the question remains whether, as citizens, we should also relinquish control to algorithmic decision-making for state governance and oversight over laws. Our trepidation over governmental algorithmic decision-making relates to our visceral dread of the inflexibility of machines—an obduracy that can wreak fatal consequences. However, although we may continue to fear algorithmic overlords, the ship has already sailed on the debate over automated governance. A path-breaking report chaired by Professors David Engstrom, Daniel Ho, Catherine Sharkey, and Justice Mariano-Florentino Cuellar provides a comprehensive overview of the automated decision-making that governmental agencies have already deployed and show that nearly half of the federal agencies studied (forty-five percent) have delved into artificial intelligence (“AI”) and related machine learning (“ML”) tools. First, the Article notes the benefits of automated governance, which include: (1) efficiency, (2) cost-savings, and (3) the capability to uncover historical patterns of bias. Thus, the only true remaining questions are: (1) Whether there are still meaningful differences in human versus algorithmic decision-making such that some scenarios should preclude the use of the latter; and (2) whether there is a right to explanation and contestation regarding automated governance? In addition to answering these questions, the Article also offers proposals for how the Equal Employment Opportunity Commission and Federal Trade Commission may make new use of automated tools to prevent racial and other types of discrimination in business decision-making. Finally, the Article details several guardrails that should be put in place to ensure that automated governance will serve the greater good.

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** Ifeoma Ajunwa, Associate Professor of Law, University of North Carolina School of Law. Many thanks to my research assistant, Jake Schindler. Thanks also to Danielle Citron, David Engstrom, and Margot Kaminsky for helpful comments.

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INTRODUCTION

In many ways, as consumers, we have already acquiesced to our algorithmic overlords.¹ We have increasingly delegated consequential business decisions about insurance,² home purchase,³ or employment opportunity⁴ to automated algorithmic processes.⁵ While governing automated decision-making in a free market (both for goods and labor) has garnered much attention from legal scholars,⁶ only more recently have there been serious scholarly investigations of how to regulate automated governmental decision-making.⁷

1. A host of scholars have written about the entrenchment of automated tools to manipulate behavior and decision-making. *See, e.g.*, Ryan Calo, *Digital Market Manipulation*, 82 GEO. WASH. L. REV. 995, 996, 999 (2014); FRANK PASQUALE, *THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION* 4–5 (2016); 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); Sandra G. Mayson, *Bias In, Bias Out*, 128 YALE L.J. 2218, 2221 (2019); Pauline T. Kim, *Manipulating Opportunity*, 106 VA. L. REV. 867, 869 (2020).

2. *See, e.g.*, Alicia Phaneuf, *How Insurtechs Are Scaling with Automated Insurance Underwriting Systems*, BUS. INSIDER (Feb. 17, 2021), <https://www.businessinsider.com/automated-insurance-underwriting> [<https://perma.cc/A8CR-CYLZ>] (“Automated insurance underwriting is the process where robotic process automation (RPA) and artificial intelligence (AI) software underwrites the risk of potential clients. The advanced tech uses AI and machine learning (ML) to evaluate risk, decide how much coverage the client should receive, and how much they should pay for it.”).

3. *See, e.g.*, Richard Waters, *Investors Move into Budding Automated Homebuying Market*, FIN. TIMES (Aug. 8, 2019), <https://www.ft.com/content/f7605c22-b9f7-11e9-8a88-aa6628ac896c> [<https://perma.cc/6G98-9WCP> (dark archive)] (“American homeowners have come to relish the guilty pleasure of a ‘Zestimate.’ Algorithmically produced by online real estate company Zillow, these are real-time measures of home values across the country, generated home-by-home from public records and the latest data on comparable sales.”).

4. *See, e.g.*, Maria Aspan, *A.I. Is Transforming the Job Interview—And Everything After*, FORTUNE (Jan. 20, 2020), <https://fortune.com/longform/hr-technology-ai-hiring-recruitment/> [<https://perma.cc/6YF9-LEKD>] (“Some of the world’s biggest companies are relying on A.I. to build a better workforce.”).

5. *See* Ryan Calo, *Artificial Intelligence Policy: A Primer and Roadmap*, 51 U.C. DAVIS L. REV. 399, 413–15 (2017) (discussing the use of AI in “consequential decision-making” and considering AI developments and potential uses).

6. *See, e.g.*, Jennifer Chapman, Kristin Johnson & Frank Pasquale, *Artificial Intelligence, Machine Learning, and Bias in Finance: Toward Responsible Innovation*, 88 FORDHAM L. REV. 499, 510–12 (2019) (discussing issues associated with the use of automated tools in the valuation of financial instruments); Ifeoma Ajunwa, *The Paradox of Automation As Anti-Bias Intervention*, 41 CARDOZO L. REV. 1671, 1699–1707 (2020) [hereinafter Ajunwa, *The Paradox of Automation*] (detailing issues associated with automated hiring).

7. *See* Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249, 1258 (2008) (offering “a new framework for administrative and constitutional law designed to address the challenges of the automated administrative state”); Ryan Calo & Danielle Keats Citron, *The Automated Administrative State: A Crisis of Legitimacy*, 70 EMORY L.J. 797, 836–38 (2021) (exploring the potential influence of AI on agency legitimacy, arguing towards “a positive vision” of the future and that the administrative state should only adopt tools when they enhance rather than undermine legitimacy); Daniel Freeman Engstrom & Daniel E. Ho, *Special Issue: Regulating the Technological Frontier*:

Although one might consider acquiescing to algorithmic decisions as a consumer a personal and private choice, the question remains whether, as citizens, we should also relinquish control to algorithmic decision-making for state governance and oversight over laws.

Much of the trepidation over governmental algorithmic decision-making harkens back to our visceral dread of the inflexibility of machines—an obduracy that can wreak fatal consequences. After all, now embedded in our cultural consciousness is the robot HAL (Heuristically programmed Algorithmic computer), which the 1968 film, *2001: A Space Odyssey*, introduced, that decides to kill crew members onboard a spaceship to blindly follow his core directives and withhold information from them.⁸ It is worth noting that the fault with HAL could be summarized as thus: the robot had been programmed with two competing directives; (1) to share information fully with the crew, and (2) to withhold a crucial piece of information from them.⁹ The contradiction between these two directives was why HAL decided to kill the crew. Thus, faulty programming was the proximate cause for HAL’s homicidal decision-making. Although a highly advanced computer, HAL simply lacked the sophistication to reconcile the two conflicting directives.

Although the example of HAL is an extreme case, a question remains as to whether the government can safely deploy automated decision-making. A path-breaking report chaired by Professors David Freeman Engstrom, Daniel E. Ho, Catherine M. Sharkey, and Justice Mariano-Florentino Cuéllar was the first to offer a comprehensive overview of the automated decision-making that governmental agencies have already deployed.¹⁰ The report found that “[n]early half of the federal agencies studied (45%) have experimented with AI and related machine learning (ML) tools.”¹¹ This conclusion came from “a rigorous canvass of AI use at the 142 most significant federal departments, agencies, and sub-agencies,”¹² which was complemented by “case studies of specific AI

Algorithmic Accountability in the Administrative State, 37 YALE J. REG. 800, 845–54 (2020); Jeff Butler, *Analytical Challenges in Modern Tax Administration: A Brief History of Analytics at the IRS*, 16 OHIO ST. TECH. L.J. 258, 275–77 (2020) (suggesting improvements for the IRS’s use of automated tools); Yiling Cao, *Research on the Application of Artificial Intelligence in Administrative Governance*, 94 ADVANCES ECON. BUS. & MGMT. RSCH. 849, 851–52 (2019) (reviewing the current use of artificial intelligence in administrative governance and suggesting recommendations for how to better regulate artificial intelligence within the same field).

8. 2001: A SPACE ODYSSEY (Stanley Kubrick Productions 1968).

9. *See id.*

10. *See* DAVID FREEMAN ENGSTROM, DANIEL E. HO, CATHERINE M. SHARKEY & MARIANO-FLORENTINO CUÉLLAR, ADMIN. CONF. OF THE U.S., GOVERNMENT BY ALGORITHM: ARTIFICIAL INTELLIGENCE IN FEDERAL ADMINISTRATIVE AGENCIES 6 (2020) (analyzing the application of artificial intelligence within 142 federal departments and agencies, and presenting an analysis of the “institutional, legal, and policy challenges” that arise from utilizing this technology on the federal administrative level).

11. *Id.*

12. *Id.*

applications at seven leading agencies covering a range of governance tasks.”¹³ As the report concluded, “the government’s AI toolkit is diverse and spans the federal administrative state” including such administrative governance tasks as: “Enforcing regulatory mandates centered on market efficiency, workplace safety, health care, and environmental protection”; adjudicating “government benefits and privileges, from disability benefits to intellectual property rights”; performing surveillance and analysis of “risks to public health and safety”; acquiring useful “information from the government’s massive data streams”; and communicating “with the public about its rights and obligations.”¹⁴

As Professors Engstrom and Ho note, before the report, “[m]ost of the scholarly literature [on algorithmic decision-making]” was “untethered from the actual state of technology, offering ‘thought experiments,’¹⁵ focusing on potential rather than actual applications, or abstracting away from any concrete applications at all.”¹⁶ The report, with its exhaustive catalog of ongoing deployment of administrative algorithmic decision-making, suggests that when it comes to discussions as to whether the government should make use of algorithmic decision-making in administrative law, that ship has sailed.¹⁷ The use of algorithmic decision-making by governmental agencies is no thought experiment, rather it is reality.¹⁸ And this idea is a reality that raises several questions including whether administrative use of automated tools may be lawfully upheld and how algorithmic decision-making tools may be properly utilized to preserve the rule of law.¹⁹

13. *Id.*

14. *Id.*

15. Engstrom & Ho, *supra* note 7, at 804 (citing Eugene Volokh, *Chief Justice Robots*, 68 DUKE L.J. 1135, 1137 (2019)) (focusing on a thought experiment of AI programs as final arbiters).

16. *Id.* (citing Niva Elkin-Koren & Michal S. Gal, *The Chilling Effect of Governance-by-Data on Data Markets*, 86 U. CHI. L. REV. 403, 405 (2019)); *cf.* Tricia Matibag, Note, *Artificial Intelligence for Local Governance*, 50 URB. LAW. 415–16 (2021) (analyzing the current state of AI use in rulemaking and how AI could “vastly improve” governance and regulatory functions).

17. See ENGSTROM ET AL., *supra* note 10, at 16.

18. See Engstrom & Ho, *supra* note 7, at 816 (discussing the Securities and Exchange Commission’s use of two tools that target “trading-based market-based misconduct”); *see also id.* at 819 (addressing the Environmental Protection Agency’s utilization of tools “designed to predict illegal conduct or more precisely allocate scarce agency resources toward audit or investigation”).

19. See Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 GEO. L.J. 1147, 1147–48 (2017) (questioning “whether the use of robotic decision tools by governmental agencies can pass muster under core, time-honored doctrines of administrative and constitutional law” and concluding that with proper safeguards it can comfortably fit within legal and ethical barriers); Engstrom & Ho, *supra* note 7, at 827 (arguing that current administrative law doctrines are better reference points for analyzing the use of AI rather than constitutional law); *cf.* Matthew B. Seipel, *Robo-Bureaucrat and the Administrative Separation of Powers*, 2020 CARDOZO L. REV. DE NOVO 99, 101–02 (warning that the use of AI by administrative agencies may “upset and undermine” the administrative separation of powers and lead agency leadership into having an excessive amount of unchecked power).

The deployment of algorithmic decision-making by governmental agencies prompts new legal questions,²⁰ particularly related to legitimacy²¹ and transparency.²² As its first contribution, in Part I, this Article explores how governmental agencies are already deploying automated tools and parses both the benefits and dangers of such automated decision-making. In Part II, the Article proceeds further along in the ongoing scholarly discussion of the legitimacy and transparency of algorithmic administrative decision-making. That part discusses whether there are qualitative differences in algorithmic versus human decision-making that should temper or disallow the deployment of AI tools by governmental agencies. Part II also delves into legal issues like the right to explanation and the right to contestation. Notably, these are not directly inscribed constitutional rights per se but are rights that several law scholars have read to exist or believe should exist for algorithmic decision-making.²³ The Article argues that in the case of the use of automated decision-making for governmental functions, the rights to explanation and contestation do exist; the issue is what form they should take.

In Part III, the Article offers two proposals for how agencies that regulate business decision-making, such as the Equal Employment Opportunity

20. As some authors have noted: “[A]t the present state of the art artificial intelligence cannot engage in analogical reasoning or legal reasoning.” Kevin Ashley, Karl Branting, Howard Margolis & Cass R. Sunstein, *Legal Reasoning and Artificial Intelligence: How Computers “Think” Like Lawyers*, 8 U. CHI. L. SCH. ROUNDTABLE 1, 19 (2001); see also Harry Surden, *Machine Learning and Law*, 89 WASH. L. REV. 87, 105–07 (2014) (outlining some of the limitations for automated learning within the legal industry, such as an algorithm’s inability to predict a case’s outcome if a law firm lacks past cases that are not “sufficiently similar to one another” and the algorithm cannot “detect patterns that are reliable predictors”).

21. See Calo & Citron, *supra* note 7, at 797 (exploring the potential influence of AI on agency legitimacy).

22. See Katherine J. Strandburg, *Rulemaking and Inscrutable Automated Decision Tools*, 119 COLUM. L. REV. 1851, 1851 (2019) (analyzing the importance of “explainability” for AI in a regulatory setting); Aram A. Gavoro & Raffi Teperdjian, *A Structural Solution to Mitigating Artificial Intelligence Bias in Administrative Agencies*, 89 GEO. WASH. L. REV. ARGUENDO 71, 71, 80 (2021) (discussing the increased use of AI by federal agencies and proposing concrete limiting factors to safeguard against biases and “eroding American values”).

23. See James Grimmelman & Daniel Westreich, *Incomprehensive Discrimination*, 7 CAL. L. REV. ONLINE 164, 177 (2016) (“Applicants who are judged and found wanting deserve a better explanation than, ‘The computer said so.’”); see also Margot E. Kaminski, *Binary Governance: Lessons from the GDPR’s Approach to Algorithmic Accountability*, 92 S. CAL. L. REV. 1529, 1529–30 (2019) (introducing three groups of concerns surrounding algorithmic decision-making (dignitary, justificatory, and instrumental) and proposing a solution to these concerns through a two-pronged “system of individual due process rights combined with systemic regulation achieved through collaborative governance”); Andrew D. Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085, 1118–26 (2018) (discussing different rationales behind the need for explanation of algorithmic decision-making). *But see* Lilian Edwards & Michael Veale, *Slave to the Algorithm? Why a ‘Right to an Explanation’ Is Probably Not the Remedy You Are Looking For*, 16 DUKE L. & TECH. REV. 18, 44 (2017) (noting that although the GDPR called for explanation the legislators at that time “had little information on the detailed issues of [machine learning]”).

Commission (“EEOC”) and the Federal Trade Commission (“FTC”), might incorporate algorithmic decision-making tools to further their regulatory goals. This third contribution is a departure from earlier law and technology literature, both mine and others, which tended to focus on the role those governmental agencies could play in the regulation or certification of automated decision-making tools used by others.²⁴ Rather, with my proposals, for both the EEOC and the FTC, I envision a future where governmental agencies could legally and ethically *make use of* automated tools to achieve administrative law goals. Finally, in Part IV, in recognition of the shortcomings of algorithmic decision-making, the Article also proposes some necessary guardrails for when agencies deploy automated decision-making. These guardrails include: (1) Standing Advisory Council of Technologists and Social Scientists, (2) Stakeholder and Constituency Engagement, and (3) Congressional Overview and Review.

A few notes are necessary to make full sense of the Article: First, note that I eschew terms like “AI” (“artificial intelligence”) in favor of terms like “automated decision-making” or “automated tools,” and I prefer “automated governance”²⁵ over terms like “government by algorithm,” as doing so offers a more precise description.²⁶ Secondly, this Article should be read to be squarely in the camp of techno-realism. I define the term “techno-realism” as a recognition of both the utility and the limits of automated decision-making capabilities. This stance is useful in thinking through regulatory mechanisms for automated systems deployed as part of the administrative work of the government.

24. See Ifeoma Ajunwa, *An Auditing Imperative for Automated Hiring Systems*, 34 HARV. J.L. & TECH. 621, 660 (2021) [hereinafter Ajunwa, *An Auditing Imperative*] (arguing for the external audits of automated hiring programs used by employers); Pauline T. Kim, *Data-Driven Discrimination at Work*, 58 WM. & MARY L. REV. 857, 933 (2017) [hereinafter Kim, *Data-Driven Discrimination*].

25. This term is also used in the *Government by Algorithm* report. ENGSTROM ET AL., *supra* note 10, at 9.

26. Most law and technology scholars use “AI” to mean “automated decision-making.” See, e.g., Margot E. Kaminski & Jennifer M. Urban, *The Right To Contest AI*, 121 COLUM. L. REV. 1957, 1959 n.1 (2021) (“For purposes of discussion, this Article uses ‘AI’ decision-making as a shorthand to refer to decision-making by algorithms more generally.”); see also Algorithmic Accountability Act of 2019, H.R. 2231, 116th Cong. § 2(1) (2019) (defining an “automated decision system” as “a computational process, including one derived from machine learning, statistics, or other data processing or artificial intelligence techniques, that makes a decision or facilitates human decision-making”); David Lehr & Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. DAVIS L. REV. 653, 717 (2017) (“[Machine learning algorithms] are the complicated outputs of intense human labor—labor from data scientists, statisticians, analysts, and computer programmers.”). The decision in *Gottschalk v. Benson*, 409 U.S. 63 (1972), defined an algorithm as a “procedure for solving a given type of mathematical problem.” *Id.* at 65 (“A procedure for solving a given type of mathematical problem is known as an ‘algorithm.’”); see also *Paine, Webber, Jackson & Curtis, Inc. v. Merrill Lynch, Pierce, Fenner & Smith, Inc.*, 564 F. Supp. 1358, 1367 (D. Del. 1983) (“[A] computer algorithm is a procedure consisting of operation[s] to combine data, mathematical principles and equipment for the purpose of interpreting and/or acting upon a certain data input.”).

Although I have previously criticized the social phenomena of techno-solutionism,²⁷ this Article operates on the realist normative stance that automated tools could be useful tools for administrative governance *and* that, given their growing ubiquity, they are likely to be deployed as part of administrative governance. Note that this is not techno-determinism, as the Article does not advocate for a *laissez-faire* approach to governmental adoption of automated tools; on the contrary, the Article advocates for necessary guardrails as a check to the deployment of automated tools in governance. Finally, the proposals in this Article should not be read as support for a *carte blanche* approach to the adoption of automated tools both in the governmental or private sectors. Some automated tools should be banned altogether, either because of a fatal flaw in the underlying premise in their conception or because of their deleterious effect when put into practice.²⁸

I. THE ALGORITHMIC HAND IN GOVERNMENT

This part attempts to provide a clear-eyed survey of both the benefits and drawbacks of algorithmic administration. The aim of this part is both to give the reader a general sense of the utility of algorithmic administration and to provide adequate warnings about its shortcomings. This part also offers a discussion of whether algorithmic administration as a socio-legal phenomenon may be inevitable. Note that the pros and cons of automated governance offered in this part are general. For a specific examination, in *Automated Legal Guidance*, Professors Joshua D. Blank and Leigh Osofsky offer the case study of the Internal Revenue Service's "Interactive Tax Assistant."²⁹ One specific critique they share (which also could have general applicability) is that automated legal guidance tends towards "simplicity," wherein complex law is presented overly simplistically. This in turn may lead to the public receiving less precise and possibly inaccurate legal advice.³⁰

A. *The Benefits of Algorithmic Administration*

As noted in the report, *Government by Algorithm*,³¹ there are tangible benefits to deploying algorithmic processes for administrative decision-

27. Ajunwa, *An Auditing Imperative*, *supra* note 24, at 645–46.

28. See, e.g., Evan Sellinger & Woodrow Hartzog, *The Inconsistency of Facial Surveillance*, 66 LOY. L. REV. 101, 120 (2019) (arguing that valid consent cannot be given for facial surveillance and that thus the use of facial surveillance technologies both in the private and public sectors should be banned); see also Ifeoma Ajunwa, *Automated Video Interviewing as the New Phrenology*, 36 BERKELEY TECH. L.J. 101, 101 (2021) [hereinafter Ajunwa, *Automated Video Interviewing*] (questioning both the efficacy and legality of automated video interviewing tools which operate on pseudo-science).

29. Joshua D. Blank & Leigh Osofsky, *Automated Legal Guidance*, 106 CORNELL L. REV. 179, 205 (2020).

30. See *id.* at 208–21.

31. *Id.* at 206.

making.³² Here, I briefly discuss some of those benefits, including efficiency, cost-savings, and the ability of algorithmic systems to discern patterns displaying historical bias in their rulemaking or adjudication.

1. Efficiency

Given that computerized algorithms can process information at a much faster rate than humans, efficiency gains from deploying automated decision-making systems for administrative law work cannot be denied.³³ Beyond speed, some algorithmic processes have evinced more accuracy than humans, especially in consequential decision-making. For example, automated underwriting systems are more accurate at predicting mortgage default than humans and have thus resulted in previously-overlooked applicants receiving home loans.³⁴ Other researchers have also found that applying machine learning algorithms to pretrial detention decisions could reduce the jailing rate by forty-two percent without any attendant increase in crime.³⁵ A word of caution here. Efficiency should not be the paramount consideration for adopting algorithmic systems for government work. A crucial question when contemplating efficiency gains is to ask: Who benefits? After all, deploying machines to become more efficient in ways that might benefit the majority, but leave minorities out in the cold, would not serve the common good.

2. Cost-Savings

Cost-savings are an important consideration for the adoption of any technological tool; and even more so when the taxpayers bear that cost. As noted by *Forbes* magazine, automating work processes can result in cost savings of forty to seventy-five percent.³⁶ Consider that the budget of a single governmental agency can be in the hundreds of millions or even billions of dollars.³⁷ So, with the adoption of automated tools, the federal government

32. ENGSTROM ET AL., *supra* note 10, at 14.

33. See Sara Reardon, *Artificial Neurons Compute Faster Than the Human Brain*, NATURE (Jan. 26, 2018), <https://www.nature.com/articles/d41586-018-01290-0> [<https://perma.cc/X6C5-ZYXS>] (“Superconducting computing chips modelled after neurons can process information faster and more efficiently than the human brain.”).

34. See Susan Wharton Gates, Vanessa Gail Perry & Peter M. Zorn, *Automated Underwriting in Mortgage Lending: Good News for the Underserved?*, 13 HOUS. POL’Y DEBATE 369, 385 (2002) (explaining that “[a]n examination of Freddie Mac data suggests that [Automatic Underwriting] systems are more accurate” than human, manual underwriting and “[u]nderserved populations, particularly, appear to benefit from the system’s greater accuracy”).

35. See Jon Kleinberg, Himabindu Lakkaraju, Jure Leskovec, Jens Ludwig & Sendhil Mullainathan, *Human Decisions and Machine Predictions*, 133 Q.J. ECON. 237, 238 (2017).

36. David Kirk, *How Much Is Intelligent Automation Saving You?*, FORBES (Sept. 21, 2017), <https://www.forbes.com/sites/kpmg/2017/09/21/how-much-is-intelligent-automation-saving-you/?sh=56cd8188604c> [<https://perma.cc/RA2F-U8LD> (dark archive)].

37. See *Agency Profiles*, USASPENDING.GOV, <https://www.usaspending.gov/agency> [<https://perma.cc/3BU2-ZGAF>] (listing the budget of each U.S. government agency).

could also see hundreds of millions in cost-savings. Cost-savings, however, can never be the sole consideration for adopting automated decision-making tools. As several legal scholars have noted, equity and justice should remain the paramount guide.³⁸ Furthermore, the displacement or redundancy of workers is a direct result of the sort of labor cost-savings that automated decision-making systems bring about.³⁹ Thus, any saved funds resulting from automation in governmental agencies should also be earmarked for the upskilling or reskilling of displaced workers.⁴⁰

3. Uncovering Historical Patterns of Bias

A largely overlooked utility of computerized algorithmic processes is their capability to uncover patterns that would otherwise escape human detection, and which could thus serve as a precursor to redressing historical patterns of bias. This capability is termed “pattern recognition” and it is the use of computer algorithms to recognize data regularities and patterns.⁴¹ In governmental processes, pattern recognition is a process that could uncover historical patterns of bias within agencies. This uncovering could potentially include divergent patterns in the application of the rules or patterns demonstrating bias in both present and missing data. For example, in 2012, the Justice Mapping Center, using geospatial models, was able to map the residential addresses of prisoners to reveal what it dubbed “million-dollar blocks.”⁴² These are single city blocks where more than \$1 million had been

38. See Karen Tani, *The Limits of the Cost-Benefit Worldview: A Disability Informed Perspective*, LAW & POL. ECON. BLOG (Oct. 12, 2021), <https://lpeproject.org/blog/the-limits-of-the-cost-benefit-worldview-a-disability-informed-perspective/> [<https://perma.cc/EN65-LABE>] (“To the extent that CBA distracts lawmakers, regulators, and the broader public from seeing the injustice in the status quo, it is a problem.”); see also Cass R. Sunstein, *Cost-Benefit Analysis and the Separation of Powers*, 23 ARIZ. L. REV. 1267, 1272–75 (1981) (decrying the inappropriateness of cost-benefit analysis for certain kinds of statutes).

39. See, e.g., MARK MURO, ROBERT MAXIM, JACOB WHITON & IAN HATHAWAY, METRO. POL’Y PROGRAM AT BROOKINGS, AUTOMATION AND ARTIFICIAL INTELLIGENCE: HOW MACHINES ARE AFFECTING PEOPLE AND PLACES 1, 32, 57 (2019), https://www.brookings.edu/wp-content/uploads/2019/01/2019.01_BrookingsMetro_Automation-AI_Report_Muro-Maxim-Whiton-FINAL-version.pdf [<https://perma.cc/Z35Z-3ZGM>] (“Over the past 30 years, automation has displaced millions of workers.”).

40. See, e.g., *id.* at 52–54 (“To better facilitate this shift, businesses, educational institutions, governments, and nonprofit organizations should work to refine and scale up emerging models for accelerated learning . . .”); see also Joshua La Bella, *Hey Siri, What Is California Doing To Prepare for the Growth of Artificial Intelligence?*, 51 UNIV. PAC. L. REV. 315, 329–30 (2020) (offering an example of how California legislators introduced a bill with the goal of managing the potential displacement of workers due to automation).

41. Ann Waweru, *Understanding Pattern Recognition in Machine Learning*, SECTION (Mar. 31, 2021), <https://www.section.io/engineering-education/understanding-pattern-recognition-in-machine-learning/> [<https://perma.cc/F4XB-72HE>].

42. Diane Orson, *Million-Dollar Blocks’ Map Incarceration’s Cost*, NPR (Oct. 2, 2012, 6:13 PM), <https://www.npr.org/2012/10/02/162149431/million-dollar-blocks-map-incarcerations-costs> [<https://perma.cc/L4CU-9AYC>].

dispensed on incarcerating the denizens there.⁴³ The recognition of this pattern not only highlighted the cost of incarceration but also underscored the concentrated pattern of incarceration among minority neighborhoods in cities, thus lending credence to the theorization of sociologists like Loïc Wacquant who have argued against the term “mass incarceration,” in favor of the more precise term of “hyperincarceration.”⁴⁴

Automated systems could prove useful to the work of the EEOC and the FTC. For example, the EEOC could deploy automated processes to efficiently audit the hiring practices of certain companies or even entire industry sectors. The FTC could also use automated processes to check for such issues as the digital redlining of certain communities and the effect on consumer choices.⁴⁵ This does not so much follow the ideology of fighting fire with fire as it does the logic of using appropriate and efficient technological tools to address problems that are enabled or exacerbated by similar existing technological tools.

B. *The Technical Dangers*

The technical dangers of algorithmic administration are those that are endemic to any type of automated decision-making. This section catalogs two major technical dangers that could arise from governmental use of automated algorithms as part of its administrative process. This section also discusses whether the use of automated tools in government represents a form of techno-solutionism or, rather, a techno-realist ideal.

1. Flawed Models

A prevailing issue for automated decision-making systems is whether their premise is based on flawed logic, that is, whether the model created to return

43. *Id.*

44. Loïc Wacquant, *Class, Race & Hyperincarceration in Revanchist America*, 139 DAEDALUS 74, 74–90 (2010), <https://www.jstor.org/stable/pdf/20749843.pdf> [<https://perma.cc/8LU6-SJ9A>] (making the point that incarceration in the United States is not so much “mass” incarceration, rather it is “hyper” targeted on certain minority communities).

45. See Lior Jacob Strahilevitz, *Toward a Positive Theory of Privacy Law*, 126 HARV. L. REV. 2010, 2022–33 (2013) (analyzing the discriminatory effect of big data on some consumers); see also Tal Z. Zarsky, *Online Privacy, Tailoring, and Persuasion*, in PRIVACY AND TECHNOLOGIES OF IDENTITY 209, 213–14 (Katherine Strandburg & Daniela Stan Raicu eds., 2006) (discussing the concerns surrounding algorithms targeting specific consumers for particular products by invoking emotional responses in the consumers, inducing these consumers to act). See generally John Detrixhe & Jeremy B. Merrill, *The Fight Against Financial Advertisers Using Facebook for Digital Redlining*, QUARTZ (Nov. 1, 2019), <https://qz.com/1733345/the-fight-against-discriminatory-financial-ads-on-facebook/> [<https://perma.cc/PRU2-UXUQ>] (indicating that financial institutions that used Facebook’s “Lookalike Audience” targeting algorithm to “exclude[] protected categories like age and race from seeing credit ads” could subject those financial institutions to legal action under the Equal Credit Opportunity Act).

answers to a given problem is flawed or biased.⁴⁶ Solon Barocas and Andrew Selbst discuss this problem in *Big Data's Disparate Impact* and note that models for automated decision-making can introduce bias at the very onset based on how the “target variable” and “class labels” are defined.⁴⁷ Target variables refer to the outcomes of interest. To illustrate, when trying to solve $X + Y = Z$, the target variable is Z , which means that X and Y will be dependent on what Z is defined as. As Barocas and Selbst note: “The proper specification of the target variable is frequently not obvious, and the data miner’s task is to define it.”⁴⁸ Therein lies the danger. An issue arises when the Z variable is (un)intentionally defined as being linked to an X that is also a class label such as race, age, etc. As Barocas and Selbst further note: “Through this necessarily subjective process of translation, data miners may unintentionally parse the problem in such a way that happens to systematically disadvantage protected classes.”⁴⁹

In a governmental context, ensuring that automated decision-making systems are based on the correct models becomes an equal protection issue.⁵⁰ A poorly specified model may be efficient while still harming protected categories.⁵¹ It is also worth noting that automated decision-making systems work better for “problems that lend themselves to formalization as questions about the state or value of the target variable.”⁵² Not all problems lend themselves easily to such formalization. Barocas and Selbst point to fraud detection as an example of a problem that works well for automated decision-making because, as they conclude, determining fraud relies on “extant, binary categories.”⁵³ But I quibble with this conclusion. A determination of fraud is still a value judgment as to what is regular and what is then deemed irregular.

46. See Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 4 (2014) (“Because human beings program predictive algorithms, their biases and values are embedded into the software’s instructions . . .”); Citron, *supra* note 7, at 1254 (“Programmers routinely change the substance of rules when translating them from human language into computer code.”).

47. See Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CALIF. L. REV. 671, 677–92 (2016).

48. *Id.* at 678.

49. *Id.*

50. See, e.g., Margaret Hu, *Algorithmic Jim Crow*, 86 FORDHAM L. REV. 633, 668–71 (2017) (suggesting a need to broaden equal protection classifications so that automated immigration and security vetting protocols are covered by the Equal Protection Clause). But the government has also acknowledged “that big data analytics have the potential to eclipse longstanding civil rights protections in how personal information is used in housing, credit, employment, health, education, and the marketplace.” EXEC. OFF. OF THE PRESIDENT, *BIG DATA: SEIZING OPPORTUNITIES, PRESERVING VALUES* (2014), https://obamawhitehouse.archives.gov/sites/default/files/docs/big_data_privacy_report_may_1_2014.pdf [<https://perma.cc/ZXB4-SDL9>].

51. See, e.g., Mayson, *supra* note 1, at 2277–81 (discussing technology used to determine sentencing and how it fails racial minorities).

52. Barocas & Selbst, *supra* note 47, at 678.

53. *Id.*

Consider, for example, the recent news of the Biden administration's proposal⁵⁴ to allow the Internal Revenue Service ("IRS") to monitor transactions in personal and banking accounts that exceed \$600 in value.⁵⁵ The proposal would allow the IRS to tax more easily individuals who use peer-to-peer payment transaction apps if their transactions are greater than \$600.⁵⁶ This proposal seems to imply, for example, that the IRS will be more likely to flag individuals for tax fraud if they receive familial help or remittance payments in small, multiple payments than wealthier individuals, who may not receive such assistance. Could such surveillance also reveal a value judgment against people whose income is piecemeal as opposed to the traditional salary model?

2. Tainted Training Data

My past writings have criticized the conventional perspective that algorithmic processes are objective and therefore free of bias, noting that, even with a perfect model, the data that trained the model may introduce bias into the system.⁵⁷ This is because data is not objective; rather, it can become tainted with past decisions, such as what counts as data, and collection strategies, both of which reflect historical biases and underrepresentation.⁵⁸ As Professor Anupam Chander notes in *The Racist Algorithm?*, "Algorithms trained or operated on a real-world data set that necessarily reflects existing discrimination may well replicate that discrimination."⁵⁹ Consequently, such data may not be truly representative for some protected groups and thus could not serve as a nondiscriminatory basis for decision-making.⁶⁰

This raises an important question for governmental agencies to consider when they deploy automated decision-making tools that make use of training data: Should such training data be subject to review and revision? Professor Chander maintains that the answer to this question can only be yes, and he has

54. See U.S. DEP'T OF THE TREASURY, GENERAL EXPLANATIONS OF THE ADMINISTRATION'S FISCAL YEAR 2022 REVENUE PROPOSALS 1, 88–89 (2021), <https://home.treasury.gov/system/files/131/General-Explanations-FY2022.pdf> [<https://perma.cc/HGT7-URYJ>].

55. Patrick Gleason, *Biden's Proposed IRS Bank Account Snooping Authority Runs into State Resistance*, FORBES (Sept. 22, 2021), <https://www.forbes.com/sites/patrickgleason/2021/09/22/bidens-proposed-irs-bank-account-snooping-authority-runs-into-state-resistance/?sh=648a29493f2d> [<https://perma.cc/MX76-8TG8>].

56. *Id.*

57. Ajunwa, *The Paradox of Automation*, *supra* note 6, at 1685–90 ("[B]ecause data are historically biased towards certain groups or classes, discriminatory results may still emerge from automated algorithms that are designed in racial- or gender-neutral ways.").

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

59. *Id.* at 1036.

60. Barocas & Selbst, *supra* note 47, at 687.

called for what he terms “algorithmic affirmative action.”⁶¹ I concur and underline here that revising training data to remove historical bias is a heightened responsibility when there is state action—i.e., a governmental agency deploys automated decision-making to carry out its enforcement duties. Only in doing so can the agency fulfill its charge of equal protection under the law for all citizens.⁶²

C. *Techno-Solutionism or Techno-Realism?*

A socio-technical counterargument to automated governance is that this represents a form of techno-solutionism or an embrace of the ideology of tech as an oracle. Techno-solutionism, as a term, stands for the idea that societal problems can be easily or better solved with AI technology.⁶³ “Tech as oracle” refers to when automated decision-making decisions are accepted at face value and without critical evaluation.⁶⁴ The introduction of automated governance to governmental administrative processes could give rise to a two-fold problem: an undue reliance on technological tools that results in techno-solutionism, wherein automated decision-making is deployed to solve every problem without close examination of whether such use is appropriate; and an oracular acceptance of automated decision-making without critical reflection.

Although my previous articles have reflected some level of techno-skepticism, though not Luddism in the now common definition of the word,⁶⁵

61. See Chander, *supra* note 58, at 1027. This call for algorithmic affirmative action rests on the belief that since data are already tainted with bias, algorithms should be designed in “race- and gender-conscious ways to account for the already existing bias lurking in the data.” *Id.*

62. See, e.g., Kate Crawford & Jason Schultz, *AI Systems As State Actors*, 119 COLUM. L. REV. 1941, 1941 (2019) (arguing that in adjudicating cases that deal with AI systems used in government decision-making, “courts should adopt a version of the state action doctrine”).

63. Evgeny Morozov is widely credited with coining the term “technosolutionism.” See Adi Kuntsman & Esperanza Miyake, *The Paradox and Continuum of Digital Disengagement: DeNaturalising Digital Sociality and Technological Connectivity*, 41 MEDIA, CULTURE & SOC’Y 901, 902–03 (2019) (discussing Evgeny Morozov’s argument that solutionists are able to solve problems created or propagated by the internet “through technological and networked mediation”). See generally EVGENY MOROZOV, *TO SAVE EVERYTHING, CLICK HERE: THE FOLLY OF TECHNOLOGICAL SOLUTIONISM* (2013) (discussing the limitations of technological solutionism and internet-centrism).

64. See Ajunwa, *The Paradox of Automation*, *supra* note 6, at 1688. I discussed this phenomenon of “tech as oracle” in an earlier article. See *id.* An example of those espousing this belief is Chris Anderson who argues: “With enough data, the numbers speak for themselves.” See, e.g., Chris Anderson, *The End of Theory: The Data Deluge Makes the Scientific Method Obsolete*, WIRE (June 23, 2008, 12:00 PM), <https://www.wired.com/2008/06/pb-theory/> [<https://perma.cc/2B4V-6LSD> (dark archive)]; cf. Citron, *supra* note 7, at 1271–72 (describing “automation bias”); Lee A. Bygrave, *Minding the Machine: Article 15 of the EC Data Protection Directive and Automated Profiling*, 17 COMPUT. L. & SEC. REP. 17, 18 (2001) (noting the “automatic acceptance of the validity of the decisions reached”).

65. See generally KEITH GRINT & STEVE WOOLGAR, *THE MACHINE AT WORK: TECHNOLOGY, WORK AND ORGANIZATION* (1997) (countering the idea that the Luddites were antitechnology). Rather, the authors make the case that the Luddite’s quarrel was with how technology was changing the nature of work and eroding an artisanal way of life. *Id.*

Chekhov's maxim also comes to mind when contemplating automated decision-making as a part of the administrative process. To paraphrase Chekhov: once a gun is introduced in a story, it must be used.⁶⁶ A similar logic applies to automated decision-making technologies. Now that such technologies have become ubiquitous, it stands to reason that the government will and has deployed them. This is techno-realism. Techno-realism is the normative belief that automated systems, in and of themselves, are neither good nor bad.⁶⁷ Rather, automated systems are merely tools. And as tools, automated tools may be wielded to beneficial or ill-effects. The onus on the government, then, is to ensure that any automated decision-making tool it deploys will serve the greater good.

II. ETHICAL & LEGAL CHALLENGES TO AUTOMATED GOVERNMENT

This part considers ethical and legal challenges to deploying automated decision-tools for automated decision-making. Several scholars have written about the legal issues surrounding automated decision-making, particularly related to constitutional law and administrative law concerns.⁶⁸ This Article avoids retreading old ground here and instead attempts to shed new light on other considerations, including the development of new legal doctrine related to automated decision-making (such as the rights to explanation and contestation). This part also brings in literature from the field of philosophy to examine the question of whether there are palpable qualitative differences between human and automated decision-making that should preclude the use of the latter as a paragovernmental tool.⁶⁹

66. See Michael J. Higdon, *Something Judicious This Way Comes . . . The Use of Foreshadowing as a Persuasive Device in Judicial Narrative*, 44 U. RICH. L. REV. 1213, 1257–59 (2010) (examining the background of Chekhov's maxim and the principle it attempts to highlight).

67. See Ajunwa, *Automated Video Interviewing*, *supra* note 28, at 101.

68. See Coglianese & Lehr, *supra* note 19, at 1177–1213 (“An algorithm, by its very definition, must have its parameters and uses specified by humans, and this property will likely prove pivotal in the legal assessment of specific applications of artificial intelligence by federal administrative agencies.”); see also Engstrom & Ho, *supra* note 7, at 806, 827 (arguing that administrative law doctrines rather than constitutional law provides a better framework of analysis for administrative use of AI).

69. Other legal scholars have started this conversation. See Ray Worthy Campbell, *Artificial Intelligence in the Courtroom: The Delivery of Justice in the Age of Machine Learning*, 18 COLO. TECH. L.J. 323, 324, 341–49 (2020) (investigating the idea of an “AI Judge,” and asking whether one can ethically “delegate the creation and application of legal rights and responsibilities to impersonal artificial entities”).

A. *Meaningful Differences in Human Versus Algorithmic Decision-Making?*

Humans remain skeptical about the prospect of deputizing nonhuman agents with consequential decision-making.⁷⁰ Ethicists have debated whether there is some quality (ineffable or not) inherent to human decision-making that is lacking in automated decisions.⁷¹ While some ethicists question whether what might be termed “the human factor” is really “nostalgia masquerading as an ethical qualm,”⁷² others conclude that “something of real significance is lost when we eliminate the personal integrity and responsibility of a human decision-maker.”⁷³ As the issue at hand here is the *governmental* use of automated governance, this Article will set aside, for now, deontological questions⁷⁴ around the use of automated governance. The focus will be on the equal protection doctrine,⁷⁵ which prompts the consequentialist question⁷⁶ of whether there are important differences in human decision-making versus automated decision-making for different groups of people and, furthermore, whether such use is predicated on *animus rather than a legitimate governmental purpose*. This analytical focus is predicated on the understanding that one of the prevailing principles

70. Michael Sandel asks, “[A]re certain elements of human judgment indispensable in deciding some of the most important things in life?” Christina Pazzanese, *Ethical Concerns Mount as AI Takes Bigger Decision-Making Role in More Industries*, HARV. GAZETTE (Oct. 26, 2020), <https://news.harvard.edu/gazette/story/2020/10/ethical-concerns-mount-as-ai-takes-bigger-decision-making-role/> [<https://perma.cc/DZK6-WNNR>].

71. John Tasioulas, *First Steps Towards an Ethics of Robots and Artificial Intelligence*, 7 J. PRAC. ETHICS 61, 78 (2019) (concluding that “decisions about the life and liberty of others are so significant, something of value is lost if they are not made by an agent who can take responsibility for them . . . someone who can understand and empathise with our plight as a fellow human”).

72. *Id.* at 78–79.

73. David Edmonds, *Can We Teach Robots Ethics?*, BBC NEWS (Oct. 15, 2017), <https://www.bbc.com/news/magazine-41504285> [<https://perma.cc/C362-55MD>].

74. *See generally* Larry Alexander, *Deontology at the Threshold*, 37 SAN DIEGO L. REV. 893 (2000) (articulating that the basic tenet of deontology maintains that choices cannot be justified by their effects and that, no matter the good consequences, some choices should be morally forbidden); IMMANUEL KANT, *GROUNDWORK OF THE METAPHYSICS OF MORALS* (Allen W. Wood trans., 2002) (laying a fundamental principle of morality that has and continues to influence moral philosophy).

75. *See* U.S. CONST. amend. XIV, § 1 (“All persons born or naturalized in the United States, and subject to the jurisdiction thereof, are citizens of the United States and of the State wherein they reside. No State shall make or enforce any law which shall abridge the privileges or immunities of citizens of the United States; nor shall any State deprive any person of life, liberty, or property, without due process of law; nor deny to any person within its jurisdiction the *equal protection* of the laws.” (emphasis added)).

76. *See generally* AMARTYA SEN, BERNARD WILLIAMS, R.M. HARE, JOHN C. HARSANYI, J.A. MIRRELES, PETER J. HAMMOND, T.M. SCANLON, CHARLES TAYLOR, STUART HAMPSHIRE, JOHN RAWLS, FRANK HAHN, PARTHA DASGUPTA, JON ELSTER, ISAAC LEVI, FREDERIC SCHICK & AMY GUTMANN, *UTILITARIANISM AND BEYOND* (Amartya Sen & Bernard Williams eds., 1982) (discussing Consequentialism); JOEL J. KUPPERMAN, AMARTYA SEN, JAMES GRIFFIN, R. EUGENE BALES, ROBERT MERRIHEW ADAMS, PETER RAILTON, PHILIP PETTIT, GEOFFREY BRENNAN, JOHN RAWLS, J.J.C. SMART, ALLAN F. GIBBARD, H.J. MCCLOSKEY, PETER SINGER, DAVID LEWIS, DEREK PARFIT, LARS BERSTRÖM, FRANK JACKSON, GRAHAM ODDIE, PETER MENZIES, MICHAEL SLOTE & SHELLY KAGAN, *CONSEQUENTIALISM* (Philip Pettit ed., 1991) (same).

for the law is ensuring that the way the government administers law does not have an uneven effect on any citizen or group of citizens.⁷⁷

Thus, a strictly deontological examination of differences between automated and human decision-making is both beyond the purview of the law and unnecessary in the case of government agency adoption of automated decision-making tools. The overriding ethical question in adopting automated decision-making for agency work should be whether such state action would unevenly change the consequences for citizens, either for better or worse.⁷⁸ Note also that the consequentialist view is generally agent-neutral—that is, the focus is less on the agent, and rather on the effect of the actions of the agent.⁷⁹ Second, a deontological examination of differences between automated decision-making tools for agency work is ultimately uncalled for because none of the scenarios found in the report of current automated tool deployment, or my proposals for the future deployment of work, call for the complete absence of human intervention.⁸⁰ Thus, the automated tools, themselves, will never be called upon to make any tragic moral choices;⁸¹ this duty will continue to rest on the shoulders of humans.

B. *The Right to Explanation*

Accepting a consequentialist approach to the governmental adoption of automated decision-making raises the issue of whether the citizen has a right to

77. See U.S. CONST. amend. XIV.

78. See, e.g., Brian Talbot, Ryan Jenkins & Duncan Purves, *When Robots Should Do the Wrong Thing*, in *ROBOT ETHICS 2.0: FROM AUTONOMOUS CARS TO ARTIFICIAL INTELLIGENCE* 258, 259–60 (Patrick Lin ed., 2017) (maintaining that because robots cannot be conceived of as agents, that robots' actions thus cannot violate (deontological) requirements, and that robots should act like consequentialists).

79. See generally DEREK PARFIT, *REASONS AND PERSONS* 24–49 (1984) (“[O]ur ultimate moral aim [as Consequentialists] is, not that outcomes be as good as possible, but that history go as well as possible.”); THOMAS NAGEL, *THE VIEW FROM NOWHERE* 165–81 (1986) (arguing that “most of the things we pursue, if not most of the things we avoid, are optional,” and that when we evaluate others' reasons for pursuing these optional “things” from an objective standpoint, we can acknowledge the validity of their reasons without accepting “a neutral reason for any of those things to be done”). For notable arguments for agent-centered consequentialism, see Amartya Sen, *Rights and Agency*, 11 *PHIL. & PUB. AFFAIRS* 3, 28–31 (1982); Amartya Sen, *Well-Being, Agency and Freedom: The Dewey Lectures 1984*, 82 *J. PHIL.* 169, 176–84 (1985). For challenges to agent-centered theories of consequentialism, see F.M. KAMM, *INTRICATE ETHICS: RIGHTS, RESPONSIBILITIES, AND PERMISSIBLE HARM* 26–29 (2007); T.M. SCANLON, *MORAL DIMENSIONS: PERMISSIBILITY, MEANING, BLAME* 96–97 (2008); Judith Jarvis Thomson, *Physician-Assisted Suicide: Two Moral Arguments*, 109 *ETHICS* 497, 514–16 (1999).

80. See generally ENGSTROM ET AL., *supra* note 10, at 7 (explaining that “[p]olicymakers should also consider other interventions” such as “requir[ing] agencies to engage in prospective ‘benchmarking’ of AI tools . . . thus providing critical information to smoke out when an algorithm has gone astray”).

81. See generally Martha C. Nussbaum, *The Costs of Tragedy*, 29 *J. LEGAL STUD.* 1005 (2000) (discussing situations that give rise to tragic moral choices).

explanation.⁸² Essentially, a right to explanation would necessitate that the government be able to explain the automated decision-making process (both the algorithm(s) deployed and the factors that were considered) that lead to a given decision. Should not the outcomes of an automated governmental tool be fully explainable to ensure accountability? The *Government by Algorithm* report observed: “A critical question is whether continued uptake of automated tools by enforcement agencies will, on net, render enforcement decisions more or less accountable.”⁸³ This is a valid question to raise given that the report also notes: “The black box nature of machine learning tools may exacerbate accountability concerns.”⁸⁴

Professor Katherine J. Strandburg argues that opaque algorithms “can disrupt [information] flows,” a particularly troubling reality when such algorithms are used to replace explainable, yet complex, decision-making processes.⁸⁵ Strandburg proposes that, rather than eliminate algorithmic decision-making, lawmakers should instead create a legal “framework for adequate explanation,” which would require transparency around “all of the ‘explainable components’” that inform an algorithm’s decision-making, as well as transparency about the training data and validation measures an algorithm relies on.⁸⁶ Strandburg’s approach specifically addresses algorithms used to make decisions for government agencies.⁸⁷

James Grimmelman and Daniel Westreich come to a similar conclusion in *Incomprehensible Discrimination*, wherein they examine the legal implications of a hiring model that is positively correlated to job performance yet yields a discriminatory impact.⁸⁸ Grimmelman and Westreich call for a need for explainability given the difficulty for a claimant to “improve on an algorithm it did not create and does not understand”; without this explainability, the claimant would likely fail to offer the sort of “concrete and less discriminatory alternative” needed to prevail under the current Title VII case law.⁸⁹

The issue of transparency identified by Grimmelman and Westreich is impossible to overstate and transcends the charge of Title VII, extending to all forms of bias that algorithms may perpetuate. At a basic level, discrimination

82. See Strandburg, *supra* note 22, at 1851; see also, Ashley Deeks, *The Judicial Demand for Explainable Artificial Intelligence*, 119 COLUM. L. REV. 1829, 1829–30 (2019) (arguing that AI used in criminal, administrative, and criminal cases should require explanations for algorithmic outcomes to avoid the “black box” problem).

83. ENGSTROM ET AL., *supra* note 10, at 28.

84. *Id.*

85. See Strandburg, *supra* note 22, at 1851.

86. *Id.* at 1882–83.

87. See *id.* at 1858 (“This essay focuses on the implications for the creation of decision criteria—or rulemaking.”).

88. Grimmelman & Westreich, *supra* note 23, at 170.

89. *Id.* at 168–69.

must be visible to be identified and remedied. The workings of machine learning algorithms, however, can be notoriously opaque.⁹⁰ Without any real legal mandate around algorithmic transparency, bias may proliferate in any automated decision-making system. Consider, for example, a disabled individual who is taking an algorithm-based video interview for employment. Under the Americans with Disabilities Act (“ADA”) of 1990, the individual in question has the responsibility to request a reasonable accommodation during the interview process; however, as Allan G. King and Marko J. Mrkonich point out in *“Big Data” and the Risk of Employment Discrimination*, to request a reasonable accommodation, applicants must first be “informed of the test’s elements.”⁹¹ That is, if disabled candidates do not know how or what attributes are being measured, they cannot know to request an accommodation. Thus, the “black box” nature of algorithms poses a unique threat to ADA protection.⁹²

The current legal policy simply does not mandate the level of transparency required to mitigate algorithmic discrimination. For example, while Title VII prohibits employers from considering protected characteristics in employment decisions, it fails to account for the reality that algorithms need not explicitly consider a protected characteristic to discriminate.⁹³ According to legal scholars Anya Prince and Daniel Schwarz, AI will work to make connections even in the absence of protected information if there is a link between the candidate’s “legally protected characteristic and a target variable of interest.”⁹⁴ As I explore in my recent paper, *An Auditing Imperative for Automated Hiring*, and later in this Article, mandated audits of automated systems are what can offer a more meaningful level of transparency and are necessary to ensure explainability.⁹⁵

C. *The Right to Contestation*

A relatively overlooked issue when considering automated decision-making as a paragovernmental tool is whether there should be an individual

90. See PASQUALE, *supra* note 1, at 66 (asserting that the secrecy behind machine learning algorithms “devastates our ability to understand the social world Silicon Valley is creating” and leaves “plenty of room for opportunistic, exploitative, and just plain careless conduct to hide”).

91. Allan G. King & Marko J. Mrkonich, *“Big Data” and the Risk of Employment Discrimination*, 68 OKLA. L. REV. 555, 582 (2016).

92. See Ifeoma Ajunwa, *The “Black Box” at Work*, 7 BIG DATA & SOC’Y 1, 1–3 (2020) [hereinafter Ajunwa, *The “Black Box” at Work*]; see also PASQUALE, *supra* note 1, at 40 (“Without access to the underlying data and code, we will never know what type of tracking is occurring, and how the discrimination problems long documented in ‘real life’ may even now be insinuating themselves into cyberspace.”).

93. See 42 U.S.C. § 2002e(a).

94. Anya E.R. Prince & Daniel Schwarz, *Proxy Discrimination in the Age of Artificial Intelligence and Big Data*, 105 IOWA L. REV. 1257, 1277 (2020).

95. See Ajunwa, *An Auditing Imperative*, *supra* note 24, at 659–62; see also Cary Coglianese & Erik Lampmann, *Contracting for Algorithmic Accountability*, 6 ADMIN. L. REV. ACCORD 175, 184–94 (2021) (discussing public procurement for AI tools and services and highlights four specific issues: privacy/cybersecurity, auditing, and public participation).

right to the contestation of the results.⁹⁶ As Margot Kaminski and Jennifer Urban discuss in *The Right To Contest AI*, the European Union and other governmental entities do already, in fact, recognize such a right.⁹⁷ Kaminski and Urban note:

The European Union’s (EU) General Data Protection Regulation (GDPR), which went into effect in May 2018, establishes a complex set of regulations of algorithmic decision-making that span multiple contexts and sectors.⁹⁸ The GDPR incorporates both systemic governance measures and various individual rights for data subjects: transparency, notice, access, a right to object to processing, and, for those subject to automated decision-making, the *right to contest* certain decisions.⁹⁹

Even for the United States, which has not explicitly recognized such a right, the right to contestation of AI could be derived from the legal principle of due process—the notion that there ought to be a procedure or hearing before an individual may be deprived of her rights.¹⁰⁰

Beyond the criminal context, in which the right to contestation is well established,¹⁰¹ an enduring dilemma for agency use of automated decision-making is how exactly the right to contestation should operate in practice when

96. Several scholars have written about the question of contesting automated results in various contexts, but particularly in the criminal justice context. *See, e.g.*, Deirdre K. Mulligan & Kenneth A. Bamberger, *Procurement As Policy: Administrative Process for Machine Learning*, 34 BERKELEY TECH. L.J. 781, 835–37 (2019) (arguing that impact assessments within administrative law force federal agencies to address issues they may be unfamiliar with and prevent these agencies from “rendering policy implications invisible and making choices seem . . . incontestable”); Rebecca Wexler, *Life, Liberty, and Trade Secrets: Intellectual Property in the Criminal Justice System*, 70 STAN. L. REV. 1343, 1348–64 (2018) (highlighting the debates surrounding the use of criminal justice technologies, one being the dispute over the contestability of an algorithm’s analysis of one’s guilt); Jessica M. Eaglin, *Constructing Recidivism Risk*, 67 EMORY L.J. 59, 89–92 (2017) (analyzing the use of algorithms for recidivism analysis and discussing the limitations of the accuracy measurements of these mechanisms).

97. *See, e.g.*, Kaminski & Urban, *supra* note 26, at 1957.

98. *Id.* at 1962 (citing Commission Regulation 2016/679, 2016 O.J. (L 119/1) 1 (EU) [hereinafter GDPR]); Kaminski, *supra* note 23, at 1546–47 (comparing distinctions between human and algorithmic decision making).

99. Kaminski & Urban, *supra* note 26, at 1962 (emphasis in original) (citing GDPR, *supra* note 98, art. 22(3)).

100. *See* Henry J. Friendly, “*Some Kind of Hearing*,” 123 U. PA. L. REV. 1267, 1267 (1975) (collecting cases and quoting as his title Justice White’s statement that “[t]he Court has consistently held that some kind of hearing is required at some time before a person is finally deprived of his property interests” (quoting *Wolff v. McDonnell*, 418 U.S. 539, 557–58 (1974))); *see also* Crawford & Schultz, *supra* note 62, at 1941 (arguing that in adjudicating cases that deal with AI systems used in government decision-making, “courts should adopt a version of the state action doctrine”).

101. *See* U.S. CONST. amend. VI (“In all criminal prosecutions, the accused shall enjoy the right to a speedy and public trial, by an impartial jury of the State and district wherein the crime shall have been committed, which district shall have been previously ascertained by law, and to be informed of the nature and cause of the accusation; to be confronted with the witnesses against him; to have compulsory process for obtaining witnesses in his favor, and to have the Assistance of Counsel for his defense.”).

life or liberty is not at stake, but perhaps welfare benefits, access to employment, or other tangible economic benefits are. Should the right to contestation in those cases still be individual (as in the criminal context), or could it be collective or class-based wherein a class of people denied governmental benefits can collectively contest their outcomes? Would any efficiency or cost savings from using automated governmental tools be diminished or even entirely decimated if such automated decision-making was subject to individual contestation?

III. PROPOSALS FOR MORE AUTOMATED GOVERNANCE

Notwithstanding some potential dangers arising from state algorithmic decision-making, when such action is managed properly, I maintain that there is utility in deploying automated decision-making systems for some types of agency administrative work.¹⁰² The Podesta Report, released by the White House in 2014, recommended that enforcement agencies, such as the Department of Justice, Consumer Financial Protection Bureau (“CFPB”), EEOC, and FTC, “develop a plan for investigating and resolving violations of law in such cases” (referring to cases involving “big data”).¹⁰³ Thus, in this part, I examine the role that automated decision-making tools could play to aid the administrative work of both the EEOC and the FTC in regulating certain types of business decision-making. Note that in advocating for the use of automated decision-making tools by governmental agencies, I maintain that such agencies should use only tools built in-house. The current use of automated decision-making tools runs the gamut from entirely in-house, to collaboratively created, or entirely outsourced to contractors.¹⁰⁴ But the *Government by Algorithm* report found that “[i]n-house expertise promotes AI tools that are better tailored to complex governance tasks and more likely to be designed and implemented in lawful, policy-compliant, and accountable ways.”¹⁰⁵ Some welcome news is that the report also notes that over half of all governmental automated tools are already being built in-house.¹⁰⁶

102. The authors of the *Government by Algorithm* report came to this conclusion as well:

Managed well, algorithmic governance tools can modernize public administration, promoting more efficient, accurate, and equitable forms of state action. Managed poorly, government deployment of AI tools can hollow out the human expertise inside agencies with few compensating gains, widen the public-private technology gap, increase undesirable opacity in public decision-making, and heighten concerns about arbitrary government action and power.

ENGSTROM ET AL., *supra* note 10, at 8.

103. EXEC. OFF. OF THE PRESIDENT, *supra* note 50, at 65.

104. ENGSTROM ET AL., *supra* note 10, at 18.

105. *Id.* at 7.

106. *See id.* at 18.

A. *EEOC Governance of Automated Hiring*

Title VII of the Civil Rights Act of 1964 enacted the EEOC as a federal agency with the purpose of eliminating employment-based discrimination in the United States.¹⁰⁷ While the EEOC found its footing as a Title VII enforcement mechanism in the 1970s, the scope of the EEOC's authority has since expanded to govern various other federal laws on employment discrimination.¹⁰⁸ At present, the EEOC is responsible for enforcing seven different federal laws, including the Age Discrimination in Employment Act ("ADEA") of 1967, the ADA, and the Genetic Information Nondiscrimination Act of 2008.¹⁰⁹ Given the well-established authority of the EEOC over a broad range of employment discrimination issues, and given the growing ubiquity of automated hiring,¹¹⁰ I argue that the EEOC is well suited to deploy automated tools in its administrative work against employment discrimination.

Automated hiring may both exacerbate and create new opportunities for employment discrimination.¹¹¹ Hiring algorithms may channel job advertisements to particular demographic groups,¹¹² may rely on incomplete or inaccurate training data that propagates historical and structural employment biases,¹¹³ or may be trained to favor one group of applicants at the expense of others over time.¹¹⁴ Automated interviewing, in particular, may give rise to discrimination by illegally revealing information about a candidate's protected characteristics, by systemically misinterpreting the responses of particular demographic groups, or by improperly disadvantaging members of a protected class in the algorithmic scoring process.¹¹⁵ Predictive salary algorithms may promote discriminatory pay differentials.¹¹⁶ On the whole, therefore, automated

107. Civil Rights Act of 1964, Pub. L. No. 88-352, tit. VII, § 705(a)-(d), (f)-(j), 78 Stat. 241, 258-59 (codified as amended at 42 U.S.C. § 2000e-4 (1995)); Anne Noel Occhialino & Daniel Vail, *Why the EEOC (Still) Matters*, 22 HOFSTRA LAB. & EMP. L.J. 671, 672 (2005).

108. See Occhialino & Vail, *supra* note 107, at 684-87.

109. See generally *What Laws Does EEOC Enforce?*, U.S. EQUAL EMP. OPPORTUNITY COMM'N, <https://www.eeoc.gov/youth/what-laws-does-eeoc-enforce> [<https://perma.cc/3GL2-32J8>] (discussing the laws that come under the purview of the EEOC).

110. See Ifeoma Ajunwa & Daniel Greene, *Platforms at Work: Automated Hiring Platforms and Other New Intermediaries in the Organization of Work*, in 33 WORK AND LABOR IN THE DIGITAL AGE 62, 62 (Steve P. Vallas & Anne Kovalainen eds., 2019).

111. See Ajunwa, *An Auditing Imperative*, *supra* note 24, at 635-37.

112. See Fifth Amended Class and Collective Action Complaint ¶ 84, *Bradley v. T-Mobile U.S., Inc.*, No. 17-cv-07232-BLF (N.D. Cal. Mar. 13, 2020), 2020 WL 1233924.

113. See Isobel Asher Hamilton, *Amazon Built an AI Tool To Hire People but Had To Shut It Down Because It Was Discriminating Against Women*, BUS. INSIDER (Oct. 10, 2018, 5:47 AM), <https://www.businessinsider.com/amazon-built-ai-to-hire-people-discriminated-against-women-2018-10> [<https://perma.cc/T6L3-FG5T>].

114. See Ajunwa, *An Auditing Imperative*, *supra* note 24, at 635.

115. *Id.* at 639.

116. *Id.*

hiring gives rise to many different forms of employment discrimination which all fall under the EEOC's purview.

As a regulatory agency, the EEOC may employ several different tools to regulate algorithmic employment decision-making models. Traditionally, the EEOC is tasked with interpreting statutes through the rulemaking process.¹¹⁷ During the rulemaking process, the EEOC has the authority to interpret and, where necessary, expand on federal law to create official regulations.¹¹⁸ Stakeholders are given the chance to provide input as to the content and form of the final rules.¹¹⁹ The EEOC may also issue regulatory guidance to elucidate EEOC policy concerning specific scenarios, in addition to taking specific legal enforcement action against actions they believe violated existing rules.¹²⁰ The rulemaking and subregulatory guidance processes represent significant avenues by which issues of algorithmic employment discrimination may be addressed.

Some issues inherent to automated hiring appear to violate existing federal antidiscrimination laws, such as Title VII, and therefore already fall within the bounds of EEOC regulation.¹²¹ As such, new, specific subregulatory guidance may provide valuable protection for employees. The EEOC has a history of updating rules and guidelines to adapt to technological advancements; this is a valuable first step.¹²² However, as I discuss below, addressing automated hiring issues through existing frameworks alone is complicated and incomplete. Therefore, with this Article, I draw a blueprint for the EEOC not only to bolster their existing enforcement power through updated, specific regulatory guidance, but also to expand their authority over automated hiring algorithms through new legislation and by making use of automated tools themselves.

1. The History of EEOC Regulation of Work Technologies

Since its inception, advancements in work technologies have changed the face of the workplace,¹²³ forcing the EEOC to adapt its policies in turn. The

117. See Elizabeth A. Crawford, *The Courts' Interpretations of a Disability Under the Americans with Disabilities Act: Are They Keeping Our Promise to the Disabled*, 35 HOUS. L. REV. 1208, 1209 (1998).

118. See Mark Kloempken & Tove Klovning, *Locating and Updating Federal Regulations: The Regulatory Process*, WASH. U. L. LIB. (Apr. 27, 2020), <https://libguides.law.wustl.edu/c.php?g=110784&p=1225786> [https://perma.cc/HGK9-P6TZ].

119. *Laws & Guidance*, U.S. EQUAL EMP. OPPORTUNITY COMM'N, <https://www.eeoc.gov/laws-guidance-0> [https://perma.cc/K8NA-JNUR].

120. *Id.*

121. See Barocas & Selbst, *supra* note 47, at 694.

122. See, e.g., Marianne DelPo Kulow & Scott Thomas, *Assistive Technology and the Americans with Disabilities Act*, 40 BERKELEY J. EMP. & LAB. L. 257, 270–75 (2019).

123. See Nancy B. Schess, *Then and Now: How Technology Has Changed the Workplace*, 30 HOFSTRA LAB. & EMP. L.J. 435, 438 (2013) (“PDAs, cell phones, laptops and programs that connect home and work computers have changed the traditional workspace since work can now easily be performed outside the physical office.”); CYNTHIA ESTLUND, *AUTOMATION ANXIETY: WHY AND HOW TO SAVE WORK* 80–81 (2021).

advent of the internet offers perhaps the most salient recent example of a technological development that completely overhauled business practice and procedure. Examining the nature and limitations of the EEOC's response to the proliferation of the internet and its effect on the modern workplace offers valuable insight into possible paths to automated hiring regulation.

The EEOC has a history of updating its regulatory guidance in response to the gray area threats of technological advancement. For instance, the advent of the internet created considerable confusion around the regulatory definition of a "job applicant" for EEOC requirements for federal contractors.¹²⁴ At the start of the twenty-first century, EEOC guidance was based on guidelines developed in the late 1970s; the guidelines employed a broad definition of job applicants, which encompassed any "person who has indicated an interest in being considered for hiring, promotion, or other employment opportunities."¹²⁵ As developments in communication technologies rapidly accelerated in the digital age, this definition became both vague and overbroad. The record-keeping obligation for an employer to track every individual who simply viewed their job posting, for example, differs greatly from the obligation to keep records on individuals who submit a formal, required application. The acting definition for job applicants at the time did not clarify the duty of care employers were obligated to uphold.¹²⁶ Recognizing this gray area, in 2004, the EEOC issued updated guidelines to help employers understand their record-keeping duties specifically concerning "the [i]nternet and [r]elated [t]echnologies."¹²⁷ The new three-prong definition the EEOC implemented applied exclusively to the new technology in question and offered more specific clarity on the requirements an individual must meet to be considered an applicant.¹²⁸ This regulatory response indicates that as the EEOC recognizes areas where existing guidelines fail to provide adequate guidance for employers, it can respond with updated, more specific regulatory frameworks to address the unique nature of new technology.

The EEOC has also acted to increase employers' responsibilities in response to when new technologies prompt changes in work. In the early 2000s, the EEOC issued formal guidance updates concerning an employer's

124. FindLaw Attorney Writers, *Federal Recordkeeping Requirements: Who Is a "Job Applicant"?*, FINDLAW (Mar. 26, 2008), <https://corporate.findlaw.com/law-library/federal-recordkeeping-requirements-who-is-a-job-applicant.html> [<https://perma.cc/K238-8UBV>].

125. *Id.* (quoting 44 Fed. Reg. 11996 (Mar. 2, 1979)).

126. See AKIN GUMP STRAUSS HAUER & FELD LLP, LABOR AND EMPLOYMENT ALERT: EEOC AND OFCCP ISSUE LONG-AWAITED GUIDANCE ON THE DEFINITION OF "APPLICANT" 2 (2004), <https://www.akingump.com/a/web/1032/aogHh/659.pdf> [<https://perma.cc/FLB5-5E2U>] ("The earlier EEOC/OFCCP guidance defined an applicant as any individual who 'expresses an interest in employment.'").

127. FindLaw Attorney Writers, *supra* note 124.

128. *Id.*

responsibility to provide reasonable accommodation to disabled job applicants and employees under the ADA.¹²⁹ As the internet changed the nature of work, the concept of remote work became more feasible.¹³⁰ The EEOC responded in turn with a requirement that, all else being equal, employers must consider telework as a reasonable accommodation for disabled employees, even if they otherwise prohibit telework for their general workforce.¹³¹ In this way, the EEOC demonstrated that they not only would update guidelines to adapt to new technologies but also that they would consider how new technologies impact an employer's legal duty of care. Telework meant new possibilities for disabled workers, and new responsibilities for employers in turn.¹³² Applying these precedents to automated hiring, there is a strong argument that the EEOC has a self-created obligation to engender new regulations that directly address automated hiring and to deploy automated hiring tools, when needed, to enforce those regulations.

Beyond updating formal guidance, the EEOC has also shown a willingness to regulate new avenues of discrimination through existing frameworks where possible. That is, they have not shied away from reasonably extending the scope of existing policies to regulate novel means of discrimination. In 2018, the EEOC brought a sexual harassment case against a major airline player, United Airlines, Inc. ("United"), in response to allegations that a flight attendant faced years of online harassment from a United pilot.¹³³ The pilot was charged with posting sexually explicit images of the flight attendant across multiple internet

129. See *Work at Home/Telework as a Reasonable Accommodation*, U.S. EQUAL EMP. OPPORTUNITY COMM'N (Feb. 3, 2003), <https://www.eeoc.gov/laws/guidance/work-hometelework-reasonable-accommodation> [https://perma.cc/M9DV-7JYH] [hereinafter *Work at Home*].

130. See Niraj Chokshi, *Out of the Office: More People Are Working Remotely, Survey Finds*, N.Y. TIMES (Feb. 15, 2017), <https://www.nytimes.com/2017/02/15/us/remote-workers-work-from-home.html> [https://perma.cc/E5D2-M9UC (staff-uploaded, dark archive)]; Zara Abrams, *The Future of Remote Work*, AM. PSYCH. ASS'N (Oct. 1, 2019), <https://www.apa.org/monitor/2019/10/cover-remote-work> [https://perma.cc/YW4Z-HUUC]; Susan Lund, Anu Madgavkar, James Manyika & Sven Smit, *What's Next for Remote Work: An Analysis of 2,000 Tasks, 800 Jobs, and Nine Countries*, MCKINSEY GLOB. INST. (Nov. 23, 2020), <https://www.mckinsey.com/featured-insights/future-of-work/whats-next-for-remote-work-an-analysis-of-2000-tasks-800-jobs-and-nine-countries> [https://perma.cc/T5H5-QKG4 (staff-uploaded archive)].

131. *Work at Home*, *supra* note 129.

132. See, e.g., Frances Ryan, *Remote Working Has Been Life-Changing for Disabled People, Don't Take It Away Now*, GUARDIAN (June 2, 2021, 4:00 EDT), <https://www.theguardian.com/commentisfree/2021/jun/02/remote-working-disabled-people-back-to-normal-disability-inclusion> [https://perma.cc/HM2N-TD87] ("The shift to working at home over the past year brought new opportunities to those previously excluded from the workforce.").

133. Complaint, EEOC v. United Airlines, Inc., No. 5:18-cv-817 (W.D. Tex. Aug. 9, 2018); see also *United Airlines To Pay \$321,000 and Fight Internet Harassment To Settle EEOC Discrimination Suit*, U.S. EQUAL EMP. OPPORTUNITY COMM'N (Dec. 20, 2019), <https://www.eeoc.gov/newsroom/united-airlines-pay-321000-and-fight-internet-harassment-settle-eeoc-discrimination-suit> [https://perma.cc/8M4V-GD8E] [hereinafter *United Airlines To Pay \$321,000*].

platforms; despite repeated complaints, United failed to act.¹³⁴ Ultimately, the EEOC found that United's failure constituted a violation of the flight attendant's Title VII rights.¹³⁵ In press coverage around the settlement of the case, the EEOC made clear its position on the applicability of its policies in the digital age, stating: "Employee workdays and jobsites are no longer defined by timecards and the walls of a building, but by the breadth of a digital day and the reach of electronic communications."¹³⁶ Discrimination was not permissible merely because the discrimination took place outside of the traditional bounds of the workplace. Rather, the EEOC effectively stated that the pervasive nature of internet technology completely altered the scope of the modern workplace and the applicable scope of Title VII in turn.

Regarding automated hiring and the increasingly pervasive nature of automated hiring tools, which may trawl any available information on the applicant from the web,¹³⁷ such historical precedent suggests expanding the scope of Title VII and ADA policies to cover new forms of algorithmic discrimination is entirely within the EEOC's sphere of control.

The EEOC has already taken steps to explicate how existing policies apply in the algorithmic age. Per the ADEA, employers are forbidden from considering an employee's age in the hiring process.¹³⁸ Traditionally, this has meant that job advertisements that specify applicants belong to certain age groups are unlawful except in special circumstances.¹³⁹ However, new algorithms allow employers to target jobs to specific age groups without ever specifying a preference for certain age groups in the body of the advertisement itself.¹⁴⁰ For example, a lawsuit alleged that the popular social media and advertising platform, Facebook, allowed its advertisers to specify their ads be channeled to individuals with certain demographic backgrounds, from disability

134. *United Airlines To Pay \$321,000*, *supra* note 133.

135. *Id.*

136. *Id.*

137. See Ben Dattner, Tomas Chamorro-Premuzic, Richard Buchband & Lucinda Schettler, *The Legal and Ethical Implications of Using AI in Hiring*, HARV. BUS. REV. (Apr. 25, 2019), <https://hbr.org/2019/04/the-legal-and-ethical-implications-of-using-ai-in-hiring> [<https://perma.cc/78FV-E3UY> (dark archive)] ("Big data is following us everywhere we go online and collecting and assembling information that can be sliced and diced by tools we can't even imagine yet—tools that could possibly inform future employers about our fitness (or lack thereof) for certain roles.")

138. Age Discrimination in Employment Act, Pub. L. No. 90-202, 81 Stat. 602, 603 (1967) (codified as amended at 29 U.S.C. § 623(a) (2016)).

139. Nathaniel M. Glasser, Adam S. Forman & Matthew Savage Aibel, *INSIGHT: Online Ads Targeting Job Applicants Under Scrutiny from EEOC, Plaintiffs Bar*, BLOOMBERG L. (Nov. 13, 2019, 4:01 AM), <https://news.bloomberglaw.com/daily-labor-report/insight-online-ads-targeting-job-applicants-under-scrutiny-from-eeoc-plaintiffs-bar> [<https://perma.cc/G3PD-JVGL>].

140. See *id.*

status to gender identity.¹⁴¹ This feature allowed employers advertising on Facebook to de facto discriminate against job applicants by limiting who could see the advertisement in the first place. While Facebook ultimately agreed to discontinue the demographic targeting feature for advertisements concerning employment, amongst other protected categories, the EEOC nevertheless sought enforcement actions against employers who made use of the discriminatory tool while it was still available.¹⁴² In July of 2019, the EEOC issued “reasonable cause” findings against seven major employers who engaged in discrimination when targeting certain demographic groups through Facebook ads, inviting the companies to come to a settlement agreement.¹⁴³

This EEOC enforcement action was a significant step towards regulating employment discrimination in the algorithmic age. This action by the EEOC also evinced that it is willing and able to expand existing definitions of discrimination to include the indirect forms of discrimination that algorithms perpetuate. Employers will still be held legally responsible, even when they employ automated tools, which discriminate on their behalf.¹⁴⁴

2. Limitations of Existing Doctrine To Regulate AI in the Workplace

Some scholars have suggested that current readings of Title VII are unable to accurately account for the nature of discrimination that algorithms perpetuate.¹⁴⁵ For example, the legal scholar Pauline Kim has noted that the existing applications of disparate treatment and disparate impact frameworks do not effectively govern “the data-driven nature of classification bias” inherent to algorithms.¹⁴⁶ Classification bias, according to Kim, “describes the use of classification schemes, such as data algorithms, to sort or score workers in ways that worsen inequality or disadvantage along the lines of . . . protected

141. Braktkton Booker, *After Lawsuits, Facebook Announces Changes to Alleged Discriminatory Ad Targeting*, NPR (Mar. 19, 2019, 2:32 PM), <https://www.npr.org/2019/03/19/704831866/after-lawsuits-facebook-announces-changes-to-alleged-discriminatory-ad-targeting> [https://perma.cc/TFV6-HUKF].

142. Glasser et al., *supra* note 139.

143. *In Historic Decision on Digital Bias, EEOC Finds Employers Violated Federal Law When They Excluded Women and Older Workers from Facebook Job Ads*, ACLU (Sept. 25, 2019), <https://www.aclu.org/press-releases/historic-decision-digital-bias-eec-finds-employers-violated-federal-law-when-they> [https://perma.cc/V2B4-W3X9].

144. I advocated for this in a previous article. See Ajunwa, *The Paradox of Automation*, *supra* note 6, at 1726–34.

145. See *id.* at 1712–17; Stephanie Bornstein, *Antidiscriminatory Algorithms*, 70 ALA. L. REV. 519, 570 (2018) [hereinafter Bornstein, *Antidiscriminatory Algorithms*]; Stephanie Bornstein, *Reckless Discrimination*, 105 CALIF. L. REV. 1055, 1059 (2017); Kim, *Data-Driven Discrimination*, *supra* note 24, at 908; Matthew Bodie, *The Law and Policy of People Analytics*, 88 U. COLO. L. REV. 961, 1025–28 (2017); Charles Sullivan, *Employing AI*, 63 VILL. L. REV. 395, 407–10 (2018); Grimmelmann & Westreich, *supra* note 23, at 171–72.

146. Kim, *Data-Driven Discrimination*, *supra* note 24, at 909.

characteristics.¹⁴⁷ Particularly, Kim argues that existing disparate impact doctrine is ill-equipped to handle classification bias because, unlike the employment tests, which existing precedent was largely created to address, algorithms rely entirely on correlation and found connections instead of predefined criteria.¹⁴⁸ For example, Kim suggests that, as is, employers may easily satisfy their “job related,” “business necessity” defense under disparate impact case law by showing a mere statistical correlation between their assessment and job performance.¹⁴⁹ While statistical correlation has been accepted as evidence of job-relatedness in the past, in the age of algorithms, proving this correlation is both easy and relatively meaningless in terms of justifying discrimination. Thus, even though disparate impact theory itself has the potential to remedy classification bias and algorithms, most claimants bringing a disparate impact claim are unlikely to prevail, given the high burden of statistical proof necessary to sustain such a claim.¹⁵⁰

A Title VII claim brought against a discriminatory hiring algorithm would likely follow the path of a disparate impact claim as opposed to disparate treatment. Intent is essential to disparate treatment claims, and it would be particularly difficult to prove intent when the machine acts as an opaque intermediary between employers and candidates.¹⁵¹ Disparate impact theory offers little better protection. A 2006 analysis of case outcomes conducted by Professor Michael Selmi empirically found that disparate impact cases are, on the whole, incredibly difficult for plaintiffs to win.¹⁵² In a separate study, Professor Sandra Sperino similarly concludes that outcomes of disparate impact claims often favor defendants.¹⁵³ According to legal scholar McKenzie Raub, algorithmic discrimination poses an added challenge to already unfavorable odds.¹⁵⁴ Plaintiffs may have particular issues establishing a prima facie case under disparate impact theory “when the discrimination is the result of incomplete, incorrect, or non-representative data . . . [or data that] fails to

147. *Id.* at 857.

148. *Id.* at 907.

149. *Id.* at 908.

150. See Bornstein, *Antidiscriminatory Algorithms*, *supra* note 145, at 524 (“Worse still, current scholarship suggests, the apparent neutrality of algorithms and the ‘black box’ nature of machine learning make this hiring trend a new way of doing business that could be unreachable by existing antidiscrimination law.”); McKenzie Raub, *Bots, Bias and Big Data: Artificial Intelligence, Algorithmic Bias and Disparate Impact Liability in Hiring Practices*, 71 ARK. L. REV. 529, 550 n.174 (2018).

151. See Ajunwa, *The Paradox of Automation*, *supra* note 6, at 1690–92.

152. Michael Selmi, *Was the Disparate Impact Theory a Mistake?*, 53 UCLA L. REV. 701, 738–43 (2006).

153. See Ajunwa, *An Auditing Imperative*, *supra* note 24, at 648 (citing Sandra F. Sperino, *Disparate Impact or Negative Impact?: The Future of Non-Intentional Discrimination Claims Brought by the Elderly*, 13 ELDER L.J. 339, 342, 385 (2005)).

154. See Raub, *supra* note 150, at 530, 547–48.

represent groups in accurate proportions.”¹⁵⁵ According to Raub, statistically proving discrimination, as required for a prima facie case, could be particularly complicated considering “segments of protected classes could be excluded from employment opportunities because of a lack of access to the required technology to participate in the hiring practices that use artificial intelligence.”¹⁵⁶ Even if a plaintiff succeeds on a prima facie case, it may be relatively easy for employers to establish that the models in question are job-related and constitute a business necessity. For issues concerning artificial intelligence, the primary question “seems to be ‘whether . . . the target variable . . . is job related’ . . . [and] actually predictive of the job related trait”—meaning that an employer may meet its burden to prove a model correlates to job performance even if the model has a discriminatory impact.¹⁵⁷

If an employer meets its burden to prove job-relatedness and business necessity, the claimant can prove that a less discriminatory alternative employment practice exists.¹⁵⁸ Applying this burden results in an immense weight that claimants are unlikely to shoulder successfully. As Raub observes, “If an employer fails to effectively disclose or defend the validity of its algorithm and data collection . . . the plaintiff is hamstrung.”¹⁵⁹ That is, a claimant cannot effectively defend themselves against a model they cannot examine or understand.

3. Deploying Automated Systems for EEOC Enforcement of Title VII

In this section, I detail how the EEOC could deploy automated decision-making tools as part of its enforcement action. In another article, I had previously described a certifying and auditing system for automated hiring systems.¹⁶⁰ In this Article, I propose that the EEOC, as a governmental agency, could take charge of both certifying and continual audits of all automated hiring systems used for hiring by American organizations and corporations. In a recent paper for the National Bureau of Economic Research, Jon Kleinberg, Jens Ludwig, Sendhil Mullainathan, and Cass R. Sunstein argue that algorithmic design should be federally regulated, with “detailed recordkeeping requirements” employed and “all the components of an algorithm (including the training data) . . . stored and made available for examination and experimentation.”¹⁶¹ The authors argue that these requirements would make it

155. *Id.* at 547–48.

156. *Id.*

157. *Id.* at 549.

158. *McDonnell Douglas Corp. v. Green*, 411 U.S. 792, 802 (1973).

159. Raub, *supra* note 150, at 552.

160. See Ajunwa, *An Auditing Imperative*, *supra* note 24, at 666–73.

161. Jon Kleinberg, Jens Ludwig, Sendhil Mullainathan & Cass R. Sunstein, *Discrimination in the Age of Algorithms*, 10 J. LEGAL ANALYSIS 113, 114 (2018).

easier to retroactively examine an algorithm's decision-making process, particularly in court cases concerned with discrimination.¹⁶²

I argue that procedural mandates around algorithmic data collection and decision criteria would serve as a valuable safeguard against the dangers of black box algorithms. Employers would no longer be able to shield their discriminatory algorithms in secrecy, and this would afford plaintiffs better opportunities for prevailing on disparate impact claims by challenging job-relatedness claims or offering an alternative employment practice. Given that the EEOC already mandates record-keeping requirements for employers,¹⁶³ it may easily implement these procedural protections through new guidance, which specifically requires record-keeping around algorithmic models used to evaluate job applicants and employees. The records kept by corporations and organizations would then be available for the EEOC to deploy its automated tools to audit.

Beyond procedural safeguards around how algorithms are built and recorded, other scholars have proposed more substantive changes to the disparate impact doctrine, which would directly protect plaintiffs who fall victim to discriminatory algorithms. James Grimmelman and David Westreich, along with Pauline Kim, propose a heightened standard to prove business necessity, which would require an employer “to show not just that its model’s scores are . . . *correlated* with job performance but *explain* it.”¹⁶⁴ Kim goes further to argue that data on protected characteristics should be maintained in datasets to better retroactively see manifestations of bias, and that merely showing an algorithm produced biased outcomes that disadvantaged a protected class should be enough for plaintiffs to establish a *prima facie* case under disparate impact theory.¹⁶⁵ Kim is also in favor of permitting a “bottom-line defense,” which would allow for potentially unequal effects at certain stages “of a larger selection process that is not biased overall,” a move Kim believes will encourage internal auditing and reduce discriminatory outcomes overall.¹⁶⁶ While the EEOC itself cannot mandate that the courts employ a particular method of analysis or reading of the law when deciding cases, it may issue guidance that implicitly supports proposals to alter disparate impact doctrine, such as implementing guidance and creating tools that allow hiring algorithms to be audited for explainability to prove they are nondiscriminatory.

162. See *id.* at 114–16.

163. See *EEOC Announces Opening of 2019 and 2020 EEO-1 Component 1 Data Collection*, U.S. EQUAL EMP. OPPORTUNITY COMM’N (Apr. 26, 2021), <https://www.eeoc.gov/newsroom/eeoc-announces-opening-2019-and-2020-eeo-1-component-1-data-collection> [https://perma.cc/5TV4-KRWZ] [hereinafter *EEOC Announces Opening*].

164. Grimmelman & Westreich, *supra* note 23, at 170; Kim, *Data-Driven Discrimination*, *supra* note 24, at 917, 921.

165. See Kim, *Data-Driven Discrimination*, *supra* note 24, at 917–19 (2017).

166. *Id.* at 923–25.

Several scholars, along with myself, have proposed mandatory auditing as a meaningful tool in and of itself to build significant transparency and accountability into algorithmic decision-making.¹⁶⁷ Professor Kim argues that audits are a legal and valuable way to increase transparency, particularly “[w]hen the goal is nondiscrimination,” providing external validation to ensure algorithms are adhering to antidiscrimination laws in both design and output.¹⁶⁸ Professor Chander envisions auditing as part of a broader antidiscrimination mandate, which would require that algorithms are trained on diverse, complete data sets, monitoring for disparate impact in outcomes, and making necessary changes to address any such impact as time goes on.¹⁶⁹

As I explicate in my recent article, *An Auditing Imperative for Automated Hiring Systems*, “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.”¹⁷⁰ Calling on the work of Professors Richard Thompson Ford, James Grimmelman, Robert Post, David Benjamin Oppenheimer, and Noah Zatz, I argue that there is legal precedent for imposing a duty of affirmative care on employers and that, in the context of automated hiring, this duty of care should entail an “auditing imperative.”¹⁷¹ My auditing proposal includes requirements for both internal and external auditing, heightened record-keeping requirements to better identify output-bias, detailed standards audits must meet, and a certification scheme to verify compliance.¹⁷² This auditing system could fall under the EEOC’s regulatory and enforcement authority as a natural extension of its antidiscrimination mission. The EEOC is already experienced in employer oversight; for example, they have existing mechanisms in place for annual employer data collection and review.¹⁷³ Auditing guidelines can therefore be built into existing EEOC infrastructure without requiring any serious agency overhaul.

Such a scheme would not do away with internal audits, rather it would complement them. Thus, new EEOC guidelines could mandate that hiring bodies conduct annual self-audits of their hiring outcomes.¹⁷⁴ By definition, the internal auditing process involves “a ‘department, division, team of consultants, or other practitioner(s) [providing] independent, objective assurance and consulting services designed to add value and improve an organization’s

167. See, e.g., Ajunwa, *An Auditing Imperative*, *supra* note 24, at 666–73; Coglianese & Lampmann, *supra* note 95, at 192–94; Pauline T. Kim, *Auditing Algorithms for Discrimination*, 166 U. PA. L. REV. ONLINE 189, 190 (2017) [hereinafter Kim, *Auditing Algorithms*].

168. Kim, *Auditing Algorithms*, *supra* note 167, at 190.

169. See Chander, *supra* note 58, at 1039–45.

170. See Ajunwa, *An Auditing Imperative*, *supra* note 24, at 625–26.

171. *Id.* at 652–59.

172. See *id.* at 659–73.

173. See *EEOC Announces Opening*, *supra* note 163.

174. See Ajunwa, *An Auditing Imperative*, *supra* note 24, at 661.

operations.”¹⁷⁵ For purposes of EEOC regulation, one objective of internal audits should be for companies to ensure their algorithmic outcomes comply with antidiscrimination law, producing accurate predictions free from inherited bias.¹⁷⁶

To facilitate internal (and external) audits, EEOC guidance must first specify that companies who employ algorithmic models to make decisions that affect employee outcomes meet specific record-keeping requirements. Algorithms should collect and segregate sensitive demographic data about applicants; this data, similar to a historical “tear-off sheet,” may only be accessed after employment decisions have been made.¹⁷⁷ Employees or applicants must be made aware that this information will be collected but kept separately.¹⁷⁸ Employers will be required to use this demographic information to conduct an annual internal audit to examine whether their algorithms are producing biased outcomes. EEOC guidance will require regular reporting of these audit procedures and results, as well as summary reports of original demographic data, for external review.

EEOC guidance must also provide clarity on how employers should proceed if their self-audits suggest algorithmic discrimination is present. If an employer finds evidence of biased outcomes against specific demographic groups, they must immediately cease all use of the algorithm in question until they develop a fix that proves to yield less discriminatory results. A company must draw up an additional report describing the issue identified and the algorithmic changes it made, to be submitted for EEOC review alongside its initial audit records and results.

The EEOC should clarify that all steps of the internal auditing process are governed by the standards and practices of the Institute of Internal Auditors (“IIA”).¹⁷⁹ The IIA lays out the following ten principles of an effective audit:

- [1] Demonstrates integrity. [2] Demonstrates competence and due professional care. [3] Is objective and free from undue influence (independent). [4] Aligns with the strategies, objectives, and risks of the organization. [5] Is appropriately positioned and adequately resourced. [6] Demonstrates quality and continuous improvement. [7] Communicates effectively. [8] Provides risk-based assurance. [9] Is

175. *Id.* (quoting THE INST. OF INTERNAL AUDITORS, INTERNATIONAL STANDARDS FOR THE PROFESSIONAL PRACTICE OF INTERNAL AUDITING 23 (2016), <https://na.theiia.org/standardsguidance/public%20documents/ippf-standards-2017.pdf> [<https://perma.cc/GPK3-UN7Q> (staff-uploaded archive)]).

176. *See id.* at 661–62 (describing proposed New York City Council legislation that would require hiring algorithms to undergo a “bias audit”).

177. *Id.* at 662–64.

178. *Id.*

179. *See id.* at 664.

insightful, proactive, and future-focused. [10] Promotes organizational improvement.¹⁸⁰

4. An Alternative to EEOC Automated Governance?

While valuable, internal audits alone are not enough to prevent algorithmic discrimination; external validation is necessary to affirm that internal audits are serving a meaningful function and that algorithms are genuinely free of discrimination. Theoretically, the task of external validation could fall entirely on the EEOC. However, I argue that such delegation may constitute an unnecessary “financial and time burden . . . on governmental resources.”¹⁸¹ Thus, one alternative is that the EEOC could sponsor and promote the role of a nongovernmental entity in the external validation process. The nongovernmental entity would serve a role similar to the Leadership in Energy and Environmental Design (“LEED”) system of the 1990s, which established “a ‘green certification program for building design, construction, operations, and maintenance.’”¹⁸² The Fair Automated Hiring Mark program (“FAHM”), as it would be called, would “involve periodic audits of the hiring algorithms to check for disparate impact on vulnerable populations.”¹⁸³ In exchange for participating in these external audits, an employer “would earn the right to use a Fair Automated Hiring Mark [FAHM] . . . for its online presence, for communication materials, and for display on hiring advertisements to attract a more diverse pool of applicants.”¹⁸⁴ The FAHM program would not only include data scientists or engineers on its auditing teams, but also lawyers who could offer clear opinions on how an algorithm implicates federal antidiscrimination law.¹⁸⁵

Although the EEOC would not directly oversee external algorithmic audits as a part of the FAHM certification program, following in the footsteps of late legal scholar Joel Reidenberg, I argue that the EEOC can still indirectly influence the creation of a FAHM authority through funding, lobbying, and creating regulations in favor of employers who seek FAHM certification.¹⁸⁶ The

180. *Core Principles for the Profession of Internal Auditing*, INST. INTERNAL AUDITORS, <https://www.theiia.org/en/standards/what-are-the-standards/core-principles/> [<https://perma.cc/W2CP-E5XM>].

181. See Ajunwa, *An Auditing Imperative*, *supra* note 24, at 667.

182. *Id.* at 668 (quoting *Global Dow Center Earns LEED Silver Certification*, FACILITY EXEC. (Jan. 27, 2020), <https://facilityexecutive.com/2020/01/global-dow-center-earns-leed-silver-certification> [<https://perma.cc/44BM-Z7KM>]).

183. *Id.*

184. *Id.*

185. *Id.*

186. See Joel R. Reidenberg, *Lex Informatica: The Formulation of Information Policy Rules Through Technology*, 76 TEX. L. REV. 553, 586 (1998) (describing his theory of Lex Informatica as a set of extra-legal, natural rules that information flows yield over time and highlighting that, rather than a

EEOC should maintain the ultimate power to “audit and certify [algorithmic decision-making tools],” with the final say on what “[tools] could lawfully be deployed in the [decision-making] process.”¹⁸⁷ That is, the EEOC will retain the power to subject an employer’s algorithm to its external audit at any time. However, it can and should incentivize employers to participate in the FAHM program by favorably considering FAHM participation when reviewing a company’s annual auditing reports. For example, a company that does not seek FAHM approval may be required to receive annual EEOC recertification—based on a review of their internal audit reports—that its algorithms appear bias-free before it is allowed to deploy its automated tools for that year. Participation in the FAHM program may be accepted instead of annual recertification, and companies may continue to use their algorithms uninterrupted while the EEOC reviews their internal auditing reports.

Such a solution will preserve EEOC authority while somewhat insulating the auditing process from regulatory capture.¹⁸⁸ The EEOC may require that FAHM program audits meet certain standards to qualify for favorable treatment. Any FAHM program would need to employ high data security measures to insulate user data from third-party access and adhere to standardized procedures concerning the scope and nature of the external audit.¹⁸⁹ Outside of formal guidance, by exerting early influence and providing early funding for a FAHM program, the EEOC can further ensure that it develops reputable auditing processes that genuinely root out and correct for bias.

B. *FTC Enforcement of the Fair Credit Reporting Act*

Established in 1914 by the Federal Trade Commission Act, the FTC is a federal agency charged with the broad task of “protect[ing] consumers and competition.”¹⁹⁰ Its origins trace to the Progressive Era of the early twentieth century when fair market competition and antitrust measures were primary issues of public concern.¹⁹¹ The FTC’s broad discretion over unfair trade practices and vast regulatory toolkit especially positions the agency to address the serious consumer harms wrought by Big Data and the collection of personal

replacement for all traditional regulation, “Lex Informatica must be seen as a distinct source of policy action” and “[e]ffective channeling of Lex Informatica requires a shift in the focus of government action away from direct regulation and toward indirect influence”).

187. See Ajunwa, *An Auditing Imperative*, *supra* note 24, at 667.

188. See *id.* at 667, 670.

189. See *id.* at 671, 673.

190. *Mission*, FED. TRADE COMM’N, <https://www.ftc.gov/about-ftc/what-we-do> [<https://perma.cc/X2KY-7AUC>].

191. Gerald Berk & Marc Schneiberg, *Varieties in Capitalism, Varieties of Association: Collaborative Learning in American Industry, 1900 to 1925*, 33 *POL. & SOC’Y* 46, 52 (2005).

information in the algorithmic age, for both employees and general consumers alike.

The primary issue with algorithmic decision-making tools is the privacy risk they pose to job applicants, employees, and other algorithmic consumers.¹⁹² These tools collect vast amounts of private, personal consumer information yet face little to no legal requirements concerning how that information is used, stored, or protected.¹⁹³ Furthermore, consumers—especially job applicants subject to the imbalanced employee-employer power dynamic—often have no choice but to engage with these tools in pursuit of necessary economic resources, especially employment.¹⁹⁴ However, with proper privacy regulations, consumers can hedge against these undesirable, discriminatory outcomes. As legal scholar Jessica L. Roberts argues, “A person cannot consider information that she does not have.”¹⁹⁵ Given the inherently economic nature of the relationships where these tools are deployed, I argue that the FTC has both the legal duty and proper tools to assert its power as a privacy authority to correct harmful algorithmic trade practices.

The FTC is comprised of three bureaus: the Bureau of Competition, the Bureau of Consumer Protection, and the Bureau of Economics.¹⁹⁶ Privacy protections generally flow from the Bureau of Consumer Protection, which is tasked with protecting consumers against “unfair, deceptive, and fraudulent false business practices.”¹⁹⁷ These protections stem from the FTC’s mission as defined under Section 5 of the Federal Trade Commission Act,¹⁹⁸ which tasks the FTC with “prevention of ‘unfair methods of competition in commerce.’”¹⁹⁹ This provision is considered central to the FTC’s mission, and Congress has taken explicit steps to preserve the FTC’s authority and autonomy over regulation of unfair trade practices.

In the 1930s, when the U.S. Supreme Court narrowly interpreted Section 5 rights and prohibited any FTC enforcement action over unfair competition, Congress “responded” with new amendments that explicitly affirmed their

192. See Ajunwa, *The Paradox of Automation*, *supra* note 6, at 1735.

193. See Ajunwa, *An Auditing Imperative*, *supra* note 24, at 624; Kim, *Data-Driven Discrimination*, *supra* note 24, at 863–64.

194. See generally Ajunwa, *The “Black Box” at Work*, *supra* note 92, at 3–4 (describing the data-driven workplace where workers are compelled to surrender intimate and personal data while simultaneously being prevented from knowing how such data will be used).

195. Jessica L. Roberts, *Protecting Privacy To Prevent Discrimination*, 56 WM. & MARY L. REV. 2097, 2097 (2015).

196. Jennifer K. Wagner, *The Federal Trade Commission and Consumer Protections for Mobile Health Apps*, 48 J.L. MED. & ETHICS 103, 104 (2020).

197. Bureau of Consumer Protection, FED. TRADE COMM’N, <https://www.ftc.gov/about-ftc/bureaus-offices/bureau-consumer-protection> [<https://perma.cc/4EZL-QGEX>].

198. See Federal Trade Commission Act, ch. 311, § 5, 1914 Stat. 717, 719–21 (1914) (codified at 15 U.S.C. § 45(a)(1) (2006)).

199. Wagner, *supra* note 196, at 104.

broad intentions for FTC authority.²⁰⁰ The Wheeler-Lea Amendments not only guaranteed the FTC's right to prevent "'unfair methods of competition' but also 'unfair or deceptive acts or practices.'"²⁰¹ In the 1970s, "[t]he FTC was further strengthened . . . by judicial rulings affirming its broad powers to define unfair practices and by additional legislation enabling, for example, the agency to appear in court on its own behalf and take action against practices 'in or affecting commerce.'"²⁰² Despite congressional attempts to curb the agency's power in the 1980s, on the whole, FTC regulatory authority remains uniquely strong to this day with the "statutory authority to take the first steps" on issues Congress has yet to address.²⁰³ Given its position of broad power, resources, and discretion, the FTC is therefore well situated to address issues of algorithmic decision-making as they impact employees and other consumers.²⁰⁴

1. How the FTC Has Asserted Regulatory Authority in the Past

The FTC is often considered remarkable "given the breadth of powers (a mix of judicial, legislative, and executive functions) that were entrusted and delegated to a single government agency to carry out its mission."²⁰⁵ Perhaps, then, it is unsurprising that the history of FTC regulation is vast and varied. In its earliest years, the FTC took a "punitive and positive" approach to its mission of regulating market competition: "[C]hecking predatory actions before they hardened into market power" and "cultivating business capacities to compete over productivity, service, and product quality."²⁰⁶ The agency sought to give businesses the tools to compete and succeed in the open market, introducing uniform cost accounting principles and benchmarking across firms to accurately regulate and stabilize prices.²⁰⁷ This probusiness, procompetition approach was supported at the time by President Wilson, who publicly stated his belief that the commission would "set [businessmen] upon the road of hopeful and confident enterprise."²⁰⁸ Over time, the FTC shifted course as Congress

200. *See id.*

201. *Id.* (quoting Federal Trade Commission Act, Pub. L. No. 75-447, § 3, 52 Stat. 111 (1938) (Wheeler-Lea Amendments) (codified as amended at 15 U.S.C. § 45 (2006)); 15 U.S.C. § 52(b)).

202. Wagner, *supra* note 196, at 104 (citing *FTC v. Sperry & Hutchinson*, 405 U.S. 233 (1972)).

203. *See id.* at 105.

204. *See generally* Rebecca Kelly Slaughter, Janice Kopec & Mohamad Batal, *Algorithms and Economic Justice: A Taxonomy of Harms and a Path Forward for the Federal Trade Commission*, 23 *YALE J.L. & TECH.* 1 (2021) (describing "harms caused by algorithmic decision-making in the high-stakes spheres of employment, credit, health care, and housing, which profoundly shape the lives of individuals" and "explores how new legislation or an FTC rulemaking under section 18 of the FTC Act could help structurally address the harms generated by algorithmic decision-making").

205. Wagner, *supra* note 196, at 104.

206. Berk & Schneiberg, *supra* note 191, at 52.

207. *See id.*

208. Woodrow Wilson, President of the U.S., Speech of Acceptance at the National Democratic Convention (Sept. 2, 1916), <https://millercenter.org/the-presidency/presidential-speeches/september-2-1916-speech-acceptance> [<https://perma.cc/637Q-RBR8>].

increased its powers and responsibilities. While FTC action initially focused on helping businesses, the modern FTC is more focused on regulating businesses to protect consumers.²⁰⁹

A major way the FTC has moved to protect consumers is through formal and informal privacy laws and protections.²¹⁰ In 1970, Congress passed the Fair Credit Reporting Act (“FCRA”) “to regulate the credit reporting industry because of concerns about the fairness and accuracy of credit reports.”²¹¹ Some scholars mark this as a turning point in FTC history, as the agency shifted to protecting consumer privacy for the first time.²¹² Around the same time, the U.S. Department of Health, Education, and Welfare (“HEW”) established the first information privacy regulations in the United States called the “Fair Information Practice Principles (“FIPPs”).”²¹³ Enforcement of these nonbinding principles was eventually taken on by the FTC, who updated the FIPPs in 2000 “as guidance for [businesses] designing commercial privacy policies.”²¹⁴ Though nonbinding, the power of the FIPPs as privacy regulation largely comes through the FTC’s enforcement power. According to legal scholar Daniel Susser, “Businesses are encouraged to issue privacy policies” that align with the FIPPs, as noncompliance may result in “Federal Trade Commission (FTC) enforcement actions” on the basis of “unfair and deceptive’ trade practices.”²¹⁵ Therefore, while to this day there is no broad, formalized federal privacy law, the FTC over time has asserted its regulatory powers to create a patchwork of privacy protections in the name of consumer interest.²¹⁶

209. See *About the FTC*, FED. TRADE COMM’N, <https://www.ftc.gov/about-ftc> [<https://perma.cc/QC5H-RSSL>].

210. See Daniel Susser, *Notice After Notice-and-Consent: Why Privacy Disclosures Are Valuable Even if Consent Frameworks Aren’t*, 9 J. INFO. POL’Y 37, 41–42 (2019).

211. Pauline T. Kim & Erika Hanson, *People Analytics and the Regulation of Information Under the Fair Credit Reporting Act*, 61 ST. LOUIS U. L.J. 17, 20 (2016); Karen Sanzaro, *Big Data: FTC Issues Report Cautioning That Use of Big Data May Violate Federal Consumer Protection Laws or Raise Ethical Considerations*, ALSTON & BIRD: PRIVACY, CYBER, & DATA STRATEGY BLOG (Jan. 19, 2016), <https://www.alstonprivacy.com/big-data-ftc-issues-report-cautioning-that-use-of-big-data-may-violate-federal-consumer-protection-laws-or-raise-ethical-considerations/> [<https://perma.cc/P96N-MNAP>] (summarizing FTC warning that companies using Big Data may be subject to the FCRA, references FTC enforcement actions against a firm that used consumer data for “eligibility determinations” without complying to FCRA); see also 114 Cong. Rec. 24,902 (1968).

212. See Maureen K. Ohlhausen, *Privacy Challenges and Opportunities: The Role of the Federal Trade Commission*, 33 J. PUB. POL’Y & MTKG. 4, 4 (2014); Daniel J. Solove & Woodrow Hartzog, *The FTC and the New Common Law of Privacy*, 114 COLUM. L. REV. 583, 602–03 (2014).

213. Susser, *supra* note 210, at 39; U.S. DEP’T OF HEALTH, EDUC. & WELFARE, RECORDS, COMPUTERS AND THE RIGHTS OF CITIZENS: REPORT OF THE SECRETARY’S ADVISORY COMMITTEE ON AUTOMATED PERSONAL DATA SYSTEMS 41–42 (1973).

214. Susser, *supra* note 210, at 41.

215. See *id.* (quoting Fred H. Cate, *The Failure of Fair Information Practice Principles, in CONSUMER PROTECTION IN THE AGE OF THE INFORMATION ECONOMY* 343, 352 (2006)).

216. Solove & Hartzog, *supra* note 212, at 649–50.

Many of the most significant examples of the FTC asserting its regulatory authority come in the form of specific enforcement actions.²¹⁷ The extent of FTC enforcement action is so vast that legal scholars Daniel J. Solove and Woodrow Hartzog argue that “the FTC’s privacy jurisprudence is functionally equivalent to a body of common law.”²¹⁸ Using FTC regulation of internet practices as a case study, it is clear that the FTC’s response to new, disruptive technologies tends to follow this same infraction-driven pattern. For example, between 1994 and 1999, when the internet was still in its nascent stages of development, the FTC brought 100 cases against “Internet scam[mers]” alone.²¹⁹ Beginning in 1996, the FTC also began the practice of “Internet ‘Surf Day(s),” where the commission teamed up with other agencies to scan the internet for websites that appeared to violate federal law or FTC policy.²²⁰ If fraud was identified, the FTC would notify the website owners in question; it found that “20 to 70 percent [would] improve or remove their sites” in response, while others risked specific enforcement action down the line.²²¹ The effectiveness of “Surf Days” hinged largely on the threat of FTC enforcement action, even if no action would likely have ever been taken. Therefore, overall, the large shadow cast by small-scale interventions came to form the backbone of FTC regulation of new internet technology.

While this pattern of identifying-and-penalizing legally deviant behavior continues, the FTC has also taken more proactive action to regulate the challenges to consumers brought about by the digital revolution. According to an FTC status report from December 1999, the commission held workshops to discuss possible regulatory issues brought on by internet technology and best practices for regulation, ultimately creating a “blueprint for its role in the nascent market place.”²²² The FTC’s plan relied on “existing law enforcement under existing statutes and rules” but also extended to “the development of policy in areas that raise new consumer protection concerns.”²²³ It is likely that the FIPPs, updated shortly after this report was commissioned, exemplified the fruits of such policy development.²²⁴

217. *See id.* at 604.

218. *Id.* at 586.

219. FED. TRADE COMM’N, THE FTC’S FIRST FIVE YEARS: PROTECTING CONSUMERS ONLINE i (1999) [hereinafter FED. TRADE COMM’N, THE FTC’S FIRST FIVE YEARS], <https://www.ftc.gov/sites/default/files/documents/reports/protecting-consumers-online/fiveyearreport.pdf> [https://perma.cc/587G-U9X8].

220. *Id.* at 6.

221. *Id.* at 7.

222. *Id.* at i.

223. *Id.*

224. *See* Susser, *supra* note 210, at 41–42.

2. Limitations of FTC Power

When it comes to enforcing the privacy of consumers, much of the FTC's privacy regulation exists as an extension of its Section 5 authority to prohibit unfair trade practices.²²⁵ While this clause grants the FTC considerable strength, it does not constitute unlimited power. To regulate consumer privacy in the digital age, for example, the FTC established guidelines in the form of the FIPPs and then used the specter of enforcement action under Section 5 to encourage compliance.²²⁶ According to Solove and Hartzog, this strategy proved effective, “codif[ying] certain norms and best practices and . . . develop[ing] some baseline privacy protections” to regulate the digital privacy landscape.²²⁷ However, many scholars critique the FTC's privacy regime as procedural, requiring that companies *notify* consumers their information is being collected and used, yet placing no substantive regulations on those use cases.²²⁸

Therefore, when looking at FTC tools to regulate the algorithmic landscape, it is not clear that Section 5 enforcement power as it stands is enough to regulate the serious privacy concerns emanating from algorithmic decision-making. The FTC itself seems to concur.²²⁹ When asked about FTC regulation of Big Data under the aegis of Section 5, Associate Director of the FTC's Division of Privacy and Identity Protection, Maneesha Mithal, went on record to state that “[o]ur tools are limited . . . [w]e're using them as much as we can. Beyond that, we've asked for more tools.”²³⁰ In February 2020, FTC Commissioner Christine S. Wilson testified before the Future of Privacy Forum in Washington, D.C., her “belie[f] that federal privacy and data security legislation is necessary.”²³¹ I agree with Wilson that federal privacy law is a valuable step to protect both employees and, more broadly, consumers, if

225. “The primary source of authority for FTC privacy enforcement was Section 5,” Solove & Hartzog, *supra* note 212, at 599 (citing Marcia Hoffmann, *Federal Trade Commission Enforcement of Privacy*, in PROSKAUER ON PRIVACY: A GUIDE TO PRIVACY AND DATA SECURITY LAW IN THE INFORMATION AGE § 4:1.2 (Ryan P. Blaney ed., 2d ed. 2020)), which prohibits “unfair or deceptive acts or practices in or affecting commerce,” *id.* (quoting 15 U.S.C. § 45(a)(1)) (discussing FTC's authority to ensure individuals and businesses do not engage in unfair or deceptive acts).

226. See Solove & Hartzog, *supra* note 212, at 592–93, 598–99.

227. *Id.* at 583.

228. See Terrell McSweeney, *Psychographics, Predictive Analytics, Artificial Intelligence, & Bots: Is the FTC Keeping Pace?*, 2 GEO. L. TECH. REV. 514, 516–24 (2018) (discussing the FTC's current protection framework).

229. See David Lazarus, *Column: FTC Is Falling Short in Protecting Consumers' Data Used by Businesses*, L.A. TIMES (Jan. 12, 2016, 3:00 AM), <https://www.latimes.com/business/la-fi-lazarus-20160112-column.html> [<https://perma.cc/M8HX-A5AP> (dark archive)].

230. *Id.*

231. Christine S. Wilson, Comm'r, U.S. Fed. Trade Comm'n, *A Defining Moment for Privacy: The Time Is Ripe for Federal Privacy Legislation* 3 (Feb. 6, 2020), https://www.ftc.gov/system/files/documents/public_statements/1566337/commissioner_wilson_privacy_forum_speech_02-06-2020.pdf [<https://perma.cc/9W8D-JHWJ>].

approached the right way.²³² However, I also argue that there are immediate steps the FTC may take, independent of additional legislation, to regulate the immanent privacy harms plaguing algorithmic decision-making tools in employment and other forums.

3. The FTC Needs New Regulations and Automated Tools

I contend that the FTC should draw on its statutory authority under the FCRA and issue new guidelines under this statute that specifically regulate algorithmic decision-making tools in employment and other reasonable contexts. In recent years, legal scholars, and even the FTC itself, have suggested that consumer privacy protections under the FCRA may extend to businesses using consumer data and data-based insights.²³³ Thus, the following section will examine the scope, nature, and limitations of privacy protections emanating from the FCRA.

The FCRA governs “compan[ies] . . . collecting and sharing third-party data that is used or expected to be used as a factor in determining eligibility for credit, insurance, employment, or other purpose[s] authorized under the FCRA.”²³⁴ These companies are considered “consumer reporting agencies” (“CRAs”) under the FCRA, formally defined as “any person which, for monetary fees, dues, or on a cooperative nonprofit basis, regularly engages in whole or in part in the practice of assembling or evaluating consumer credit information or other information on consumers for the purpose of furnishing consumer reports to third parties.”²³⁵ Thus, companies providing algorithmic hiring and decision-making tools may be governed by the FCRA to the extent that the data they collect is (1) for commercial use and (2) considered a consumer report.²³⁶ As I argue in my recent paper, *The Paradox of Automation As Anti-Bias Intervention*, many companies that screen job applicants “could be considered CRAs, as they regularly process and evaluate ‘other information on consumers’ for the purpose of providing reports to employers.”²³⁷ Legal scholars Pauline T. Kim and Erik A. Hanson note that “entities that assemble and

232. See Ifeoma Ajunwa, Kate Crawford & Jason Schultz, *Limitless Worker Surveillance*, 105 CALIF. L. REV. 735, 772–74 (2017).

233. See FED. TRADE COMM’N, *BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION?* 14–17 (2016), <https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf> [<https://perma.cc/V2TR-SK2X>]; Kim & Hanson, *supra* note 211, at 20.

234. Chi Chi Wu, *Data Gatherers Evading the FCRA May Find Themselves Still in Hot Water*, NAT’L CONSUMER L. CTR. (June 14, 2019), <https://library.nclc.org/data-gatherers-evading-fcra-may-find-themselves-still-hot-water> [<https://perma.cc/9WBZ-8XMA>]; see also Fair Credit Reporting Act, Pub. L. No. 91-508, § 603(f), 84 Stat. 1128, 1129 (1970) (codified as amended at 15 U.S.C. § 1681a(f) (2019)).

235. Fair Credit Reporting Act § 603(f).

236. See *id.*

237. Ajunwa, *The Paradox of Automation*, *supra* note 6, at 1737 (quoting Fair Credit Reporting Act § 603(f)).

evaluate information for non-commercial uses as well as entities that assemble information about the entity's own interactions with its customers" are not considered CRAs.²³⁸ I argue that algorithmic decision-making tools, at least concerning employment, do not fall within this exception since an employment decision is an "economic decision" based on information acquired from online job brokers; employment decisions are necessarily commercial in nature. Further, this logic extends to some use cases outside of the employment relationship. For example, the FTC has already warned that some companies that employ algorithms to collect and sell consumer data to third parties, known as data brokers, may qualify as CRAs under the FCRA.²³⁹

The question thus falls to whether the data that algorithmic hiring companies compile qualifies as a consumer report. Courts have developed a three-prong framework to determine if "information constitutes a consumer report under the law"²⁴⁰:

- 1) the information was communicated by the consumer reporting agency;
- 2) it bears on the "consumer's 'credit worthiness . . . character, general reputation, personal characteristics, or mode of living;'" and 3) it was "used or expected to be used or collected in whole or in part" for one of the enumerated purposes.²⁴¹

All "elements" must be "satisfie[d]" to constitute a consumer report.²⁴² I argue that many algorithmic hiring tools fall within this definition. In *The Paradox of Automation*, I offer a case study of "two algorithm-based employment screening companies—Monster Hiring and Paycor" to support this argument.²⁴³ In the case of Monster Hiring, the company's terms of service suggest that it collects and arranges both consumer-provided and external information about a candidate, which it then provides to employers.²⁴⁴ Given that Monster "retain[s] the right to add any information it discovers online, it is clear that Monster takes an active role in distributing information related to an applicant's job prospects, making its reports qualify as 'consumer reports' under the definition of the FCRA."²⁴⁵ Paycor, on the other hand, offers background checks and "resume-parsing tools and interview-streamlining . . .

238. Kim & Hanson, *supra* note 211, at 21–22 (citing *Porter v. Talbot Perkins Child.'s Servs.*, 355 F. Supp. 174, 178 (S.D.N.Y. 1973); *Tierney v. Advoc. Health & Hosps. Corp.*, 797 F.3d 449, 451–54 (7th Cir. 2015)).

239. See *FTC Warns Data Broker Operations of Possible Privacy Violations*, FED. TRADE COMM'N (May 7, 2013), <https://www.ftc.gov/news-events/press-releases/2013/05/ftc-warns-data-broker-operations-possible-privacy-violations> [<https://perma.cc/YNG8-NCFS>].

240. *Ernst v. Dish Network, LLC*, 49 F. Supp. 3d 377, 381 (S.D.N.Y. 2014).

241. *Id.* (quoting *Yang v. Gov't Emps. Ins. Co.*, 146 F.3d 1320, 1323 (11th Cir. 1998)).

242. See *id.*

243. Ajunwa, *The Paradox of Automation*, *supra* note 6, at 1737.

244. See *id.* at 1737–38.

245. *Id.* at 1738.

reports”; given its level of involvement in compiling this information, I argue it also generates “consumer reports” under the FCRA.²⁴⁶ As these cases exemplify, from compiling public information about a job applicant to reformatting and scanning resumes, the FCRA casts a wide net over the kinds of services provided by employment-centric screening tools as well as other algorithm-generated reports.

Yet, FCRA is no panacea to unfair algorithmic outcomes. These protections do not control what kind of invasive data employers collect and how they use it. As I and other scholars have noted, the protections afforded by the FCRA remain procedural.²⁴⁷ In the words of legal scholar Spencer Mainka, “The FCRA provides no relief for an applicant who was denied an opportunity based on inaccurate data because the FCRA only regulates the process.”²⁴⁸ Indeed, the FCRA does not offer job applicants any substantive right to privacy and does not “limit[] . . . the *types* of information that can be collected or reported.”²⁴⁹ However, it “may . . . enable the job applicant to discover if the employer had access to discriminatory information or even to establish a pattern of discriminatory information furnished to the employer for protected groups, thus perhaps assisting in a disparate impact cause of action.”²⁵⁰ Therefore, it represents a valuable tool for redressing algorithmic discrimination and misuse.

The FTC can use its powers under FCRA to regulate the emerging field of algorithmic hiring and decision-making. To start, the FTC should issue new guidance that specifically designates online job brokers and other qualifying algorithm-based employment decision tool vendors as CRAs under the FCRA. Officially designating such companies’ tools as CRAs will afford job candidates and other consumers alike significant procedural protections against unfair algorithmic outcomes. As CRAs, vendors will be required to allow “consumers to review information in their files without charge, investigat[e] alleged inaccuracies, and provid[e] information to consumers about their rights.”²⁵¹ Employers, as the entity using the consumer report, will, in turn, be required to

provide a clear, conspicuous, and stand-alone disclosure [to applicants] that a consumer report may be obtained for employment purposes; obtain written authorization from the applicant or employee for procurement of the report; and certify to the consumer reporting agency

246. *Id.* at 1738–39.

247. *See id.* at 1735; Kim & Hanson, *supra* note 211, at 24–25.

248. Spencer M. Mainka, *Algorithm-Based Recruiting Technology in the Workplace*, 5 TEX. A&M J. PROP. L. 801, 815 (2019).

249. Kim & Hanson, *supra* note 211, at 25 (emphasis in original).

250. Ajunwa, *The Paradox of Automation*, *supra* note 6, at 1735.

251. Kim & Hanson, *supra* note 211, at 22–23.

its compliance with the requirements of the statute and that it will not violate any equal employment opportunity law.²⁵²

Furthermore, the FCRA will require that an employer “provide notice before rejecting a job application . . . or taking any other adverse employment action” in addition to “provid[ing the applicant] a copy of the consumer report relied upon and a description of the individual’s rights under the FCRA,” which includes “an opportunity to review the report and attempt to correct any mistakes.”²⁵³ After rejecting the applicant, the employer will further have to follow through with several more procedural steps, including providing information about the CRA who provided the report and “notice of the individual’s rights to dispute the accuracy or completeness of the report and to receive an additional copy of the report if requested within sixty days.”²⁵⁴ Failure to comply will result in FTC enforcement action.²⁵⁵ To ensure full compliance, the FTC must not merely threaten enforcement action, but take meaningful punitive steps when noncompliance is evident. Just as the FTC established standards in the early days of the internet through strategic action,²⁵⁶ it must do the same for algorithmic decision-making tools under the FCRA.

For example, a cost-effective path for the FTC to establish good practices for CRAs involved in automated hiring is to create automated tools in-house that could be used to scan the information collected by companies like Monster Hiring and check that data for systemic bias. This data could also provide insight into what types of information are being collected and whether any such data could be deemed proxy variables for protected variables. The use of this automated tool could also open opportunities for collaboration between the FTC and the EEOC for curbing algorithmic employment discrimination.

Beyond using the FCRA to regulate automated tools in hiring, the FTC must also clarify the statute’s applicability to general data brokers who collect and sell consumer information to third parties. In a 2014 report, the commission distinguished between “entities subject to the FCRA,” “entities that maintain data for marketing purposes,” and “non-FCRA covered entities that maintain data for non-marketing purposes that fall outside of the FCRA.”²⁵⁷ It notes that marketing and seemingly non-FCRA data brokers “remain opaque” concerning

252. *Id.* at 23 (citing 15 U.S.C. § 1681b(b)(1), (2)(A)(i)–(ii)).

253. *Id.* (citing § 1681b(b)(3)(A)).

254. *Id.* at 23–24 (citing § 1681m(a)).

255. *See id.* at 30.

256. *See generally* FED. TRADE COMM’N, THE FTC’S FIRST FIVE YEARS, *supra* note 219 (describing the FTC’s approach to regulating commerce in the era of the internet).

257. FED. TRADE COMM’N, DATA BROKERS: A CALL FOR TRANSPARENCY AND ACCOUNTABILITY 1 (2014), <https://www.ftc.gov/system/files/documents/reports/data-brokers-call-transparency-accountability-report-federal-trade-commission-may-2014/140527databrokerreport.pdf> [<https://perma.cc/SWF3-U2B8>].

their data practices, calling for legislation to improve transparency.²⁵⁸ I argue that the FTC both has, and must exercise, existing power under the FCRA to mandate such transparency. Where a data broker or other entity may reasonably seem to be subject to the FCRA, the FTC must reserve the right to audit their practices for FCRA compliance. Through a strategic enforcement campaign that targets these data brokers, the FTC will develop the necessary precedent to ensure more uniform compliance across the largely unregulated data broker industry. The advantage of such intervention will be allowing consumers more information about, and in turn more control over, data practices and their personal information.

IV. NECESSARY GUARDRAILS TO AUTOMATED GOVERNANCE

In this part, I propose several mechanisms for ensuring that algorithmic administration will comport with the spirit of the law. These proposals are both *ex ante* and *ex post*—this ensures that there is a safeguard against all instances of automated governance going off the rails. The proposals here are inspired by the work of David Freeman Engstrom and Daniel E. Ho who have observed: “[E]x post judicial review of algorithmic governance tools and their outputs under current doctrine, where it can be had at all, does not address key concerns and suffers from a substantial mismatch in judicial capacity and the technical demands of algorithmic oversight.”²⁵⁹ Furthermore, a report on the use of automated decision-making by federal agencies has found that “[c]ontrary to much of the literature’s fixation on the procurement of algorithms through private contracting, over half of applications (eighty-four use cases, or fifty-three percent) were built in-house.”²⁶⁰ This DIY nature of automated decision-making implementation by administrative agencies is a favorable circumstance that will allow for greater ease of implementation of guardrails and fail-safes.

A. *Standing Advisory Council of Technologists and Social Scientists*

If the government decides to adopt automated decision-making as a paragonovernmental tool, those tools will benefit from oversight over their design by a standing advisory council of technologists and social scientists. As the Obama administration noted in 2016: “[W]e need to develop a principle of ‘equal opportunity by design’—designing data systems that promote fairness and safeguard against discrimination from the first step of the engineering process and continuing throughout their lifespan.”²⁶¹ Thus, any agency that seeks to deploy an automated tool would first convene a standing advisory panel

258. *Id.*

259. Engstrom & Ho, *supra* note 7, at 806–07.

260. ENGSTROM ET AL., *supra* note 10, at 18.

261. EXEC. OFF. OF THE PRESIDENT, BIG DATA: A REPORT ON ALGORITHMIC SYSTEMS, OPPORTUNITY, AND CIVIL RIGHTS 5–6 (2016).

of technologists (i.e., computer scientists, data scientists, etc.) and social scientists who are experts in the given area. The advisory panel scientists will think through the problem at hand for any given agency and will develop a report on how best to design, implement, and audit an automated tool adopted by said agency. Thus, the work of the advisory panel will be iterative. The agency may call upon the advisory council beyond the implementation of the automated tool as new questions arise. The advisory council may also raise new questions as new technological capabilities develop and may issue advisories regarding the continued implementation of the automated tool or any need for redesigning the tool.

One counterargument to this proposal is that technologists and social scientists may not be adequately attuned to the nuances of administrative law to predict future legal controversies or challenges that could arise from automated governance.²⁶² This points, then, to a need for multidisciplinary experts—individuals who are well versed in the technological capabilities of automated decision-making tools, who possess a good sociological understanding of the impact of such tools on society, are cognizant of the strictures of administrative law, and are aware of the constitutional law constraints to decision-making in the public interest. Some law schools have recognized the need for this multidisciplinary expertise, and this has, in turn, prompted a change to legal education, with many law schools increasingly focusing training for law students on law and technology issues and offering dual degrees with computer science programs or data science programs.²⁶³

B. *Stakeholder and Constituency Engagement*²⁶⁴

Beyond relying on the expertise of technologists and social scientists, agency use of automated decision-making tools should also be predicated on first creating public awareness of the intended use and inviting the testimonies of the lived experiences of stakeholders and constituencies who will be affected by the automated tools.²⁶⁵ Taking the work of the FTC as an example, any

262. See Daniel N. Kluttz & Deirdre K. Mulligan, *Automated Decision Support Technologies and the Legal Profession*, 34 BERKELEY TECH. L.J. 853, 854 (2019).

263. See, e.g., *Joint Degree and Cooperative Programs: Law and Computer Science*, STAN. L. SCH., <https://law.stanford.edu/education/degrees/joint-degrees-within-stanford-university/law-and-computer-science/> [<https://perma.cc/DPF6-LKVP>] (highlighting Stanford's joint Juris Doctor and Master of Computer Science program, which focuses on having law students “engage with world-class computer scientists, entrepreneurs, legal practitioners, and policy makers” to engage in the “questions of code . . . that cannot be resolved within a single domain”).

264. I credit Margot Kaminski for sparking my idea to add stakeholder engagement as a necessary guardrail for algorithmic administrative governance.

265. Legal scholars have noted the lack of “meaningful public input” to tech development as “[t]echnology companies often lack diverse voices and fail to adequately consider social impact, resulting in numerous fiascos—from Google’s image recognition algorithm that classified black people

enforcement action campaign must also be paired with a consumer awareness campaign. For both employees and general consumers alike, the FTC must produce targeted training and information concerning consumer rights under the FCRA and reasons explaining the importance of consumers accessing their data (the goals of ensuring accuracy and allowing recourse being chief among them). While the FCRA mandates that employers and other CRAs inform consumers of their rights, consumers would also need to know where to look.²⁶⁶ For industries such as data brokerage, a general lack of consumer knowledge concerning its existence or the big firms in play means consumers rarely actually exercise their FCRA rights.²⁶⁷ Therefore, a public awareness campaign is an essential first step to ensuring the FCRA's procedural protections can be used to make a substantive difference.

A downfall of this guardrail to automated governance is that public engagement can be a fraught process. For one, raising public awareness is expensive.²⁶⁸ The government would need to expend significant sums of money to engage a public firm to devise methods of reaching the public such as television or other advertisements.²⁶⁹ Another issue is determining who is a stakeholder or properly delineating the constituency group whose advocacy on the decision-making process should be privileged. Take, for example, the use of automated tools in employment, these can have implications that not only impact the job applicant but may also impact other parts of society, especially for jobs that are client-facing or customer-serving.²⁷⁰ One scenario is where the EEOC decides to use automated tools to find and disallow automated hiring

as gorillas, to Amazon's job-recruiting engine that discriminated against women." See Margot E. Kaminski & Andrew D. Selbst, *The Legislation That Targets Racist Impacts of Tech*, N.Y. TIMES (May 7, 2019), <https://www.nytimes.com/2019/05/07/opinion/tech-racism-algorithms.html> [<https://perma.cc/K2ZV-VQXP> (staff-uploaded, dark archive)].

266. See Fair and Accurate Credit Transactions Act of 2003, Pub. L. No. 108-159, § 211(b), 117 Stat. 1952, 1971 (2003) (codified at 15 U.S.C. § 1681x (2003)).

267. See Steven Melendez & Alex Pasternack, *Here Are the Data Brokers Quietly Buying and Selling Your Personal Information*, FAST CO. (Mar. 2, 2019), <https://www.fastcompany.com/90310803/here-are-the-data-brokers-quietly-buying-and-selling-your-personal-information> [<https://perma.cc/BK26-GZHY> (dark archive)].

268. See U.S. GOV'T ACCOUNTABILITY OFF., PUBLIC SERVICE ANNOUNCEMENT CAMPAIGNS: ACTIVITIES AND FINANCIAL OBLIGATIONS FOR SEVEN FEDERAL DEPARTMENTS 2-3 (2006), <https://www.gao.gov/assets/gao-06-304.pdf> [<https://perma.cc/5A7W-KXK8>].

269. See *id.*

270. See, e.g., Kathryn Zickuhr, *Exploring the Impact of Automation and New Technologies on the Future of U.S. Workers and Their Families*, WASH. CTR. FOR EQUITABLE GROWTH (Dec. 17, 2021), <https://equitablegrowth.org/exploring-the-impact-of-automation-and-new-technologies-on-the-future-of-u-s-workers-and-their-families/> [<https://perma.cc/WGB8-9L29>] (“[E]mployers have displaced workers with ‘so-so’ technologies—such as automated customer service options . . . that provide a similar, or even inferior, service, compared to the human labor they displaced . . .”).

programs that discriminate against those who have been convicted of a felony.²⁷¹ However, one constituency, survivors of violent crimes, could raise objections to this Agency's use of automated tools, as they may feel they have a stake in allowing employers to take steps to prevent assaults in the workplace. This indicates then that that Agency must be prepared to balance the interests of various stakeholders and constituencies as part of its decision to deploy automated decision-making tools.

C. *Congressional Overview and Review*

Any initial deployment of an automated decision-making system for an agency use should not be taken as *carte blanche* for continued future use of the said tool. Rather, agency use of automated decision-making tools should be subject to congressional overview and review. Thus, I propose a dedicated congressional committee that would be charged with reviewing all agencies' use of automated tools within a certain number of years to determine if continued use of such tools serves both the goals of the agency and the common good. This safeguard would also prevent any technological capture of government and would ensure that the automated systems being deployed are the best at the job rather than ones that have managed to gain a monopoly.

One problem with instituting the congressional review of automated decision-making by agencies is that this could subject the process to the vagaries and wind shifts of politics.²⁷² For one, the congressional review could be dictated by the agenda of each new administration.²⁷³ Furthermore, the congressional review process could also be subject to capture by partisan forces.²⁷⁴ This all

271. See generally Ifeoma Ajunwa & Angela Onwuachi-Willig, *Combating Discrimination Against the Formerly Incarcerated in the Labor Market*, 112 NW. U. L. REV. 1385 (2018) (discussing discrimination against the formerly incarcerated in the labor market).

272. See, e.g., Scott Hempling, "Regulatory Capture": Sources and Solutions, 1 EMORY CORP. GOVERNANCE & ACCOUNTABILITY REV. 23, 24–25 (introducing the concept of "regulatory capture," where legislators are "captured" in a "constant state of 'being persuaded' . . . based on a persuader's identity rather than an argument's merits" while acting like a robot that is controlled by political interest groups); see also Lauren Cohen Bell, *Senatorial Discourtesy: The Senate's Use of Delay To Shape the Federal Judiciary*, 55 POL. RSCH. Q. 589, 589 (2002) ("Legislators have long recognized that delaying tactics are powerful tools for preventing the passage of laws they deem unsatisfactory.").

273. See, e.g., Coral Davenport, *Restoring Environmental Rules Rolled Back by Trump Could Take Years*, N.Y. TIMES (Oct. 6, 2021), <https://www.nytimes.com/2021/01/22/climate/biden-environment.html> [<https://perma.cc/U5BW-G34C> (dark archive)] (last updated Oct. 6, 2021) (discussing how the Biden administration's plan to roll back "environmental protections frayed" during the Trump administration).

274. See, e.g., MEL BARNES, NORMAN EISEN, JEFF MANDELL & NORMAN ORNSTEIN, BROOKINGS INST., *FILIBUSTER REFORM IS COMING—HERE'S HOW: SEVEN IDEAS FOR CHANGE* 9–10 (2021), https://www.brookings.edu/wp-content/uploads/2021/09/Filibuster-Reform-is-Coming_Heres-How_Sept2021.pdf [<https://perma.cc/5F6W-XJ7T>] (addressing the history of the filibuster in the United States and arguing that reform is needed as "[t]he current iteration of the filibuster has been obstructing routine governance and a properly functioning Senate").

means that the congressional overview and review process, rather than being a helpful safeguard, could instead become a roadblock that derails agencies from making positive use of automated decision-making tools in the service of agency goals.

CONCLUSION

In Greek mythology, Cassandra was cursed with the ability to see the future by Apollo.²⁷⁵ Although foresight is usually considered a gift, for Cassandra it was a burden because Apollo had also decreed that no one would believe Cassandra's prophecies.²⁷⁶ She was doomed to know the future and have no power to change it.²⁷⁷ Many law and technology scholars feel like Cassandra—a deep understanding of automated tools may bring greater awareness of the risks associated with their deployment, but a lack of governmental regulation means such scholars remain powerless to change any predicted harm. The techno-realist approach of this Article acknowledges that automated decision-making by governmental agencies will happen. When contemplating the adoption of automated tools by governmental agencies, a crucial first step is understanding the limitations of such tools. These limitations are best surfaced by maintaining the rights to explanation and contestation. After a sober assessment of these limitations, governmental agencies that choose to make use of them should also embrace the concept of “human in the loop”²⁷⁸ or even better, “society in the loop,”²⁷⁹ and should ensure that there are adequate guardrails in place to ensure that the use of automated tools comports with the law. This means that there must always be a level of human oversight auditing the returned results of the automated decision-making and appropriate societal safeguards to ensure those automated tools continue to serve the public good. Finally, we must also never lose sight of the question of whether there might be scenarios in which automated decision-making by governmental agencies is simply inappropriate.

275. See Michael Ray, *Cassandra*, BRITANNICA (Dec. 4, 2022), <https://www.britannica.com/event/Trojan-War> [<https://perma.cc/78BQ-ECHN>].

276. See *id.*

277. See *id.*

278. See generally Ge Wang, *Humans in the Loop: The Design of Interactive AI Systems*, STAN. UNIV. HUM.-CENTERED A.I. (Oct. 20, 2019), <https://hai.stanford.edu/news/humans-loop-design-interactive-ai-systems> [<https://perma.cc/B2D4-TLM6>] (describing a “[h]umans-in-the-loop system” as one that “puts humans in the decision loop”).

279. See generally Iyad Rahwan, *Society-in-the Loop: Programming the Algorithmic Social Contract*, 20 ETHICS & INFO. TECH. 5 (2018), <https://link.springer.com/content/pdf/10.1007/s10676-017-9430-8.pdf> [<https://perma.cc/Z3N4-KFNG> (staff-uploaded, dark archive)] (proposing and advocating for the adoption of the society-in-the-loop agenda).