

LOCKED OUT BY BIG DATA: HOW BIG DATA, ALGORITHMS AND MACHINE LEARNING MAY UNDERMINE HOUSING JUSTICE

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ABSTRACT

As housing-related decisions are increasingly being made by algorithms instead of individuals, it is critical that the technologies used to make those decisions do not replicate or even worsen patterns of discrimination and segregation. While it may be convenient to believe that bias can be eliminated by putting decision-making authority in the hands of machines instead of people, studies have shown that technologies such as algorithms and machine learning are often infected with bias.

Provisions of the Fair Housing Act (“FHA”) and its accompanying regulations that protect individuals from discriminatory algorithms are under attack from the Department of Housing and Urban Development (“HUD”), the agency responsible for enforcing the FHA. In particular, HUD recently issued a proposed rule that, if enacted, would undermine disparate impact jurisprudence and specifically exempt many housing providers who rely on algorithms developed by third parties. With the FHA under attack from the agency charged with its enforcement, it is particularly important to study how technological advancements might be used to either improve or undermine the law’s effectiveness.

This article describes the advent of big data, algorithmic decision-making, and machine learning, as well as HUD’s recent proposal to specifically immunize housing providers who rely on

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algorithms from disparate impact liability. It then discusses how the use of big data and algorithmic decision-making has touched all parts of the rental housing market, from advertising to tenant selection processes. Finally, it offers policy prescriptions that could help mitigate the discriminatory impacts of algorithmic decision-making in ways that are aligned with the FHA or, in some cases, that reach further than the protections currently offered under the FHA.

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INTRODUCTION

Social media and big data companies, such as Facebook and CoreLogic, amass gargantuan amounts of data about individuals that can help decision-makers act more efficiently and effectively. Ostensibly, the use of data and algorithms should diminish the effect of personal bias and racism in decision-making, leading to more just and race-neutral results. Evidence has emerged, however, that suggests that the use of big data, algorithms, machine learning, and artificial intelligence in housing-related decisions can perpetuate patterns of discrimination and thwart the efficacy of our antidiscrimination laws.¹

In the past five years, there has been an increased scholarly focus on both the potential for big data, algorithms, and machine learning to diminish the effects of personal prejudice in decision-making and the possibility that these technologies might, in the end, replicate or even worsen discrimination.² This article focuses on the

1. James A. Allen, *The Color of Algorithms: An Analysis and Proposed Research Agenda for Deterring Algorithmic Redlining*, 46 *FORDHAM URB. L.J.* 219, 229 (2019) (“Ample research has shown that by using biased data and potentially biased code, algorithms are creating a funneling effect that perpetuates discrimination and stereotypes.”); see also Mathias Risse, *Human Rights and Artificial Intelligence: An Urgently Needed Agenda*, 41 *HUM. RTS. Q.* 1, 11 (2019) (“Anti-discrimination provisions are threatened if algorithms used in areas ranging from health care to insurance underwriting to parole decision are racist or sexist because the learning they do draws on sexism or racism.”); EXEC. OFF. OF THE PRESIDENT, *BIG DATA: A REPORT ON ALGORITHMIC SYSTEMS, OPPORTUNITY, AND CIVIL RIGHTS* 1, 5 (2016), https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/2016_0504_data_discrimination.pdf [<https://perma.cc/B42Y-GE3F>] (“Big data techniques have the potential to enhance our ability to detect and prevent discriminatory harm. But, if these technologies are not implemented with care, they can also perpetuate, exacerbate or mask harmful discrimination.”).

2. See Nicol Turner Lee et al., *Algorithmic Bias Detection and Mitigation: Best Practices To Reduce Consumer Harms*, BROOKINGS (May 2019), <https://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms> [<https://perma.cc/6K6Y-LXNG>] (“[S]ome algorithms run the risk of replicating and even amplifying human biases, particularly those affecting protected groups”); see also Allen, *supra* note 1, at 229; Lorna McGregor et al., *International Human Rights Law as a Framework for Algorithmic Accountability*, 68 *INT’L & COMPAR. L. Q.* 309, 319 (2019) (discussing the risks and potential human rights violations that can be caused by discriminatory algorithms); Aziz Z. Huq, *Racial Equity in Algorithmic Criminal Justice*, 68 *DUKE L.J.* 1043, 1054 (2019) (identifying the “possibility that an algorithm will generate patterns of error that are systematically skewed between racial groups” as an issue with their use in the criminal legal system).

intersection of the use of big data and algorithms in rental housing and the protections of the Fair Housing Act. This article concentrates on rental housing as opposed to other parts of the housing market for three reasons. First, compared to white Americans, minorities disproportionately live in rental housing; thus, the Fair Housing Act has its greatest potential to affect change for minorities in the realm of rental housing.³ Second, rental housing decisions are increasingly being made not by landlords or individuals in management companies, but by algorithms created by third parties. Finally, under the Trump Administration, the Department of Housing and Urban Development (“HUD”) has moved to dismantle one of the main avenues for recourse for renters under the Fair Housing Act—disparate impact analysis—and has proposed to specifically immunize housing providers that rely on algorithms in decision-making from liability.⁴

This article proceeds in five parts. Part I describes the advent of big data, algorithmic decision-making, and machine learning. Part II describes the relevant provisions of the Fair Housing Act and HUD’s recent proposal to specifically immunize housing providers who rely on algorithms from disparate impact liability. Part III discusses how the use of big data and algorithmic decision-making has affected tenant selection. Part IV discusses how the Fair Housing Act’s prohibition on discriminatory advertising is being undermined by big data companies such as Facebook. Part V offers some policy

3. See Eloisa C. Rodriguez-Dod & Olympia Duhart, *Evaluating Katrina: A Snapshot of Renters' Rights Following Disasters*, 31 NOVA L. REV. 467, 471–72 (2007) (“[B]efore the storm, nearly one in two black households in St. Bernard’s and one in three Hispanic households in the parish were renters. By contrast, only one in four white households in St. Bernard were renters before the storm.”).

4. HUD’s Implementation of the Fair Housing Act’s Disparate Impact Standard, 84 Fed. Reg. 42854 (proposed Aug. 19, 2019) (to be codified at 20 C.F.R. pt. 100). See *infra* Part II.B for a discussion of how HUD’s proposed rule would weaken the disparate impact theory and specifically immunize housing providers who use algorithms to make housing decisions from liability provided that such housing providers show that the inputs are not proxies for race or that the algorithm was created or verified by a third party; see also Howard University School of Law, Comment Letter on Proposed Rule Governing HUD’s Implementation of the Fair Housing Act’s Disparate Impact Standard (Oct. 18, 2019), <https://www.regulations.gov/document?D=HUD-2019-0067-2779> (on file with the *Columbia Human Rights Law Review*) (“The Proposed Rule ignores the reality that one variable alone may not have a discriminatory effect; rather, it is the power of algorithms to combine seemingly neutral inputs that together may become a close proxy or substitute for a protected class.”).

prescriptions that could help mitigate the discriminatory impacts of algorithmic decision-making in ways that are aligned with the Fair Housing Act or, in some cases, that reach further than the protections currently offered under the Fair Housing Act.

I. BIG DATA, ARTIFICIAL INTELLIGENCE, & MACHINE LEARNING— DEFINING THE TERMS

As the Federal Trade Commission stated in a 2016 report, “[w]e are in the era of big data.”⁵ Big data companies are “more powerful than oil companies ever were, and this is presumably just the beginning of their ascension.”⁶ With the advent of smart phones, social media, search engines, and near constant connectivity, companies are constantly collecting immense amounts of data about most Americans.⁷ Data mining attempts to “locate statistical relationships in a data set” and it “automates the process of discovering useful patterns, revealing regularities upon which subsequent decision making can rely.”⁸ Data is mined about virtually every aspect of modern life: search queries, online transactions, links “clicked,” social networking interactions, global positioning satellites, online subscriptions, public records, and more.⁹ Even after logging out

5. FED. TRADE COMM’N, *BIG DATA, A TOOL FOR INCLUSION OR EXCLUSION* (2016), <https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf> [<https://perma.cc/Y2P2-SWK9>]; see also Risse, *supra* note 1, at 2 (“Artificial intelligence (AI) is increasingly present in day-to-day life, reflecting a growing tendency to turn for advice, or turn over decisions altogether, to algorithms.”); Jonas Lerman, *Big Data and Its Exclusions*, 66 STAN. L. REV. ONLINE 55, 55 (2013) (“The big data revolution has arrived.”).

6. Risse, *supra* note 1, at 12; see also *The World’s Most Valuable Resource is No Longer Oil, But Data*, THE ECONOMIST (Mar. 4, 2020), <https://www.economist.com/leaders/2017/05/06/the-worlds-most-valuable-resource-is-no-longer-oil-but-data> (on file with the *Columbia Human Rights Law Review*); EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 5 (“As data-driven services become increasingly ubiquitous . . . we must address concerns about intentional or implicit biases that may emerge from both the data and the algorithms used as well as the impact they may have on the user and society.”).

7. See Risse, *supra* note 1, at 12; see also EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 4 (warning that burgeoning technology will only “spur broader use of big data”).

8. Solon Barocas & Andrew D. Selbst, *Big Data’s Disparate Impact*, 104 CAL. L. REV. 671, 677 (2016).

9. Liane Colonna, *A Taxonomy and Classification of Data Mining*, 16 SMU SCI. & TECH. L. REV. 309, 311 (2013); see also Risse, *supra* note 1, at 2 (“The

of an application, many social media platforms continue to collect data on an individual's location, browser history, and purchases via the use of "cookies."¹⁰

Data on its own is not particularly valuable; it must be organized, collated, and analyzed in order to have utility.¹¹ As the collection of data has become routinized, entire industries have emerged to make that data useful. Thus "big data" companies do not merely collect data; they, along with other technology companies, develop computer programs known as algorithms—"sets of step-by-step instructions"—that enable the recognition of patterns, which allows for the accurate prediction of particular results.¹² These algorithms "increasingly determine what information we are exposed to and what decisions are made about us."¹³ Historically, algorithms have worked like a flowchart or decision tree. For example, an algorithm might be programmed so that if X and Y variables are present, then a prospective renter should get a score of Z.

Technology has developed so that algorithms need not remain static; instead, they can now be programmed to "learn" from patterns

effectiveness of algorithms is increasingly enhanced through 'Big Data:' the availability of an enormous amount of data on all human activity and other processes in the world."); Max N. Helveston, *Consumer Protection in the Age of Big Data*, 93 WASH. U. L. REV. 859, 868 (2016) ("the average person has little understanding of exactly how much information about herself is being collected by third parties or how private companies and the government have begun to use this data").

10. 6 *The Law of Advertising IV* (2019).

11. Roger W. Reinsch & Sonia Goltz, *Big Data: Can the Attempt to Be More Discriminating Be More Discriminatory Instead?*, 61 ST. LOUIS U. L.J. 35, 37 (2016) ("Although Big Data is characterized by volume, it would be relatively useless without the sophisticated algorithms that can process incredibly large amounts of data, allowing people to find patterns not normally visible.").

12. Omer Tene & Jules Polonetsky, *Taming the Golem: Challenges of Ethical Algorithmic Decision-Making*, 19 N.C. J. L. & TECH. 125, 128 (2017). For a definition of "algorithm," see *Gottschalk v. Benson*, 409 U.S. 63, 65 (1972) ("A procedure for solving a given type of mathematical problem is known as an 'algorithm.'"); see also 3 CHISUM ON PATENTS § 8.04 (2019) ("[A]n algorithm is defined as a fixed, step-by-step procedure for accomplishing a given result."); Kal Raustiala & Christopher Jon Sprigman, *The Second Digital Disruption: Streaming and the Dawn of Data-Driven Creativity*, 94 N.Y.U. L. REV. 1555, 1583 (2019) ("An 'algorithm' is defined as a 'prescribed set of well-defined rules or instructions for the solution of a problem, such as the performance of a calculation, in a finite number of steps.'" (citing *Algorithm*, Oxford Reference: A Dictionary of Computer Science (Andrew Butterfield et al., eds., 7th ed. 2016))).

13. Tene & Polonetsky, *supra* note 12, at 128.

and to adjust in order to make more precise predictions for future behaviors.¹⁴ This type of responsive algorithm is often referred to as “artificial intelligence” or “machine learning.” The static “step-by-step” instructions that originally made up the algorithm can now change in response to previous results via artificial intelligence or machine learning, sometimes in ways that the original programmers cannot predict or control.¹⁵ These advanced algorithms “collect training data, learn from it, and then apply what they learned to larger datasets to determine or predict something about reality.”¹⁶

The notion that algorithms can learn from past patterns seems to be a good thing at first blush, given that efficiency and accuracy are improved when algorithms can automatically become more precise without any need for additional input.¹⁷ However, if an algorithm learns from existing patterns, and those patterns are infected with racial inequality, the algorithm may “learn” to replicate and reinforce that inequality.¹⁸ If algorithms, by their nature, rely on

14. Mark MacCarthy, *Standards of Fairness for Disparate Impact Assessment of Big Data Algorithms*, 48 CUMB. L. REV. 67, 74 (2018) (explaining that machine learning programs improve as they are exposed to more data, adjusting over time according to their original design as well as the training data to which they were originally exposed).

15. See EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 10 (noting that machine learning is the “science of getting computers to act without being explicitly programmed.” (internal citations omitted)); see also Ignacio N. Cofone, *Algorithmic Discrimination Is an Information Problem*, 70 HASTINGS L.J. 1389, 1395 (2019) (“[M]achine learning algorithms are given large amounts of data with output variables for the algorithm to self-adjust. Instead of determining decision rules, human intervention is limited to selecting features for the training data and attaching labels to the output data.”).

16. Cofone, *supra* note 15, at 1395.

17. For a discussion of potential impacts of artificial intelligence on the legal field, see Mariano-Florentino Cuéllar, *A Simpler World? On Pruning Risks and Harvesting Fruits in an Orchard of Whispering Algorithms*, 51 U.C. DAVIS L. REV. 27, 35 (2017) (“If society enhances the artificially intelligent tools available for addressing challenges of such enormous legal consequence, we will gain new opportunities to close the considerable gap between legal aspirations and reality that currently bedevils aspirations for justice.”).

18. See Risse, *supra* note 1, at 11 (stressing that human rights organizations are invested in exploring the “potential for discrimination within the use of machine learning, particularly with regard to policing, criminal justice, and access to essential economic and social services” based on discriminatory inputs).

data that captures a racist past and present, they may automate the inequitable “status quo unless preventative measures are taken.”¹⁹

The use of big data, algorithms, and machine learning always involves a “form of statistical (and therefore seemingly rational) discrimination.”²⁰ The purpose of using big data, algorithms, and artificial intelligence is to “provide a rational basis upon which to distinguish between individuals”²¹—e.g., to predict if one applicant for an apartment is more likely than another applicant to pay rent on time or abide by the lease. Some claim that in addition to being more efficient and potentially more effective than leaving decisions to individuals, the use of big data can diminish the effects of discrimination by removing potentially biased individuals from the decision-making process.²² The problem with big data, however, is that it must use existing data, which often reflects existing patterns of discrimination and this can perpetuate the unequal status quo. Consequently, the use of big data and algorithms “holds the potential to unduly discount members of legally protected classes.”²³ In other words, the benefit of using predictive algorithms is that they can make decision-making more efficient, and, in some cases, can help erase human bias decisions.²⁴ The downside, however, is that such algorithms may be used to deny opportunities to individuals based on

19. *Id.* at 2.

20. Barocas & Selbst, *supra* note 8, at 677.

21. *Id.*

22. Some scholars have noted that, because humans create algorithms, human bias can never truly be removed from algorithmic decision-making. Cofone, *supra* note 15, at 1401 (“The biases of humans that program and apply the algorithm can translate into the algorithm, and sometimes stereotypes and negative associations can be codified in and amplified by the algorithm.”); *see also* MacCarthy, *supra* note 14, at 74 (explaining that while algorithms can benefit historically disadvantaged groups to remedy discrimination, there are also fairness concerns).

23. Barocas & Selbst, *supra* note 8, at 677; *see also* Tene & Polonetsky, *supra* note 12, at 130 (asserting that no algorithm is “fully immune” from humans, because they are made by human designers, are trained on human-generated data, and codify human choices).

24. MacCarthy, *supra* note 14, at 74 (noting that discussions of algorithmic fairness have increased recently); *see also* Tene & Polonetsky, *supra* note 12, at 132 (arguing that the benefits of the use of algorithms include “unearthing and mitigating formerly discrete and muted discrimination.”); Pauline T. Kim, *Data-Driven Discrimination At Work*, 48 WM. & MARY L. REV. 857, 871 (2017) (“[A]lthough algorithms offer the potential for avoiding or minimizing bias, the real question is how the biases they may introduce compare with the human biases they avoid.”).

their membership in or association with a particular group while hiding behind a cloak of mathematical neutrality.²⁵

The uses of algorithms, artificial intelligence, and machine learning are ubiquitous. They are used across industries including in decisions related to housing, health, hiring, transportation, and policing.²⁶ A recent proliferation of scholarship about the use of algorithms, artificial intelligence, and machine learning in decision-making has settled the debate as to whether bias and harm flows from the use of these technologies: “the evidence [of bias] has mounted beyond a doubt . . . [and] [t]he task now is addressing these harms.”²⁷

The remainder of this article will address how algorithms are used in one of the most intimate and important aspects of our society,—housing—and in relation to one of our most important civil rights laws—the Fair Housing Act. Ultimately, it will offer suggestions for addressing the negative effects of the use of

25. FED. TRADE COMM’N, *supra* note 5, at 8; *see also* Miranda Bogen & Aaron Rieke, *Help Wanted: An Examination of Hiring Algorithms, Equity and Bias*, UPTURN (Dec. 2018), <https://www.upturn.org/reports/2018/hiring-algorithms> [<https://perma.cc/2JNL-3RMB>] (“A phenomenon known as automation bias occurs when people give undue weight to the information coming through their monitors.” (internal citations and quotation marks omitted)); Cofone, *supra* note 15, at 1396 (“Algorithmic decision-making is sometimes taken to imply that the prevalence of biases for discrimination decreases. . . . However, in the last few years, piles of documented cases have appeared regarding decision-making processes in which algorithms also produce a discriminatory outcome—even assuming no discriminatory intent.”); MacCarthy, *supra* note 14, at 75 (“The output of an analytical process can have a disparate impact on a protected class when a variable or combination of variables correlates both with the suspect classification and the output variable. These correlations may be the result of historical discrimination that put vulnerable people at a disadvantage.”).

26. Ryan C. LaBrie & Gerhard H. Steinke, *Towards a Framework for Ethical Audits of AI Algorithms*, TWENTY-FIFTH AMERICAS CONFERENCE ON INFORMATION SYSTEMS, CANCUN, 1 (2019); *see also* Lee et al., *supra* note 2 (“Private and public sectors are increasingly turning to artificial intelligence (AI) systems and machine learning algorithms to automate simple and complex decision-making processes. The mass-scale digitization of data and the emerging technologies that use them are disrupting most economic sectors, including transportation, retail, advertising, and energy, and other areas.”). *See generally*, Cofone, *supra* note 15, at 1389 (discussing the use of algorithms in hiring decisions, policing, healthcare, and other contexts).

27. Cofone, *supra* note 15, at 1394 (“The resulting discrimination can be classified along three categories. . . . The first is a bias in the process, the second is a bias in the input (sample), and the third is a societal bias captured in representative data.”).

algorithms in the rental housing market, particularly where these harms are obscured by perceived neutrality.

II. THE FAIR HOUSING ACT, DISPARATE IMPACT, AND THE USE OF ALGORITHMS

A. The Fair Housing Act's Broad Purpose

The Fair Housing Act, enacted in 1968, did not anticipate the interplay between technology and our civil rights laws. The use of algorithms, artificial intelligence, or machine learning in housing-related decisions was likely far from the minds of the drafters.²⁸ Regardless, the Fair Housing Act is structured to address both intentionally discriminatory policies as well as decisions that have a discriminatory effect.²⁹ This second theory for recovery under the Fair Housing Act—the “disparate impact” theory—is particularly well suited to address algorithmic discrimination.

The purpose of the Fair Housing Act, per its declaration of policy, is “to provide, within constitutional limitations, for fair housing throughout the United States.”³⁰ Courts have consistently held that, given its purpose, the Fair Housing Act should be interpreted broadly.³¹

The most frequently cited language of the Fair Housing Act makes it illegal to “refuse to sell or rent . . . or to refuse to negotiate for the sale or rental of . . . a dwelling to any person because of race, color, religion, sex . . . or national origin.”³² This language prohibits intentional discrimination or “disparate treatment;” that is, it subjects housing providers to liability if they intentionally refuse to sell or rent to a person because of that person’s membership in a protected class.

28. An early influential algorithm, Quicksort, was developed in 1961 by Tony Hoare only seven years prior to the passage of the Fair Housing Act. *See* C.A.R. Hoare, *Quicksort*, 5 COMPUT. J. 10, 11 (1962).

29. *Tex. Dep't of Hous. & Cmty. Affairs v. Inclusive Cmty. Project, Inc.*, 135 S. Ct. 2507, 2519 (2015).

30. 42 U.S.C. § 3601 (1968) [hereinafter “FHA”].

31. *See, e.g., Miami Valley Fair Hous. Ctr., Inc. v. Connor Grp.*, 725 F.3d 571, 577 (6th Cir. 2013) (“The Fair Housing Act's language is purposely broad.”); *see also* *Trafficante v. Metro. Life Ins. Co.*, 409 U.S. 205, 211–12 (1972) (finding that the Fair Housing Act must be generously construed to foster integration).

32. FHA, *supra* note 30, at § 3604.

The Fair Housing Act also contains language that has consistently been interpreted to support a disparate impact theory of liability. Under this theory, litigants can bring claims asserting that a facially neutral policy or action has a disproportionately adverse effect on members of a protected class. Since the 1970s, every circuit court that has considered the question has determined that the Fair Housing Act's prohibition on acts that would "otherwise make unavailable or deny"³³ housing due to membership in a protected class allows potential litigants to bring disparate impact claims.³⁴

In 2013, after the Supreme Court granted certiorari in *Mt. Holly Gardens Citizens In Action, Inc. v. Township of Mount Holly*, a case that brought into question whether disparate impact claims are cognizable under the Fair Housing Act, HUD promulgated regulations (the "2013 Disparate Impact Regulations") that recognized and formalized the existing disparate impact jurisprudence.³⁵ *Mount Holly* settled before the Supreme Court heard oral arguments, but in 2015 the Supreme Court granted certiorari on another case that called into question whether disparate impact claims are cognizable under the Fair Housing Act: *Texas Department of Housing and Community Affairs v. Inclusive Communities Project, Inc.*³⁶ In its decision in *Inclusive Communities*, the Supreme Court gave its stamp of approval to existing federal court jurisprudence and the 2013 Disparate Impact Regulations, holding that disparate impact claims are cognizable under the Fair Housing Act, and these

33. *Id.* at § 3604 (a).

34. The Supreme Court noted that nine Courts of Appeals had concluded the Fair Housing Act encompassed disparate-impact claims. *See Inclusive Cmty. Project, Inc.*, 135 S. Ct. at 2519; *Huntington Branch, NAACP v. Town of Huntington*, 844 F.2d 926, 935–36 (2d Cir. 1988); *Arthur v. City of Toledo*, 782 F.2d 565, 574–75 (6th Cir. 1986); *Hanson v. Veterans Admin.*, 800 F.2d 1381, 1386 (5th Cir. 1986); *United States v. Marengo Cty. Comm'n*, 731 F.2d 1546, 1559, n.20 (11th Cir. 1984); *Smith v. Town of Clarkton*, 682 F.2d 1055, 1065 (4th Cir. 1982); *Halet v. Wend Inv. Co.*, 672 F.2d 1305, 1311 (9th Cir. 1982); *Resident Advisory Bd. v. Rizzo*, 564 F.2d 126, 146 (3d Cir. 1977); *Metro. Hous. Dev. Corp. v. Vill. of Arlington Heights*, 558 F.2d 1283, 1290 (7th Cir. 1977); *United States v. City of Black Jack*, 508 F.2d 1179, 1184–85 (8th Cir. 1974).

35. *Mt. Holly Gardens Citizens in Action, Inc. v. Twp. of Mount Holly*, 658 F.3d 375, 377 (3d Cir. 2011); *see also* Implementation of the Fair Housing Act's Discriminatory Effects Standard, 78 Fed. Reg. 11,460, 11,479 (Feb. 15, 2013) (to be codified at 24 C.F.R. pt. 100) ("formaliz[ing] the longstanding interpretation of the Fair Housing Act to include discriminatory effects liability").

36. *Inclusive Cmty. Project, Inc.*, 135 S. Ct. at 2507.

claims should be evaluated via the burden-shifting analysis outlined in the 2013 Disparate Impact Regulations.³⁷

Though neither HUD nor the Supreme Court mentioned the use of big data, algorithms, or artificial intelligence in their approvals of disparate impact jurisprudence, there is no reason to believe that decisions made by facially neutral algorithms would fall outside of the purview of disparate impact analysis.

B. HUD's Attempt to Immunize Housing Providers Who Use Algorithms

Despite the long line of cases supporting disparate impact liability and HUD's 2013 Disparate Impact Rule, in August 2019, HUD promulgated a proposed rule ("Proposed Rule") that would weaken the disparate impact theory and specifically immunize from Fair Housing Act liability housing providers who use algorithms to make housing decisions provided that such housing providers "identify[] the inputs used in the model and show[] that these inputs are not substitutes for a protected characteristic and that the model is predictive of risk or other valid objectives."³⁸ Housing providers using algorithms could also avoid liability by showing that "a recognized third party, not the defendant, is responsible for creating or maintaining the model."³⁹ Yet another provision of the Proposed Rule would also allow housing providers to avoid liability if they show that "a neutral third party has analyzed the model in question and determined it was empirically derived, its inputs are not substitutes for a protected characteristic, the model is predictive of risk or other valid objective and is a demonstrably and statistically sound algorithm."⁴⁰ Essentially, under the Proposed Rule, housing providers

37. *Id.* at 2514 ("While the Department's appeal was pending, the Secretary of Housing and Urban Development (HUD) issued a regulation interpreting the FHA to encompass disparate-impact liability. . . . The regulation also established a burden-shifting framework for adjudicating disparate-impact claims." (internal citation omitted)); *see generally* Valerie Schneider, *In Defense of Disparate Impact: Urban Redevelopment and the Supreme Court's Recent Interest in the Fair Housing Act*, 79 MO. L. REV. 539 (2014) (discussing the nuances of a burden-shifting analysis alongside the Supreme Court's "apparent interest in limiting the use of disparate impact analysis in Fair Housing cases").

38. HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. 42,854, 42,859 (proposed Aug. 19, 2019) (to be codified at 24 C.F.R. pt. 100) (providing this defense in § 100.500 (c)(2)(i)).

39. *Id.* (providing this defense in § 100.500 (c)(2)(ii)).

40. *Id.* (providing this defense in § 100.500 (c)(2)(iii)).

could avoid liability for disparate impacts that would otherwise be prohibited simply by pointing to a facially neutral algorithm and saying “the inputs are race-neutral,” “someone else created it,” or “someone else looked at it and approved it.”⁴¹

Many fair housing advocates have expressed concern that HUD’s Proposed Rule will make it nearly impossible for those who suffer discrimination at the hands of an algorithm to prevail on a Fair Housing Act claim.⁴² Public Knowledge, a think tank focused on policy issues related to freedom of expression and consumer advocacy, issued a public comment noting that the Proposed Rule was “in tension with the growing legal precedent that people should be able to challenge the accuracy of technological systems used to their detriment.”⁴³ The Proposed Rule, Public Knowledge argued, “threatens to create an environment where the claims of companies

41. Howard Univ. Sch. of L., Comment Letter on Proposed Rule Governing HUD’s Implementation of the Fair Housing Act’s Disparate Impact Standard, at 7–8 (Oct. 21, 2019), <https://www.regulations.gov/document?D=HUD-2019-0067-2779> [<https://perma.cc/4RFC-JLFS>].

42. See Comment Letters on Proposed Rule Governing HUD’s Implementation of the Fair Housing Act’s Disparate Impact Standard (2019), <https://www.regulations.gov/docketBrowser?rpp=50&so=DESC&sb=postedDate&po=0&dt=PS&D=HUD-2019-0067> [<https://perma.cc/ZPV4-PT7L>]. Over 4,000 individuals and organizations submitted public comments regarding HUD’s Proposed Rule, and many of those commenting specifically noted that the defenses given to those who employ algorithms would immunize huge sectors of the housing market from disparate impact liability. The author, along with clinical colleagues and students at Howard University School of Law submitted a public comment criticizing the Proposed Rule as an attack on the broad purpose of the Fair Housing Act. The Howard Comment notes that the “current disparate impact standard has its roots in efforts to combat [the] history of policies and practices that appeared to be neutral, but, in practice, had discriminatory effects on members of protected classes.” Howard Univ. Sch. of L., *supra* note 41, at 2–3 [hereinafter “Howard Comment”]. Other commenters echoed our concerns. The Metropolitan St. Louis Equal Housing and Opportunity Council, for example, wrote “HUD’s Proposed Rule creates a vague standard with many undefined terms that will shield housing providers from disparate impact liability whenever they use an algorithm to make a housing decision.” Metro. St. Louis Equal Hous. & Opportunity Council, Comment Letter on Proposed Rule Governing HUD’s Implementation of the Fair Housing Act’s Disparate Impact Standard, at 8 (Oct. 31, 2019), <https://www.regulations.gov/document?D=HUD-2019-0067-3946> [<https://perma.cc/SZG3-8WYS>].

43. Pub. Knowledge, Comment Letter on Proposed Rule Governing HUD’s Implementation of the Fair Housing Act’s Disparate Impact Standard, at 1 (Oct. 21, 2019), <https://www.publicknowledge.org/wp-content/uploads/2019/10/Public-Knowledge-HUD-Comment-Final.pdf> [<https://perma.cc/884G-BZVU>].

cannot be tested or challenged by those seeking housing at a time when affordable housing options are limited.”⁴⁴ The Center for Democracy and Technology wrote that the “algorithmic defenses seriously undermine HUD’s ability to address discrimination, are unjustified in the record, and have no basis in computer or data science.”⁴⁵ The Shriver Center on Poverty Law commented that, “[t]he broad and unprecedented algorithmic model defenses proposed by HUD would categorically insulate landlords and tenant screening companies from disparate impact liability, contradicting HUD’s own determination that disparate impact should be ‘ultimately a fact-specific and case-specific inquiry.’”⁴⁶ One organization concluded that the Proposed Rule would “eviscerate . . . plaintiffs’ ability to address discriminatory effects arising from the use of algorithmic models . . . in spite of the fact that such models are ‘increasingly commonly used’ in determining people’s eligibility for a range of housing opportunities.”⁴⁷

The Proposed Rule seems to rely on a form of “data fundamentalism” that the Obama Administration warned against in a 2016 report.⁴⁸ This type of “data fundamentalism” centers around the “belief that numbers cannot lie and always represent objective truth.”⁴⁹ Such a belief can “present serious and obfuscated bias

44. *Id.* at 5.

45. Ctr. for Democracy & Tech., Comment Letter on Proposed Rule Governing HUD’s Implementation of the Fair Housing Act’s Disparate Impact, at 1 (Oct. 28, 2019), <https://www.regulations.gov/document?D=HUD-2019-0067-3852> [<https://perma.cc/492E-L2PH>].

46. Shriver Ctr. on Poverty L., Comment Letter on Proposed Rule Governing HUD’s Implementation of the Fair Housing Act’s Disparate Impact Standard, at 16 (Oct. 22, 2019), <https://www.regulations.gov/document?D=HUD-2019-0067-3649> [<https://perma.cc/R57M-RAKE>] (citing U.S. Dep’t of Hous. & Urban Dev., Office of General Counsel Guidance on Application of Fair Housing Act Standards to the Use of Criminal Records by Providers of Housing and Real Estate-Related Transactions, at 4 (Apr. 4, 2016), https://www.hud.gov/sites/documents/hud_ogcguidappfhastandcr.pdf [<https://perma.cc/99PY-UZW5>]).

47. Upturn, Comment Letter on Proposed Rule Governing HUD’s Implementation of the Fair Housing Act’s Disparate Impact Standard, at 2 (Oct. 22, 2019), <https://www.regulations.gov/document?D=HUD-2019-0067-3608> [<https://perma.cc/9YSY-J7NG>].

48. EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 10.

49. *Id.*; see also Kate Crawford, *The Hidden Biases in Big Data*, HARV. BUS. REV. (Apr. 1, 2013), <https://hbr.org/2013/04/the-hidden-biases-in-big-data> (on file with the *Columbia Human Rights Law Review*) (defining data fundamentalism as “the notion that correlation always indicates causation, and that massive data sets and predictive analytics always reflect objective truth”).

problems that negatively impact people's lives."⁵⁰ In summary, HUD's Proposed Rule would thwart efforts to determine whether specific algorithms may, even inadvertently, result in unlawful discrimination. It would relieve housing providers from accountability when algorithmic decision-making has unjustifiable discriminatory effects.⁵¹ Even the National Association of Realtors and many large banks,—entities that might be expected to support any weakening of disparate impact jurisprudence—recently expressed disapproval of HUD's Proposed Rule.⁵²

At the same time that HUD's Proposed Rule immunizes many housing providers from liability when algorithms are used, there has been an increase in products offered to housing providers that focus on replacing human decision-makers with algorithms.⁵³ The next section addresses how algorithms have taken over for human decision-makers in many aspects of the tenant selection process.

III. TENANT SELECTION

A. The Growth of Big Data in Tenant Selection

Decision-making is one of the most expensive elements of any business, including in the rental housing market.⁵⁴ Historically,

50. EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 10.

51. *Cf. id.* at 23 (noting that “[o]rganizations, institutions, and companies should be held accountable for the decisions they make with the aid of computerized decision-making systems and technology”).

52. ED. BD., *In Housing, A Surprising Piece of Evidence that the Fight Against Racism is Working*, WASH. POST (July 21, 2020), https://www.washingtonpost.com/opinions/in-housing-a-surprising-piece-of-evidence-the-fight-against-racism-is-working/2020/07/21/787b3838-c60c-11ea-8ffe-372be8d82298_story.html (on file with the *Columbia Human Rights Law Review*) (relaying that a top Bank of America executive wrote, “Given the recent protests and events, and the recognition of where we are as a country, we would respectfully offer that the time is not right to issue a new rule on disparate impact.”).

53. *See* Shriver Ctr. on Poverty L., *supra* note 46, at 17 (noting that the “tenant screening industry is not new” but “[w]ith modern technology, screening companies . . . will often provide landlords with more than a simple report. Using parameters set by the landlord, companies now offer products that compare the retrieved records against the landlord’s stated admission policy and use an algorithm to [assess applicants]”).

54. Ifeoma Ajunwa, *The Paradox of Automation As Anti-Bias Intervention*, 41 CARDOZO L. REV. 1671, 1734 (2020) (“Employers save significant amounts of money and time by using automated hiring platforms.”).

housing providers used individual employees to gather information, conduct research, engage others, and weigh competing factors when making housing decisions.⁵⁵ Increasingly, however, decision-making has become an automated process that wrests control from individuals and places it in the hands of algorithms.⁵⁶ By “gathering personally identifiable information and optimizing data aggregating techniques,” big data companies are able to “refine algorithms, making them more efficient” and more able to quickly produce “rational decisions” without cost-intensive input from individuals.⁵⁷

Big data companies have multiplied in the past ten years.⁵⁸ In fact, the amount of stored data is growing four times faster than the world economy.⁵⁹ Decisions that were previously made by individuals are now often relegated to complex algorithms. As the amount of available data grows, businesses have begun to rely on big data in hopes of faster and better decision-making. Companies such as CoreLogic, General Information Solutions LLC, and Inflection Risk Solutions LLC were developed specifically to use massive amounts of

55. Steven Melendez, *How Big Data Could Help Make it Easier for Landlords to Evict You*, FAST COMPANY (Sept. 7, 2019), <https://www.fastcompany.com/90400284/how-big-data-could-help-make-it-easier-for-landlords-to-evict-you> [https://perma.cc/4D32-E82B].

56. Allen, *supra* note 1, at 226. See Anna Reosti, “We Go Totally Subjective”: *Discretion, Discrimination, and Tenant Screening in A Landlord’s Market*, 45 LAW & SOC. INQUIRY 618, 622 (2020) (discussing how housing providers utilize “commercial tenant screening products” to obtain information about tenants and make renting decisions).

57. *Id.*; see also Barocas & Selbst, *supra* note 8, at 677 (explaining that big data “automates the process of discovering useful patterns, revealing regularities upon which subsequent decision-making can rely. The accumulated set of discovered relationships [] can be employed to automate the process of classifying entities or activities of interest, estimating the value of unobserved variables, or predicting future outcomes.”).

58. See Louis Columbus, *10 Charts that Will Change Your Perspective of Big Data’s Growth*, FORBES (May 23, 2018) <https://www.forbes.com/sites/louiscolombus/2018/05/23/10-charts-that-will-change-your-perspective-of-big-datas-growth/#6ca2045c2926> [https://perma.cc/6YFA-CK2B] (showing that the global big data market’s revenue has already gone from \$7.6 billion in 2011 to \$56 billion in 2020 and is expected to reach \$103 billion in 2027).

59. VIKTOR MAYER-SCHÖNBERGER & KENNETH CUKIER, *BIG DATA: A REVOLUTION THAT WILL TRANSFORM HOW WE LIVE, WORK, AND THINK* 9 (2013); see also Jonathan Shaw, *Why “Big Data” is a Big Deal*, HARV. MAG. 1, 8–9 (Mar.–Apr. 2014) (on file with the *Columbia Human Rights Law Review*).

data to assist organizations in making decisions about who to hire, who to trust, and who to grant access to housing.⁶⁰

Increasingly, rental housing providers are relying on big data companies to make decisions related to accepting and rejecting tenant applications.⁶¹ One such company, CoreLogic, promises on its website that its algorithms will “power . . . rental insights” and “propel . . . leasing decisions.”⁶² Using its service to screen tenants, the website claims it will “improve fee income, reduce bad debt and mitigate risk.”⁶³ It pulls data from its “proprietary records” including an applicant’s “eviction records, address history, criminal records, identity fraud and credit data.”⁶⁴

The Connecticut Fair Housing Center and an individual plaintiff sued CoreLogic for violations of the Fair Housing Act. The suit, which is currently before the U.S. District Court for the District of Connecticut, alleges that CoreLogic’s automated tenant screening software tool discriminates on the basis of race, national origin, and disability.⁶⁵ The individual plaintiff in the case, Carmen Arroyo, asked her landlord for permission to move her disabled son, Mikhail, from a nursing facility into her home. Mikhail had been injured in an accident and was unable to speak, walk, or care for himself. Ms. Arroyo submitted a rental application on her son’s behalf, but his application was denied because CoreLogic’s background check stated that Mikhail had a “disqualifying [criminal] record.”⁶⁶ Ms. Arroyo later learned that her son’s “disqualifying” record related to a shoplifting charge from before his accident that was dropped—he was never convicted of a crime.⁶⁷

60. See Lerman, *supra* note 5, at 55.

61. Shriver Ctr. on Poverty L., *supra* note 46 (noting that, since the 1970s, housing providers have used third parties to conduct background checks on rental applicants, but that, with modern technology, screening companies have a much larger role in housing providers’ decisions).

62. *Rental Property Solutions*, CORELOGIC, <https://www.corelogic.com/industry/rental-property-solutions.aspx> [<https://perma.cc/CD7L-827J>].

63. *Id.*

64. *Id.*

65. Conn. Fair Hous. Ctr. v. Corelogic Rental Prop. Sols., LLC, 369 F. Supp. 3d 362, 369 (D. Conn. 2019).

66. *Id.* at 367.

67. *Id.*

CoreLogic moved for dismissal, arguing that it was not a housing provider covered by the Fair Housing Act.⁶⁸ In March 2019, the district court denied CoreLogic’s motion to dismiss, holding that because CoreLogic “held itself out as a company with the knowledge and ingenuity to screen housing applicants by interpreting criminal records and specifically advertised its ability to improve ‘Fair Housing compliance,’” it could be held liable for violations of the Fair Housing Act.⁶⁹

Although CoreLogic is one of the biggest data companies in the housing industry, competitors with similar practices continue to join the space.⁷⁰ TenantAlert, for example, advertises that it “utilizes nationwide databases consisting of [hundreds] of millions of records including credit, criminal [records], and eviction[s].”⁷¹ SmartMove, a

68. See *id.* at 370 (noting that CoreLogic claims that, as a screening company, it isn’t bound by the FHA, and even if it were, “it cannot be liable because its policies and actions do not have a sufficient nexus to the denial of housing,” and plaintiffs “cannot state a claim for disparate treatment or disparate impact”).

69. *Id.* at 372.

70. See Melendez, *supra* note 55, at 3 (stating that the National Apartment Association’s conference in June 2019, which the group claims had over 10,000 attendees, “hosted numerous exhibits by data providers.”); see also Barocas & Selbst, *supra* note 8, at 673 (“‘Big Data’ is the buzzword of the decade.”).

71. See *Instant Tenant Screening*, TENANT ALERT, <https://www.tenantalert.com> [<https://perma.cc/D35P-WP79>]. Similar websites purport to offer the same types of services. See, e.g., *Services*, AMRENT INC., <https://www.amrent.com/services.html> [<https://perma.cc/XF9A-D4PV>] (offering background checks for renters including criminal credit, and eviction records); *Residential Screening*, BACKGROUND INFORMATION SERVICES INC., <https://www.bisi.com/index.php?pg=servicestenantscreen> [<https://perma.cc/83QD-BMSX>] (describing background check services for landlords and renters); *Background Checks*, GENERAL INFORMATION SOLUTIONS LLC – HIRE RIGHT, <https://www.hireright.com/> [<https://perma.cc/FLE9-QWZ4>] (offering background check services for employers); *Inflection: Building Trust At the Point of Connection*, INFLECTION RISK SOLUTIONS LLC, <https://www.inflection.com/> [<https://perma.cc/Y4C5-ZSTN>] (describing broad range of background check services for companies); *TurboTenant: Free property management software for landlords*, TURBO TENANT, <https://www.turbotenant.com/> [<https://perma.cc/U9KD-6A5F>] (describing Turbo Tenant’s services as the “world’s easiest way to screen tenants, market your rental, receive applications and collect rent online”); *Advance Your Hiring Practices*, INTELICORP, <https://www.intellicorp.net/marketing> [<https://perma.cc/6Y6S-PKJ4>] (describing Intellicorp’s employment background check services); *Info Cubic: Hassle Free Background Checks*, INFO CUBIC, <https://infocubic.com/> [<https://perma.cc/277A-8CTX>] (offering background checks for employers and other businesses); *Background check services for small*

division of TransUnion, states on its website that its “enhanced criminal searching delivers more accurate results” and that its program “predicts evictions better” than credit reports in order to ensure landlords pick the “right tenant for the right property.”⁷² All of these companies rely on eviction histories, criminal histories, prior addresses, internet browser histories, and many other sources to predict whether certain applicants will be successful tenants. Problems arise, however, when the data fed into the algorithms is incorrect or when the algorithm itself is designed in a way that perpetuates existing patterns of discrimination or tends to have an unjustified disparate impact based on a protected class.

B. Bad Data In; Bad Data Out

An article in a Washington State Bar publication illuminates a major problem with relying on big data when making rental housing decisions. The article describes Fara, a reliable renter who wished to remain in her unit.⁷³ She and her landlord signed an agreement renewing her lease for another term, but, just a few weeks after signing the renewal, Fara’s landlord sold the building and the new owners refused to honor the agreement. The new owners sued to evict Fara, but just before the scheduled show cause hearing, the new owners made Fara an offer: in exchange for her agreement to vacate the unit, the new owners would pay Fara three months’ rent. Fara accepted the offer.⁷⁴

Fara did not expect that her move-out agreement would serve as a barrier to finding new housing, but, relying on data from tenant-screening firms, landlord after landlord rejected her application.⁷⁵ Many tenant-screening firms assign scores or ratings to applicants

businesses just got better, ACCURATE NOW, <https://accuratenow.com/> [<https://perma.cc/3Q48-BG6V>] (offering background checks for small businesses); *American DataBank: Home*, AMERICAN DATABASE, <https://www.americandatabank.com/> [<https://perma.cc/P9NW-A8PR>] (stating that American DataBank provides criminal background checks in accordance with country-specific requirements).

72. See *Why Choose SmartMove*, SMARTMOVE, <https://www.mysmartmove.com/SmartMove/Create-Account.page> [<https://perma.cc/CV2F-6J22>].

73. Eric Dunn & Merf Ehman, *Rental Housing’s Elephant in the Room—The Probable Disparate Impact of Unlawful Detainer Records*, 65 WASH. ST. B. NEWS 35, 35 (July 2011).

74. *Id.*

75. *Id.*

using algorithms that fail to distinguish between eviction suits that result in judgments against the tenants and those that result in an agreement like Fara's or a disposition in favor of the tenant. They simply evaluate whether the tenant has been sued for eviction, not whether the tenant prevailed in the suit or settled it.⁷⁶ Further, tenant-screening firms do not provide applicants with an opportunity to correct the record or offer explanations.⁷⁷ As Fara's case indicates, not all eviction suits are the result of tenant wrongdoing, and even those that do relate to tenant wrongdoing are not always reasonably predictive of future performance.⁷⁸

Like eviction records, criminal records are often riddled with inaccuracies which, when relied upon by algorithms, lead to unjust barriers for housing applicants, particularly minority applicants who disproportionately interact with the criminal legal system as a result of unfair policing practices.⁷⁹ In testimony before the District of Columbia Council Committee of the Judiciary, one attorney reported that her client was denied housing because he received a low score from a tenant-screening company; the cause of his low rating was that he had the same first initial and last name as someone with a criminal record.⁸⁰ By the time the potential tenant provided proof that he did not have a criminal record, the unit had been promised to someone else.⁸¹

Even if the records themselves are accurate, the criminal legal system is, in and of itself, a reflection of the disparate treatment

76. *Id.* at 38.

77. Scholars have noted that the use of big data is often in conflict with a legal system whose purpose is to resolve conflicts in a nuanced and individualized manner. *See generally* Caryn Devins et. al., *The Law and Big Data*, 27 CORNELL J.L. & PUB. POL'Y 357, 360 (2017) (finding that Big Data, which is by nature acontextual, cannot interpret or discern indeterminate boundaries in legal principles or adapt to new legal challenges).

78. *Id.*

79. EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 21 (finding that criminal justice data are insufficient where the Federal Bureau of Investigation's Uniform Crime Report relies on voluntary contributions that are not rich enough or comprehensive enough to meet the requirements for in-depth analysis).

80. *Fair Criminal Record Screening for Housing Act of 2016: Hearing on Bill 21-0706 Before the D.C. Council Comm. of the Judiciary*, 114th Cong. 103 (2016) (statement of Amber W. Harding, Att'y, Wash. Legal Clinic for the Homeless).

81. *See id.* at 103.

of minorities.⁸² One scholar stated that, “[s]tarting with ‘stop and frisks,’ and continuing through arrests, trials, sentencing, and post-sentencing relief, the criminal justice system treats minorities differently than whites.”⁸³ Studies show that police officers stop Black people disproportionately on sidewalks and streets yet generally find contraband at lower rates for Black people than for white people.⁸⁴ A 2009 study by the ACLU, for example, showed that police were 127% more likely to search Black people during traffic stops than white people, and 43% more likely to search Hispanic people during traffic stops than white people.⁸⁵ Despite the higher “search rates” for minorities, Black people were less likely to be found with drugs than white people.⁸⁶ In New York City between 2014 and 2017, young Black and Latino males between the ages of fourteen and twenty-four “account[ed] for only five percent of the city’s population, [but made up] 38 percent of reported stops.”⁸⁷

Despite the clear evidence that criminal background checks have a disparate impact on minorities, a 2015 study of over 300 written admissions policies of federally-funded local housing

82. See MICHELLE ALEXANDER, *THE NEW JIM CROW: MASS INCARCERATION IN THE AGE OF COLOR BLINDNESS* 4 (2011); see also Elizabeth Kai Hinton et al., *An Unjust Burden: The Disparate Treatment of Black Americans in the Criminal Justice System*, VERA INST. FOR JUST. (2018), <https://www.vera.org/publications/for-the-record-unjust-burden> [<https://perma.cc/VA8M-Y4HG>] (researching the effects of disparate treatment of Black people in the criminal legal system).

83. Valerie Schneider, *Racism Knocking at the Door: The Use of Criminal Background Checks in Rental Housing*, 53 U. RICH. L. REV. 923, 925–26 (2019) (footnote omitted); see also Alexander, *supra* note 81, at 4 (arguing that individuals that are not directly subject to the social control of incarceration tend to view it conceptually through a lens of social science, accepting the plight of communities of color as predictable, though unfortunate); 24 C.F.R. § 100.500 (2018) (prohibiting discriminatory effect, regardless of intent, in the practice of fair housing); Rebecca J. Walter et al., *One Strike to Second Chances: Using Criminal Backgrounds in Admission Decisions for Assisted Housing*, 27 HOUSING POL’Y DEBATE 1, 1–2 (2017) (finding that racial disparities are reflected in the corrections system, where 690 per 100,000 U.S. residents are incarcerated, while 4,347 per 100,000 Black males are incarcerated).

84. MICHAEL TONRY, *PUNISHING RACE: A CONTINUING AMERICAN DILEMMA* 50 (Oxford Univ. Press 2011).

85. *Id.* at 69.

86. *Id.*

87. *Stop-and-Frisk in the de Blasio Era*, NYCLU (Mar. 14, 2019), <https://www.nyclu.org/en/publications/stop-and-frisk-de-blasio-era-2019> [<https://perma.cc/AF5B-RBQS>].

authorities found that the majority of those housing authorities used tenant screening criteria that were overly broad, i.e., included information on crimes that were not predictive of success as a tenant.⁸⁸ Housing authorities went so far as to rely on arrest records, which are not indicative of whether a person committed a crime, or to bar applicants whose crimes were committed a long time ago.⁸⁹

Even putting aside racial disparities in the criminal legal system, the use of criminal records often leads to confusion rather than clarity, as housing providers frequently misunderstand their meaning.⁹⁰ Screening companies often conduct name-based checks, which, as noted above, decrease the accuracy of the information produced and can cause an individual to be associated with the crimes of similarly-named people.⁹¹ Additionally, court records and “rap sheets” used by such companies provide little information about a person’s conduct beyond the name of the case and its disposition, providing little or no data that would be predictive of success as a tenant. Further, 97% of criminal convictions are the result of plea bargains, and a guilty plea often says little about an individual’s involvement in a crime or potential to be a successful tenant and instead says more about his or her assessment of his or her chances at trial.⁹² It is even more troubling that the quality of records may be worse for certain classes of individuals; there is some evidence that record-keepers “might maintain systematically less accurate, precise, timely and complete records for certain classes of people,” meaning that the same algorithm might have a higher error rate for minority applicants than for white applicants.⁹³

Under the Obama Administration, HUD recognized the potential disparate impacts of the use of criminal background checks

88. Marie Claire Tran-Leung, *When Discretion Means Denial: A National Perspective on Criminal Records Barriers to Federally Subsidized Housing* 4, SHRIVER NAT’L CTR. ON POVERTY L. (Feb. 2015), <https://www.povertylaw.org/wp-content/uploads/2019/09/WDMD-final.pdf> [<https://perma.cc/SU6B-58V5>].

89. *Id.*

90. See Schneider, *supra* note 83, at 939–40; see also Rebecca Oyama, *Do Not (Re)enter: The Rise of Criminal Background Tenant Screening as a Violation of the Fair Housing Act*, 15 MICH. J. RACE & L. 181, 188 (2009) (recounting frequent inaccuracies in background data utilized by housing providers).

91. Shriver Ctr. on Poverty L., *supra* note 46, at 19.

92. *Id.*

93. Barocas & Selbst, *supra* note 8, at 684; see also Cofone, *supra* note 15, at 1402 (arguing that use of datasets with quality problems can lead to discriminatory outcomes for historically disadvantaged groups).

in rental housing decisions. In 2016, HUD issued guidance advising that because African Americans and Latinos are “arrested, convicted and incarcerated at rates disproportionate to their share of the general population,” any policy that “restricts access to housing on the basis of criminal history” may have an unlawful disparate impact based on race (the “Guidance”).⁹⁴ The Guidance warns that a housing provider “violates the Fair Housing Act when the provider’s policy or practice has an unjustified discriminatory effect, even when the provider had no intent to discriminate.”⁹⁵

Whether in the context of evictions records, arrest records, conviction records, or other available records, data fed into algorithms is often riddled with errors and infected with racial bias. Unfortunately, as explained below, algorithms tend to amplify racial bias contained in the data upon which they rely, particularly when those algorithms employ machine learning or artificial intelligence.

C. Machine Learning Doubles Down on Past Discrimination

Bad or incorrect data is not the only problem with the use of big data in housing decisions; the use of big data and algorithms in the context of housing has the potential to “reproduce existing patterns of discrimination, inherit the prejudice of prior decision makers, or simply reflect the widespread biases that persist in society.”⁹⁶ Algorithms, by their nature, use historical data as input to produce a rule that is applied to a current situation.⁹⁷ To the extent that historical data reflects the results of de jure segregation, Jim Crow laws, redlining, restrictive covenants, white flight, and other

94. U.S. DEP’T OF HOUS. & URB. DEV., OFFICE OF GENERAL COUNSEL GUIDANCE ON APPLICATION OF FAIR HOUSING ACT STANDARDS TO THE USE OF CRIMINAL RECORDS BY PROVIDERS OF HOUSING AND REAL ESTATE-RELATED TRANSACTIONS 2 (2016), https://www.hud.gov/sites/documents/hud_ogcguidappfhastandcr.pdf [<https://perma.cc/ZB8K-DMC4>] [hereinafter “HUD GUIDANCE”]; see also Schneider, *supra* note 82, at 924–25 (summarizing the history of HUD guidance on the use of criminal background checks).

95. HUD GUIDANCE, *supra* note 94, at 2 (footnote omitted).

96. Barocas & Selbst, *supra* note 8, at 674; see also MacCarthy, *supra* note 14, at 69, 75 (noting the difficulties of creating a “fair” algorithm for the purpose of reducing discrimination).

97. Lee Rainie and Janna Anderson, *Code-Dependent: Pros and Cons of the Algorithm Age*, Pew Research Ctr. (Feb. 8, 2017), <https://www.pewresearch.org/internet/2017/02/08/code-dependent-pros-and-cons-of-the-algorithm-age/> [<https://perma.cc/LLU6-9D5W>].

explicitly and implicitly racist laws, policies, and actions, any given algorithmic “rule” is likely to produce racist results.⁹⁸ Even more troubling, artificial intelligence systems, or “deep learning” algorithms, allow machines to “learn” from past data, refining algorithms to more accurately draw from patterns, including when those patterns reflect past discrimination.⁹⁹ Often, algorithms are constructed so that this “deep learning” happens without human intervention and in ways that programmers could not have predicted.¹⁰⁰ As one author put it, artificial intelligence systems allow machines to “inherit biases and discriminatory practices inherent in the data,” and, as the system “learns” from such data, it perpetuates “unfair outcomes” and biases.¹⁰¹

98. See Moritz Hardt, *How Big Data is Unfair*, MEDIUM (Sep. 26, 2014), <https://medium.com/@mrtz/how-big-data-is-unfair-9aa544d739de> [<https://perma.cc/75SZ-K54A>] (arguing that bias in training data will likely lead to a biased algorithm); see also Cofone, *supra* note 15, at 1402 (arguing that variations in the quality and representativeness of data are more likely to negatively impact historically disadvantaged groups); Sanya Mansoor, *A Viral Tweet Accused Apple’s New Credit Card of Being ‘Sexist.’ Now New York State Regulators are Investigating*, TIME (Nov. 12, 2019), <https://time.com/5724098/new-york-investigating-goldman-sachs-apple-card/> (on file with the *Columbia Human Rights Law Review*) (noting that algorithms used by Goldman Sachs and Apple in determining credit worthiness resulted in some women with higher credit scores having a lower credit limit than their lower-credit-score husbands); EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 9–10 (“Data availability, access to technology, and participation in the digital ecosystem vary considerably, due to economic, linguistic, structural or socioeconomic barriers, among others. Unaddressed, this systemic flaw can reinforce existing patterns of discrimination by over-representing some populations and under representing others.”).

99. Anupam Datta et al., *Proxy Discrimination in Data-Driven Systems*, ARXIV.ORG 1 (2017), <https://arxiv.org/pdf/1707.08120> [<https://perma.cc/V7W6-JXTA>].

100. Huq, *supra* note 2, at 1064–65 (noting that deep learning’s features are not designed by human engineers but are learned from the data itself); see also Jon Kleinberg et al., *Discrimination in the Age of Algorithms*, 10 J. LEGAL ANALYSIS 113, 114 (2018) (“algorithms are not decipherable – one cannot determine what an algorithm will do by reading the underlying code. This is more than a cognitive limitation; it is a mathematical impossibility. To know what an algorithm will do, one must run it.” (footnote omitted)).

101. Datta et al., *supra* note 97, at 1; see also Shriver Ctr. on Poverty L., *supra* note 46, at 20 (“Because the machine-learning algorithm recognizes correlations in the training data that are not obvious to a human, the programmer may not be able to unpack the inputs and retroactively identify the factors that led to the program’s decision.”); Lee et al., *supra* note 2, at ¶ 4 (“[S]ome algorithms run the risk of replicating and even amplifying human biases, particularly those affecting protected groups.”).

Algorithms “learn” from sets of training data, i.e., sets of data that “represent the relationship between features of each observation in the training data and [a] known classification.”¹⁰² For example, training data may show that people with certain levels of debt are likely to default on additional financial obligations or that people in certain zip codes are likely to have eviction records.¹⁰³ In the context of hiring, training data might include information about past hires, and, of course, if the majority of successful past hires were men, then the algorithm might “learn” to prefer men.¹⁰⁴ In summary, if the training data reflects existing human biases or the effects of past biases, then the algorithm will “learn” to reproduce those biases.¹⁰⁵

A powerful example of how algorithms “learn” to perpetuate and even amplify racialized data comes from outside of the housing context. In 2016, Microsoft introduced an artificial intelligence chatbot named Tay that “learned” how to interact with individuals online using data from social media.¹⁰⁶ Tay “conversed” with other individuals via Twitter but was shut down a mere sixteen hours after its launch because it quickly “learned” to be anti-Semitic, racist, and sexist (after interacting with various Twitter “trolls” who posted discriminatory information).¹⁰⁷ Shortly thereafter Microsoft launched

102. Huq, *supra* note 2, at 1063.

103. See generally David Lehr & Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. DAVIS L. REV. 653, 672 (2017) (explaining how algorithms make and apply rules based on training data that can predict, among other things, the likelihood of default).

104. See Barocas & Selbst, *supra* note 8, at 682.

105. Lehr & Ohm, *supra* note 103, at 665 (“relying on data that reflect existing human biases [is] also known as the ‘garbage-in-garbage-out’ problem” (footnote omitted)).

106. See James Vincent, *Twitter Taught Microsoft’s AI Chatbot to Be a Racist Asshole in Less than a Day*, VERGE (Mar. 24, 2016), <https://www.theverge.com/2016/3/24/11297050/tay-microsoft-chatbot-racist> [<https://perma.cc/P7GQ-43EJ>]; see also Mark A. Lemley & Bryan Casey, *Remedies for Robots*, 86 U. CHI. L. REV. 1311, 1333 (2019) (“Tay’s system updated itself in real time by learning from interactions with users. Within hours of going live, however, hundreds of Twitter users began intentionally tweeting ‘misogynistic, racist, and Donald Trumpist remarks’ at the robot. Thanks to this barrage of unforeseen misuse, ‘Tay rapidly morphed . . . into an AI monster.’” (footnote and internal citations omitted)).

107. Lemley & Casey, *supra* note 106, at 1333.

“Zo,” which “exhibited similar problematic biases” despite Microsoft’s efforts to improve the artificial intelligence to weed out such biases.¹⁰⁸

While replacing individual decision-makers with algorithms can minimize the effects of individual prejudices, algorithms that “learn” from data drawn from systems riddled with discrimination can have the perverse result of “exacerbating existing inequalities by suggesting that historically disadvantaged groups actually deserve less favorable treatment.”¹⁰⁹ Even if algorithm creators have no discriminatory intent, the data that algorithms mine and the ways in which algorithms weigh certain factors may reflect unconscious bias. It is even more troubling that, because an algorithm and not a person is responsible for the resulting decision, the process may “wrongly confer the imprimatur of impartiality” on the result.¹¹⁰ For example, algorithms may give lower scores to prospective tenants with prior addresses in neighborhoods with high eviction rates, perpetuating patterns of segregation and replicating the practice of “redlining” in

108. Daniel James Fuchs, *The Dangers of Human-Like Bias in Machine-Learning Algorithms*, 2 MISSOURI S&T’S PEER TO PEER 1, 5 (2018) (“A year after Tay was shut down, Microsoft launched another chatbot known as Zo, which faced similar public backlash after exhibiting anti-Islamic learned biases. . . . Like Tay, Zo developed harmful learned biases due to improper training.”); see also Jessi Hempel, *Inside Microsoft’s AI Comeback*, WIRED (June 21, 2017), <https://www.wired.com/story/inside-microsofts-ai-comeback/> [<https://perma.cc/7WQA-JD84>] (describing ethical concerns arising with Microsoft launching Zo).

109. Barocas & Selbst, *supra* note 8, at 674; see also EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 15 (2016) (noting that if machine-learning algorithm data sources “contain historical biases, the [resulting] scores may well replicate those same biases” (footnotes omitted)); Devins et al., *supra* note 77, at 361 (“Shielded by the illusion of objectivity and ‘evidence-based’ science, Big Data-based approaches could supersede the role of judges or elected officials and exercise outsized, yet poorly understood, influence over the legal system.” (footnote omitted)).

110. Barocas & Selbst, *supra* note 8, at 674 (2016); see also EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 10 (2016) (noting that it is important to avoid placing too much reliance on data because data can obfuscate bias problems); Cofone, *supra* note 15, at 1398 (2019) (“not only does automated decision-making mirror existing biases, but it has the potential to amplify them . . . it brings the potential to discriminate systemically”); FRANK PASQUALE, *THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION* 35 (2015) (“[S]oftware engineers construct the datasets mined by scoring systems; they define the parameters of data-mining analyses; they create the clusters, links, and decision trees applied; they generate the predictive models applied. Human biases and values are embedded into each and every step of development. Computerization may simply drive discrimination upstream.”).

an online format,¹¹¹ or algorithms may give undue weight to an inconsistent rental history, disadvantaging immigrants or those who have historically been forced to seek familial support for housing as opposed to traditional landlord-tenant relationships.¹¹² The fact that these forms of redlining are generated by machines can obscure the bias inherent in the system.

In summary, algorithms and machine learning can “double down” on existing inequality in a variety of ways: programmers’ biases may seep into the algorithm or its training data; the training data may not be representative of the population in question; and, even if the training data is representative of the population in question, it may reproduce inequities reflected in the data.¹¹³

D. When it Comes to Rental Housing, Algorithmic Decision-Making Affects Minorities Disproportionately

The use of big data in the tenant selection process has a disproportionately negative impact on minorities for a variety of reasons. Nationally, just 41% of African American families and 47% of Latino families own their homes, whereas 73% of white families

111. PASQUALE, *supra* note 110, at 689; *see also* EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 9 (noting that algorithms that assume “correlation necessarily implies causation” tend to further discrimination; for example, an algorithmic system may assume that because two factors frequently occur together (e.g., having a certain income level and being of a particular ethnicity) there is a causal relationship between the two).

112. *See generally* Barocas & Selbst, *supra* note 8, at 682 (noting that, in the employment context, algorithms that give weight to past practice will perpetuate past discrimination). For example, were an employer to automate hiring decisions by inferring a rule from past decisions, the employer would likely arrive at a decision that reproduces the prejudice of prior decision makers. Automating the process this way would turn the “conscious prejudice or implicit bias of individuals involved in previous decision-making into a formalized rule that would systematically alter the prospects of all future applicants.” *Id.* An algorithm, for example, could learn to discriminate against female or Black applicants if it relied on prior hiring decisions in which jobseekers with degrees from women’s or historically Black colleges were rejected.

113. *See generally* Cofone, *supra* note 15, at 1404 (explaining how training data and representative data may still produce biased outcomes that “reflect a biased society”); *see also* Kody Glazer, *Fair Housing Act at 50: Challenging the Disparate Impact of Predictive Analytics*, 46 FLA. ST. U. L. REV. 457, 459 (2019) (“It is conceivable that, given the history of discrimination, nearly all available data will reflect racial disparities. In relying on these algorithms, companies may, intentionally or otherwise, produce discriminatory effects.” (footnote omitted)).

are homeowners.¹¹⁴ This means that people of color are far more likely to be renters, who are potentially subject to eviction proceedings, and, as explained above, many tenant-screening companies do not distinguish between eviction proceedings that resulted in a judgment *against* the tenant and eviction proceedings that resulted in a judgment *for* the tenant or a settlement on terms favorable to the tenant.¹¹⁵ Additionally, minority tenants are more likely to live in units with housing code violations.¹¹⁶ Often, the only way to get landlords to address these housing code violations is to withhold rent, wait to be sued for eviction, and then raise the housing code violations as a defense in the context of an eviction proceeding.¹¹⁷ There is also evidence that landlords subject tenants of color to eviction proceedings at higher rates than white tenants, even when controlling for all other factors.¹¹⁸

114. Jennifer Rudden, *Homeownership Rates in the United States in 1st Quarter of 2019, by Ethnicity*, STATISTA (Aug. 9, 2019), <https://www.statista.com/statistics/500069/homeownership-rates-usa-by-ethnicity/> [https://perma.cc/A8PC-KYQ8] (quoting U.S. DEP'T OF HOUS. & URB DEV., U.S. HOUSING MARKET CONDITIONS 13 (1ST QUARTER 2019), https://www.huduser.gov/portal/sites/default/files/pdf/NationalSummary_1Q19.pdf (on file with the *Columbia Human Rights Law Review*)).

115. Dunn & Ehman, *supra* note 73, at 35; see also Sophie Beiers et al., *Clearing the Record: How Eviction Sealing Laws Can Advance Housing Access for Women of Color*, ACLU (Jan. 10, 2020), <https://www.aclu.org/news/racial-justice/clearing-the-record-how-eviction-sealing-laws-can-advance-housing-access-for-women-of-color/> [https://perma.cc/S95H-RT6U] (detailing how a tenant, Ashley, still struggled to find housing based on a prior eviction filing that was tossed out by a reviewing court).

116. GREENSBORO HOUS. COAL., FAIR HOUSING/HEALTHY HOMES: DISPARITIES IN HOUSING CONDITIONS FOR MINORITIES AND IMMIGRANTS 3 (2008), <http://ghc.illkd.com/wpcontent/uploads/2009/08/FairHousingHealthyHomes.pdf> [https://perma.cc/4KSS-J2YT].

117. Eliza Berkon, *When Tenants Take on Landlords Over Bad Conditions: A Rent-Strike Explainer*, WAMU (Feb. 27, 2020), <https://wamu.org/story/20/02/27/when-tenants-take-on-landlords-over-bad-conditions-a-rent-strike-explainer/> [https://perma.cc/D5L4-MFEP].

118. See Jake Blumgart, *New Research Reveals Depth of Philadelphia's Eviction Crisis*, WHY? (Dec. 29, 2016), <https://why.org/articles/new-research-reveals-depth-of-philadelphia-s-eviction-crisis/> [https://perma.cc/ZF8L-75CW] (“Even when controlling for income and poverty, the eviction rates in majority black neighborhoods are still higher than in communities with different demographic composition.”); see also Catherine Lizette Gonzalez, *STUDY: Women of Color Living in Poverty Face Highest Risk of Eviction*, COLORLINES (Apr. 9, 2018), <https://www.colorlines.com/articles/study-women-color-living-poverty-face-highest-risk-eviction> [https://perma.cc/VA9V-MXZU] (“In a 2014 study authored

Housing providers may assume that individuals with eviction records are inherently inferior tenants compared to those without eviction records, but if the eviction records reflect bad data—like including cases that were ultimately dismissed or cases that were brought because tenants were seeking remedies to housing code violations—the prior eviction record would not be predictive of future behavior. The barrier to housing created by prior evictions is placed in front of minorities at higher rates than for white people, even where the specific circumstances surrounding the eviction may not be predictive of whether the individual will be a good tenant.¹¹⁹

The use of eviction records is not the only cause for concern when considering the potential disparate impact of the use of big data in the tenant selection process. Companies such as CoreLogic purport to rely on “address history” in addition to other factors such as eviction proceedings.¹²⁰ Presumably, this could mean that an applicant’s score in the CoreLogic algorithm could be negatively affected by a person’s prior address—e.g., if an applicant previously lived in a poor or minority neighborhood where there were frequent evictions, it is possible that the applicant will receive a lower score

by [Matthew] Desmond, Black women with low-incomes were evicted at alarmingly higher rates than other racial groups due to factors such as having children, low wages and landlord-tenant gender dynamics.”); Timothy A. Thomas et al., *The State of Evictions: Results from the University of Washington Evictions Project*, UNIV. OF WASH. (Feb. 17, 2019), <https://evictions.study/washington/> [<https://perma.cc/83HA-RF58>] (finding different trends in eviction rates by race among three different Washington counties).

119. See Rudy Kleysteuber, *Tenant Screening Thirty Years Later: A Statutory Proposal to Protect Public Records*, 116 YALE L. J. 1344, 1346 (2007) (“Today, landlords regularly purchase ‘tenant-screening reports’ that chronicle landlord-tenant disputes and court filings, often regardless of their outcomes.”); see also Robert McCartney, *Homelessness Crisis Is Expected in D.C. When Coronavirus Emergency Ends and Evictions Begin*, WASH. POST (June 15, 2020), https://www.washingtonpost.com/local/homelessness-crisis-is-expected-in-dc-when-coronavirus-emergency-ends-and-evictions-begin/2020/06/14/df52344a-acc0-11ea-9063-e69bd6520940_story.html (on file with the *Columbia Human Rights Law Review*) (“The setback risks aggravating racial inequalities, as both the layoffs and housing pressures fall most heavily on African Americans, Hispanics and other minorities.”).

120. See *Rental Property Solutions*, CORELOGIC (2020), <https://www.corelogic.com/industry/rental-property-solutions.aspx> [<https://perma.cc/4JVM-L3HW>] (“Our resident screening data can include insight from our proprietary records along with an applicant’s eviction records, *address history*, criminal records, identity fraud and credit data. Data are gathered using a network of professionals across the nation.” (emphasis added)).

from CoreLogic even if the specific tenant had never been evicted. This type of algorithm would perpetuate patterns of segregation by creating barriers for all would-be tenants who have ever lived in poor or minority areas.¹²¹ As noted above, the disparate impact of the use of algorithms in tenant screening is even more stark when tenant screening companies utilize criminal records, as those records often reflect policing practices, plea bargain logistics, and sentencing rules that are infected with racism.¹²²

Algorithms and big data are particularly likely to create a disparate impact based on a protected class because of what researchers call “redundant encodings”—i.e., when “membership in a protected class happens to be encoded in other data.”¹²³ This occurs when a particular set of data is “highly correlated with membership in specific protected classes.”¹²⁴ For example, if a tenant-screening algorithm gives lower scores to people with eviction or criminal records and such records are disproportionately prevalent in a protected class, then the algorithm will have a disparate impact on that protected class, even if the disproportionate prevalence of such records is caused by bias and/or is not predictive of whether an applicant will be a good tenant. Because a disproportionate number of minorities are renters, the adverse effects of algorithmic discrimination make minorities particularly vulnerable in the rental housing market.

E. Big Data and Intentional Discrimination

While the unchecked use of algorithms may facilitate an unintentional disparate impact, it is also possible that the use of algorithms could “breathe new life into” intentional discrimination because decision-makers can mask their discriminatory aims by

121. See Barocas & Selbst, *supra* note 8, at 674 (“Approached without care, data mining can reproduce existing patterns of discrimination, inherit the prejudice of prior decision makers, or simply reflect the widespread biases that persist in society.”).

122. See Mark Pazniokas, *A Tenant Blacklist, Compiled by Algorithm*, CT MIRROR (Mar. 28, 2019), <https://ctmirror.org/2019/03/28/a-tenant-blacklist-compiled-by-algorithm/> [<https://perma.cc/YZ2H-2DR8>] (“The suit claims that CoreLogic is guilty of racial discrimination because of its improper reliance on criminal records—and that has a disparate impact on Black and Latino applicants, according to a guidance notice published by the U.S. Department of Housing and Urban Development.”).

123. Barocas & Selbst, *supra* note 8, at 691.

124. *Id.* at 691–92.

constructing algorithms that intentionally produce discriminatory results.¹²⁵ For example, a housing provider seeking to exclude Latinos could set its algorithm to penalize individuals in particular industries in which Latinos are disproportionately represented, or as discussed in the next section, it could focus its advertising to exclude Latinos by using facially race-neutral data (such as musical tastes on social media) as a proxy for race. Of course, courts have long found that using proxies for race, like using race itself, in housing-related decisions is prohibited by the Fair Housing Act,¹²⁶ but the use of algorithms may hide intentional discrimination in ways that make successful litigation challenging.

IV. ADVERTISING

One of the primary features of collecting and analyzing massive amounts of data about individuals is the opportunity to better focus advertisements. Businesses across industries increasingly rely on big data to determine how and where to focus advertising to maximize the chances of interested individuals responding to advertisements.¹²⁷ Housing providers, of course, are interested in spending advertising dollars in a way that will maximize efficiency and profits, and, as a result, want their advertisements to be seen by the individuals most likely to be interested in the types of housing they are providing.¹²⁸ Thus, rental housing providers have strong incentives to try to get their ads in

125. *Id.* at 692.

126. Under the “proxy” theory, courts have recognized that a regulation cannot “use a technically neutral classification as a proxy to evade the prohibiting of intentional discrimination,” such as classifications based on gray hair (as a proxy for age) or service dogs (as a proxy for handicapped individuals). *Cnty. Servs., Inc. v. Wind Gap Mun. Auth.*, 421 F.3d 170, 177 (3d Cir. 2005) (quoting *McWright v. Alexander*, 982 F.2d 222, 228 (7th Cir. 1992)).

127. Max Freedman, *How Businesses Are Collecting Data (And What They’re Doing With It)*, BUS. NEWS DAILY (June 17, 2020), <https://www.businessnewsdaily.com/10625-businesses-collecting-data.html> [<https://perma.cc/B6BZ-B26A>].

128. The use of targeted advertisements by housing providers on sites like Facebook has already led to lawsuits. See Nadiyah Humber & James Matthews, *Fair Housing Enforcement in the Age of Digital Advertising: A Closer Look at Facebook’s Marketing Algorithms*, BOSTON BAR J. (Feb. 19, 2020), <https://bostonbarjournal.com/2020/02/19/fair-housing-enforcement-in-the-age-of-digital-advertising-a-closer-look-at-facebooks-marketing-algorithms-2/> [<https://perma.cc/XTM4-P9DG>].

front of home seekers who would be “appropriate” tenants, in whatever way the housing provider defines “appropriate.”

Notwithstanding housing providers’ desire to ensure that their advertisements are seen by certain segments of the population, the Fair Housing Act prohibits housing providers from discriminating in advertising.¹²⁹ Specifically, section 3604(c) of the Fair Housing Act provides that a housing provider may not “make, print, or publish, or cause to be made, printed, or published any notice, statement or advertisement . . . that indicates any preference, limitation, or discrimination based on [a protected class].”¹³⁰ HUD has interpreted this provision to apply to “[s]electing media or locations for advertising . . . which deny particular segments of the housing market information about housing opportunities because of [membership in a protected class].”¹³¹

This provision of the Fair Housing Act prohibits housing providers from using the types of blatantly discriminatory advertising that were common at the time the Fair Housing Act was passed, such as signs reading “No Blacks Allowed.”¹³² This provision also prohibits housing providers from using more subtly discriminatory advertising, such as targeting advertisements to audiences in certain zip codes or describing an “ideal applicant” in terms that suggest a particular race, ethnicity, or age group.¹³³ Of course, companies that amass

129. FHA, *supra* note 30, at § 3604(c).

130. *Id.*

131. 24 C.F.R. § 100.75(c)(3) (2018).

132. Alex Kotlowitz, *What's Past Is Present*, ATLANTIC (Nov. 2001), <https://www.theatlantic.com/magazine/archive/2001/11/whats-past-is-present/302329> (on file with the *Columbia Human Rights Law Review*); see also Robert G. Schwemm, *Discriminatory Housing Statements and Section 3604(c): A New Look at the Fair Housing Act's Most Intriguing Provision*, 29 FORDHAM URB. L.J. 187, 189–90 (2001) (listing examples of prior and recent behavior banned by the FHA).

133. See *Advertising Guidelines*, NATIONAL FAIR HOUSING ALLIANCE, <https://nationalfairhousing.org/responsibleadvertising/> [https://perma.cc/G6W2-NY6R] (suggesting that one way to avoid liability under Section 3604(c) of the Fair Housing Act—which prohibits discriminatory advertising—is to focus on the property and the amenities in a rental listing description, not on the attributes of an ideal renter). Note that advertisements can be deemed discriminatory even if none of the words are discriminatory and instead the pictures suggest that members of a protected class might be excluded. See, e.g., Julia Angwin & Terry Parris Jr., *Facebook Lets Advertisers Exclude Users by Race*, PROPUBLICA (Oct. 28, 2016), <https://www.propublica.org/article/facebook-lets-advertisers-exclude->

gargantuan amounts of data on individuals and businesses, including rental housing providers, are increasingly seeking ways to leverage data to ensure that their advertisements are seen by particular audiences.

A. Facebook

Facebook is an important and accessible example of how data collection can both make advertising more efficient and undermine the protections of the Fair Housing Act. Facebook has already amassed massive amounts of data on individuals' interests, backgrounds, musical tastes, friend groups, language use, employment status, familial status, and more.¹³⁴ Advertisers using Facebook's platform can target their ads to individuals whose online behavior suggests that they might be interested in moving, and, at the same time, the platform allows advertisers to focus on audiences with particular music tastes, hobbies, and interests. Further, a 2016 investigation by ProPublica revealed that Facebook made it simple for marketers to exclude "affinity groups" like African Americans, Asian Americans and Hispanics.¹³⁵

To show how easy it was to create a discriminatory advertisement, ProPublica reporters purchased an advertisement from Facebook that targeted individuals who showed interest in becoming a home owner and who were "likely to move;" the advertisement excluded individuals who were African American, Asian American, or "Spanish Dominant" Hispanic.¹³⁶ Facebook approved and posted the advertisement online within minutes after it was purchased.¹³⁷ Excluding individuals from seeing advertisements based on their race or ethnicity, the ProPublica report alleged, is no different than a Jim Crow era newspaper offering advertisers the

users-by-race [<https://perma.cc/H7LG-UW92>] (noting that The New York Times rejects housing ads that contain "too many photographs of white people").

134. See, e.g., Complaint at 42, Nat'l Fair Hous. All. et al. v. Facebook, Inc., No. 1:18-CV-02689 (S.D.N.Y. dismissed Mar. 29, 2019) ("Facebook . . . gathers this information both through self-reported information on Facebook, and through tracking its users' online activity—both on Facebook itself and elsewhere through the internet. The end result has been described as 'arguably the most complete consumer profile on earth' . . ." (footnote omitted)).

135. Angwin & Parris Jr., *supra* note 133, at ¶ 20.

136. Hannah Birch, *Facebook Propublica Ad* (photograph), DOCUMENT CLOUD (Mar. 10, 2020), <https://www.documentcloud.org/documents/3191165-Facebook-Propublica-Ad.html> [<https://perma.cc/A9MA-LFUN>].

137. Angwin & Parris Jr., *supra* note 133, at ¶ 22.

option of placing ads only in versions of the newspaper that would be delivered to the doorsteps of white people.¹³⁸ Because Facebook controls about 20% of online advertising in the United States,¹³⁹ Facebook's ability to hide housing advertisements from members of protected classes is particularly concerning. Nearly all of Facebook's \$55.8 billion revenue in 2018 came from its advertising business, so Facebook has a massive incentive to serve its advertisers.¹⁴⁰

In response to the 2016 ProPublica reporting, Facebook promised that it would improve its enforcement of its prohibition against discriminatory advertising.¹⁴¹ In a press release posted to its website, Facebook announced its intention to "improve [its] enforcement while preserving the beneficial uses of [its] advertising tools."¹⁴² It promised "[t]o test new technology that leverages machine learning to help . . . identify ads that offer housing, employment or credit opportunities" to more quickly "provide notices and educational information to advertisers" who may be in violation of nondiscrimination laws.¹⁴³

138. *Id.*

139. Katie Benner et al., *Facebook Engages in Housing Discrimination With Its Ad Practices, U.S. Says*, N.Y. TIMES (Mar. 28, 2019), <https://www.nytimes.com/2019/03/28/us/politics/facebook-housing-discrimination.html> (on file with the *Columbia Human Rights Law Review*).

140. Marie C. Baca, *Housing Companies Used Facebook's Ad System to Discriminate Against Older People, According to New Human Rights Complaints*, WASH. POST (Sept. 18, 2019), <https://www.washingtonpost.com/technology/2019/09/18/housing-companies-used-facebooks-ad-system-discriminate-against-older-people-according-new-human-rights-charges/> (on file with the *Columbia Human Rights Law Review*). In 2020, a campaign to divest from advertising in Facebook was initiated as a powerful method of countering its policies because it is so reliant on advertising revenue. See *Stop Hate for Profit: Calling on Facebook Corporate Advertisers to Pause Ads for July 2020*, COLOR OF CHANGE (June 19, 2020), <https://colorofchange.org/stop-hate-for-profit/> [<https://perma.cc/B93R-NPEV>]; see also Tiffany Hsu & Cecilia Kang, *'Morally Impossible': Some Advertisers Take a Timeout From Facebook*, N.Y. TIMES (June 30, 2020), <https://www.nytimes.com/2020/06/09/business/media/facebook-advertisers-trump-zuckerberg.html> (on file with the *Columbia Human Rights Law Review*) ("Some smaller advertisers . . . described their break from Facebook as a protest against the platform and its subsidiaries.").

141. See *Improving Enforcement and Promoting Diversity: Updates to Ads Policies and Tools*, FACEBOOK (Feb. 8, 2017), <https://about.fb.com/news/2017/02/improving-enforcement-and-promoting-diversity-updates-to-ads-policies-and-tools/> [<https://perma.cc/5RDW-PPHU>].

142. *Id.*

143. *Id.*

In 2017, about eight months after Facebook announced its intention to step up enforcement of its prohibition against discriminatory advertising, ProPublica released a second article reporting that it was able to purchase dozens of rental housing advisements on Facebook and ask that the advertisements not be shown to certain categories of users such as African Americans, mothers of high school students, stay at home mothers, people interested in wheelchair ramps, Jews, gay men, expats, and Spanish speakers.¹⁴⁴ ProPublica also purchased advertisements that excluded people who lived in zip codes in which most residents are minorities. As ProPublica's advertising parameters included and excluded specific neighborhoods, Facebook physically showed a blue line outlining the excluded neighborhoods—a throwback to the “redlining” done by banks in the past.¹⁴⁵ Facebook approved each of these advertisements within minutes.¹⁴⁶ The only advertisement that took longer than three minutes to be approved sought to exclude potential

144. Julia Angwin et al., *Facebook (Still) Letting Housing Advertisers Exclude Users by Race*, PROPUBLICA (Nov. 21, 2017), <https://www.propublica.org/article/facebook-advertising-discrimination-housing-race-sex-national-origin> [<https://perma.cc/8WSC-79Z4>]. The following references are examples of advertisements ProPublica purchased on Facebook. *Housing Agency New York City* (photograph), in FACEBOOK, <https://assets.propublica.org/images/articles/20171121-facebook-gay-men.jpg> [<https://perma.cc/5XMD-8JDN>]; *Housing Agency New York City* (photograph), in FACEBOOK, <https://assets.propublica.org/images/articles/20171121-facebook-family-status-parents-moms.jpg> [<https://perma.cc/T2WH-DFXV>]; *Housing Agency New York City* (photograph), in FACEBOOK, <https://assets.propublica.org/images/articles/20171121-facebook-ability.jpg> [<https://perma.cc/9N8N-C2KE>]; *Housing Agency New York City* (photograph), in FACEBOOK, <https://assets.propublica.org/images/articles/20171121-facebook-judaism> [<https://perma.cc/N5YU-YLZQ>]; *Housing Agency New York City* (photograph), in FACEBOOK, <https://assets.propublica.org/images/articles/20171121-facebook-argentina-expats.jpg> [<https://perma.cc/72RT-CJ5K>]; *Housing Agency New York City* (photograph), in FACEBOOK, <https://assets.propublica.org/images/articles/20171121-facebook-spanish-speakers-b.jpg> [<https://perma.cc/SR29-XWQY>].

145. Angwin et al., *supra* note 144, at ¶ 27; Tracy Jan, *Redlining was Banned 50 Years Ago. It's Still Hurting Minorities Today*, WASH. POST (Mar. 28, 2018), <https://www.washingtonpost.com/news/wonk/wp/2018/03/28/redlining-was-banned-50-years-ago-its-still-hurting-minorities-today/> [<https://perma.cc/HE2Y-CKMM>] (“In the 1930s, government surveyors graded neighborhoods . . . color-coding them [so that] ‘redlined’ areas were the ones local lenders discounted as credit risks, in large part because of the residents’ racial and ethnic demographics.”).

146. Angwin et al., *supra* note 144, at ¶ 24.

renters “interested in Islam, Sunni Islam and Shia Islam.” That advertisement was approved in 22 minutes.¹⁴⁷

In 2018, the National Fair Housing Alliance and other Fair Housing organizations mimicked ProPublica’s strategy and purchased discriminatory advertisements on Facebook, using Facebook’s dropdown menus that allowed them to exclude parents, Spanish speakers, people interested in disabled parking permits, people interested in Telemundo (a Spanish-language television network), and other members of protected classes.¹⁴⁸ Facebook approved all advertisements without pushing back on the discriminatory nature of the advertisements.¹⁴⁹ A few weeks after the National Fair Housing Alliance purchased its discriminatory advertisements ProPublica attempted to purchase another set of discriminatory ads and was prevented from excluding explicitly by race, but was still able to discriminate for things like nationality using close proxies; for example, it could still easily exclude all users interested in Telemundo.¹⁵⁰

Shortly after using Facebook’s advertising tool to purchase the discriminatory ads, the National Fair Housing Alliance and other organizations sued Facebook, claiming that the site’s advertising platform violated the Fair Housing Act by allowing advertisers to direct their ads away from members of a protected class.¹⁵¹ The complaint alleged that “Facebook’s algorithms can ensure exclusion and deny access to housing” and that, “[w]hereas in the past, the excluded group might see the ‘for rent’ sign . . . in a public forum, the stealth nature of Facebook’s technology hides housing ads from entire

147. *Id.*

148. Julia Angwin & Ariana Tobin, *Fair Housing Groups Sue Facebook for Allowing Discrimination in Housing Ads*, PROPUBLICA (Aug. 17, 2018), <https://www.propublica.org/article/facebook-fair-housing-lawsuit-ad-discrimination> [<https://perma.cc/79YW-MXKQ>]

149. *Id.*

150. *Id.* at ¶ 9.

151. *See id.* (reporting that Facebook claimed its advertising platform is fully immunized from liability under 47 U.S.C. § 230, the Communications Decency Act, which protects internet service providers from liability for material published by third parties in some circumstances); *see also* Fair Hous. Council of San Fern. V. v. Roommates.com, LLC, 521 F.3d 1157, 1175 (9th Cir. 2008) (holding that Section 230 of the Communications Decency Act did not apply to an online operator whose questions violated the Fair Housing Act, but could apply to portions of a website in which users made comments that were not edited or otherwise used by the website operator).

groups of people.”¹⁵² Lead counsel for the National Fair Housing Alliance commented that this type of discrimination—enabled by algorithms using massive amounts of data—is particularly difficult to uncover and combat because “[t]he person who is being discriminated against has no way to know” because the technology “keeps the discrimination hidden”¹⁵³ In March 2019, Facebook, the National Fair Housing Alliance, and other organizations announced settlements of numerous legal actions alleging that Facebook’s advertising platform enabled discrimination.¹⁵⁴

In the settlement Facebook agreed to establish a separate advertising portal for industries regulated by particular nondiscrimination laws (including housing, employment, and credit).¹⁵⁵ For advertisements in those areas, advertisers would not be able to target based on protected classes or the close proxies for protected classes that Facebook had called “multicultural affinities.”¹⁵⁶ Facebook also agreed to require that all advertisements for housing, employment, and credit target a minimum geographic

152. Complaint at 5, Nat’l Fair Hous. All et al. v. Facebook, Inc., No. 1:18-CV-02689, filed (S.D.N.Y. dismissed Mar. 29, 2019) (“[D]iscriminatory advertising is just as damaging as discrimination at the point of rental or sale.”).

153. See Angwin & Tobin, *supra* note 148, at ¶ 4.

154. See FACEBOOK, NFHA, CWA, ECBA, O&G, & ACLU, SUMMARY OF SETTLEMENTS BETWEEN CIVIL RIGHTS ADVOCATES AND FACEBOOK 1 (2019), <https://nationalfairhousing.org/wp-content/uploads/2019/03/3.18.2019-Joint-Statement-FINAL-1.pdf> [<https://perma.cc/R5EF-57SP>].

155. See *id.*; see also Humber & Matthews, *supra* note 128, at ¶ 2 (“Facebook also committed to allow experts to study its advertising platform for algorithmic bias.”); see generally FACEBOOK, FACEBOOK’S CIVIL RIGHTS AUDIT—PROGRESS REPORT (June 30, 2019), https://about.fb.com/wp-content/uploads/2019/06/civilrightaudit_final.pdf [<https://perma.cc/A7ZV-YAFF>] (describing Facebook’s other proposed reforms); Deepa Seetharaman & Jeff Horwitz, *Facebook Creates Teams to Study Racial Bias, After Previously Limiting Such Efforts*, WALL ST. J. (July 21, 2020), https://www.wsj.com/articles/facebook-creates-teams-to-study-racial-bias-on-its-platforms-11595362939?mod=hp_lista_pos1 (on file with the *Columbia Human Rights Law Review*) (reporting Facebook’s announcement of the creation of “new teams dedicated to studying and addressing potential racial bias on its core platform and Instagram unit”); Rebecca Heilweil, *Facebook is Taking a Hard Look at Racial Bias in its Algorithms*, VOX (July 22, 2020), <https://www.vox.com/recode/2020/7/22/21334051/facebook-news-feed-instagram-algorithm-racial-bias-civil-rights-audit> (on file with the *Columbia Human Rights Law Review*) (reporting on Facebook’s reexamination of racial bias built into algorithms after the audit focusing on civil rights issues at Facebook).

156. See FACEBOOK, *supra* note 154, at 1.

radius of fifteen miles from a specific address, limiting users' ability to "redline."¹⁵⁷ The National Fair Housing Alliance announced in a press release that Facebook would "undertake far-reaching changes" positioning itself to be a "pacesetter in advancing fair and equitable platforms, products and services, and making the digital marketplaces safer spaces for consumers."¹⁵⁸ One lawyer who represented plaintiffs in a case against Facebook said that the "settlement is a shot across the bow to all tech companies and platforms."¹⁵⁹

HUD sued Facebook shortly after Facebook reached a settlement with the National Fair Housing Alliance and others, claiming that, notwithstanding the announced changes, Facebook continued to discriminate in ways that violate the Fair Housing Act.¹⁶⁰ In particular, HUD claimed that Facebook's machine learning or artificial intelligence systems discriminated beyond advertiser's choices—even if an advertiser did not attempt to exclude members of a protected class, the Facebook algorithm may systematically do so in an effort to maximize its own profits.¹⁶¹ Facebook's delivery algorithm skews the audience based on the content of the ad itself, even when advertisers do not choose to exclude based on protected classes.¹⁶² To

157. Jack Gillum & Ariana Tobin, *Facebook Won't Let Employers, Landlords or Lenders Discriminate in Ads Anymore*, PROPUBLICA (Mar. 19, 2019), <https://www.propublica.org/article/facebook-ads-discrimination-settlement-housing-employment-credit> [<https://perma.cc/7R5Q-NF6K>]; see also *Facebook Settlement*, NAT'L FAIR HOUS. ALL., <https://nationalfairhousing.org/facebook-settlement/> [<https://perma.cc/AZX9-EB8B>] (detailing the eight changes required under the settlement that Facebook agreed to make).

158. NAT'L FAIR HOUS. ALL., *supra* note 157.

159. Gillum & Tobin, *supra* note 157, at ¶ 4.

160. Benner et al., *supra* note 139, at ¶ 1.

161. *Id.*; see also Aaron Rieke, *Discrimination's Digital Frontier*, ATLANTIC (Apr. 15, 2019), <https://www.theatlantic.com/ideas/archive/2019/04/facebook-targeted-marketing-perpetuates-discrimination/587059/> (on file with the *Columbia Human Rights Law Review*) ("[G]iven a large group of people who might be eligible to see an advertisement, Facebook will pick among them based on its own profit-maximizing calculations, sometimes serving ads to audiences that are skewed heavily by race and gender.").

162. Ava Kofman & Ariana Tobin, *Facebook Ads Can Still Discriminate Against Women and Older Workers, Despite a Civil Rights Settlement*, PROPUBLICA (Dec. 13, 2019), <https://www.propublica.org/article/facebook-ads-can-still-discriminate-against-women-and-older-workers-despite-a-civil-rights-settlement> [<https://perma.cc/64ND-U3EZ>] ("Facebook's ad delivery algorithm further skews the audience based on the content of the ad itself, the researchers

make sure that ads are seen by people who Facebook thinks are “most likely to click on and engage with them, Facebook selects the audience depending on the content of the ad,” not just the desires expressed by the advertiser.¹⁶³ For example, even if the advertiser expressed no preferences about race or gender, Facebook’s algorithm might show an ad for high end housing to more white men than Black men or women.¹⁶⁴ Noting how Facebook’s algorithms hide housing advertisements from historically disadvantaged groups, HUD Secretary Ben Carson commented that “using a computer to limit a person’s housing choices can be just as discriminatory as slamming a door in someone’s face.”¹⁶⁵

The lawsuit against Facebook “coincide[d] with a broader push by civil rights groups to scrutinize whether big technology companies are reinforcing real-world biases online by using algorithms to identify and target specific groups of users.”¹⁶⁶ Certainly Facebook’s algorithms allow housing providers to reach potential tenants efficiently, but that efficiency comes at a cost; just as newspaper advertisements that appear only in predominantly white markets might violate the Fair Housing Act’s prohibition on discriminatory advertising, algorithms that push advertisements only to white audiences may also violate section 3604(c).

previously found. As a result, even when advertisers try to reach a diverse audience, they aren’t always able to.” (internal citations omitted)).

163. *Id.*

164. *Id.* (providing an example of Facebook skewing the audience for employment ads for a janitor towards men, even if the advertiser expressed no gender preference).

165. Ariana Tobin, *HUD Sues Facebook Over Housing Discrimination and Says the Company’s Algorithms Have Made the Problem Worse*, PROPUBLICA (Mar. 28, 2019), <https://www.propublica.org/article/hud-sues-facebook-housing-discrimination-advertising-algorithms> [https://perma.cc/34EJ-TRNT] (noting that HUD’s suit against Facebook is an unusual move for the Trump administration which has frequently moved to curtail civil rights investigations.); *see also* Benner et al., *supra* note 139, at ¶ 22 (noting that Assistant Secretary Anna Maria Farias “dialed back all of [HUD’s] fair-housing enforcement activities”); Rieke, *supra* note 161, at ¶ 9 (noting that “[i]ronically and disturbingly, HUD is seeking to weaken disparate impact by undoing the regulatory framework supporting it, even as the agency prosecutes cutting-edge cases that might ultimately require it”).

166. Benner et al., *supra* note 139, at ¶ 4.

V. SOLUTIONS: USING ALGORITHMS FOR GOOD

Much of this article has discussed ways in which the use of algorithms and machine learning has the potential to undermine civil rights laws such as the Fair Housing Act, but algorithms can also be used to detect and combat bias and discrimination.¹⁶⁷ Recently, academics have called for developers to “infuse ethical principles” into technological advancements in the use of algorithms, artificial intelligence, and machine learning.¹⁶⁸ Technology has developed such that it is possible to identify proxies for protected classes in algorithms or artificial intelligence models and to “repair” those models so that the effect of the proxy is removed.¹⁶⁹ Technology can even be used to make normative assessments as to whether a use of a proxy for a protected class is “inappropriate,” meaning it is likely to violate the Fair Housing Act, or whether there may be a race-neutral “business necessity” or other legally sound defense to using the proxy.¹⁷⁰

Because algorithms are so complex and are “trained” to recognize and utilize patterns in ways that even their developers may not have anticipated, rooting out bias in algorithms is incredibly difficult. One might think that simply removing data that relates to a

167. Datta et al., *supra* note 99, at 6–8.

168. LaBrie & Steinke, *supra* note 26, at 1; *see also* EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 5–6 (“To avoid exacerbating biases by encoding them into technological systems, we 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.”); MacCarthy, *supra* note 14, at 73 (“For organizations using algorithms and firms designing them, the search for alternatives to algorithms that have a disproportionate adverse impact is vital.”).

169. Datta et al., *supra* note 99, at 6–8.

170. *Id.* at 3; *see also* LaBrie & Steinke, *supra* note 26, at 1 (proposing an “ethical audit framework, in which big data sources, machine learning and artificial intelligence algorithms are audited in such a way as to detect and point out biases, flaws, and harm (economic, social, political, penal, workplace advancement, etc.) to humans”); EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 22 (“Support research into mitigating algorithmic discrimination, building systems that support fairness and accountability, and developing strong data ethics frameworks.”). Recent moves in algorithm development include reducing biases and flaws to increase statistical fairness. *See* MacCarthy, *supra* note 14, at 68 (noting the difference between the statistical concepts of group fairness and individual fairness in normative assessments).

protected class would be enough to root out bias from algorithms.¹⁷¹ Studies show, however, that since the advent of artificial intelligence and machine learning, algorithms do not make predictions based on correlations between just a few pieces of data, but instead make predictions based on relationships between tens of thousands of data points.¹⁷² Simply removing data related to protected classes does little to change biased results.¹⁷³ Particularly with large-scale machine learning systems, “algorithms can effectively use omitted demographic features by combining other inputs that are each *correlated* with . . . those features, potentially nullifying any protection from discriminatory effects.”¹⁷⁴

A. Race Neutrality Does Not Work

One study of Facebook’s advertising tools displays how “merely removing demographic features from a real-world algorithmic system’s inputs”—an approach favoring race-neutrality—“can fail to prevent biased outputs.”¹⁷⁵ In that study, researchers compared two advertising tools available on Facebook’s platform. First, they examined Facebook’s “Lookalike Audiences” tool, which allowed advertisers to provide a list of ideal sample users (a “source audience”) in order to create a new list of users who share “common qualities” with those in the “source audience.”¹⁷⁶ The “Lookalike Audiences” tool was decidedly race—and protected class—conscious. It matched demographic data such as race and sex from the “source audience” to other users in order to generate a new list of users which

171. See Cofone, *supra* note 15, at 1411 (noting that, while blocking information from an algorithm might not prevent discrimination, “we can allow it to collect information and then decide whether to use it—for example by making the algorithm compare the potential decision with information and the counterfactual decision without information”).

172. See *id.* at 1420 (explaining that removal of biased data may still lead to biased results).

173. Piotr Sapiezynski et al., *Algorithms that “Don’t See Color”: Comparing Biases in Lookalike and Special Ad Audiences* 1, ARXIV (Dec. 17, 2019), <https://arxiv.org/pdf/1912.07579.pdf> [<https://perma.cc/M9X7-KTW6>] (stating that “merely removing demographic features from a real-world algorithmic system’s inputs can fail to prevent biased outputs”); see also Cofone, *supra* note 15, at 1413–14 (noting that an algorithmic process may produce a disparate impact on protected categories because unpredictable factors, in the aggregate, may alter the outcome).

174. Sapiezynski et al., *supra* note 173, at 1.

175. *Id.*

176. *Id.*

the advertisements target, such as apartment and job postings.¹⁷⁷ As noted above, the National Fair Housing Alliance and others sued Facebook in 2018, claiming that this very tool and other aspects of Facebook's advertising platform violated the Fair Housing Act's prohibition on discriminatory advertising by allowing advertisers to target individuals based on race, sex, and other categories protected by the Fair Housing Act for certain types of housing advertisements.¹⁷⁸

After the case settled in March 2019, Facebook agreed to change its targeting tool, and created the "Special Ad Audiences" tool, which worked like "Lookalike Audiences," except its algorithm did not consider user profile fields such as "age, gender, relationship status, religious views" or other demographic data that related directly to classes protected under the Fair Housing Act; in other words, it was not race or protected class "conscious."¹⁷⁹

A study that sought to determine whether the Special Ad Audience algorithm produced less biased audiences than the Lookalike Audience algorithm revealed that, even when data about protected classes was omitted from the algorithmic inputs, the results were similarly biased.¹⁸⁰ Researchers believe this occurred because algorithms easily find proxies for protected classes, combining multiple data points drawn from datasets that reflect inequities based on things like race and sex.¹⁸¹ It is not enough to simply prevent an algorithm from considering race and sex if the rest of the data upon which the algorithm relies is infected by inequities caused by racism and sexism.¹⁸² Willful blindness to race or protected class status does not prevent algorithmic discrimination; instead, it furthers inequities. As the next section details, addressing algorithmic discrimination may call for some level of race consciousness.

177. *Id.*

178. FACEBOOK et al., *supra* note 154, at 1.

179. Sapiezynski et al., *supra* note 173, at 1–2.

180. *Id.* at 2.

181. *See* Cofone, *supra* note 15, at 1416 (discussing how "blocking information on protected categories may be ineffective because an infinite number of data points will be proxies for them").

182. *Id.* at 1425 (discussing how algorithms "cannot be 'race blind' and, at the same time, not engage in disparate impact discrimination"); *see also* Kofman & Tobin, *supra* note 162, at ¶ 8 (discussing how "research shows that simply removing a few protected features from an algorithm is unlikely to provide any meaningful protection against discrimination").

B. Corrective Training and “Lying” to Algorithms—A Race Conscious Approach

Researchers have presented several ways to use algorithms and artificial intelligence to identify and correct unlawful bias or disparate impact.¹⁸³ Studies have shown that to correct for bias that is harmful to those in protected classes, programmers should not make their algorithms “race blind,” meaning that they should not program algorithms to ignore all demographic data related to protected classes; instead, programmers should be race conscious to ensure that algorithms do not further existing racial inequities.¹⁸⁴ One way to effectively use race consciousness to combat algorithmic discrimination is through the use of corrective training data.

Most machine learning algorithms are “trained” on confined data sets—a developer “exposes” the algorithm to a special set of data with specific desired outcomes to “teach” the algorithm how to solve a problem.¹⁸⁵ This type of “supervised training” allows developers to

183. LaBrie & Steinke, *supra* note 26, at 3 (arguing that “organizations and information systems that apply AI algorithms [should] be analyzed for consideration of hidden flaws and biases”); *see also* EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 6 (“This new set of practices has great potential to . . . help overcome discrimination At the same time, there are great risks that the very same innovations could perpetuate discrimination and unequal access to opportunity as the use of data expands.”). Some researchers believe that changing the algorithms themselves will reduce disparate impact, while others believe changing algorithms will not solve the deeper social issues causing the impact in the first place. *See* Tene & Polonetsky, *supra* note 12, at 135 (arguing that reengineering algorithms to foster fairness may not be the right approach for resolving inequities, and that, in fact, many celebrated critiques expose a “lingering digital divide” that may only be exacerbated by making small changes in code to mask societal problems).

184. GOOGLE, PERSPECTIVES ON ISSUES IN AI GOVERNANCE 15, <https://ai.google/static/documents/perspectives-on-issues-in-ai-governance.pdf> [<https://perma.cc/WN3D-FLRW>] (citing that “while it might seem sensible to bar the inference of a person’s gender to guard against unfair treatment, in practice doing so could inadvertently have the opposite effect, by making it hard to deliver reliable ‘mathematically fair’ gender-neutral outputs.”); *see also* Cofone, *supra* note 15, at 1415 (“Collecting more data, and especially data about protected categories, is therefore a useful first step to reduce discrimination.”).

185. Daniel J. Fuchs, *The Dangers of Human-Like Bias in Machine Learning Algorithms*, 2 MO. S&T’S PEER TO PEER, May 2018, at 1, 3; *see also* EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 9 (citing that “[d]ata sets that lack information or disproportionately represent certain populations, [may] result[] in skewed algorithmic systems that effectively encode discrimination because of the flawed nature of the initial inputs.”).

feed data in and manage the results, setting the algorithm up to react to and learn from future data in a predictable manner.¹⁸⁶ Thus, the developers of algorithms can correct biases in existing data with “specialized learners,” special data sets aimed at counteracting biases in the general data set.¹⁸⁷ As one author put it:

For algorithms, the solution is neither more data nor less data. It is more meaningful data. And more meaningful data means, counterintuitively, a data sample that is unrepresentative of the pool, because it looks like what we believe the pool *would* look like had it not embedded structural inequalities.¹⁸⁸

The process of using special data sets or even false data sets to correct for learned bias has been studied in the criminal justice context.¹⁸⁹ Courts and parole boards have used a machine learning tool called Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) to help judges weigh the likelihood of recidivism in sentencing decisions.¹⁹⁰ The initial hope was that the tool could minimize the effect of individual judges’ racial bias by minimizing the role of human decisionmakers.¹⁹¹ Unfortunately, however, COMPAS wrongly predicted that Black defendants would reoffend nearly twice as often as it made that wrong prediction for white defendants.¹⁹² A recent ProPublica article highlighted racial

186. Fuchs, *supra* note 185, at 3.

187. See EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 15 (stating that “[i]mplementation of such systems with an eye to their broader effects on fairness and equal opportunity is . . . essential.”).

188. Cofone, *supra* note 15, at 1393.

189. *Id.* at 1396.

190. COMPAS was developed on the backdrop of the criminal justice system already relying on fixed factors to predict the likelihood of recidivism. See Robin A. Smith, *Opening the Lid on Criminal Sentencing Software*, DUKE TODAY (July 19, 2017), <https://today.duke.edu/2017/07/opening-lid-criminal-sentencing-software> [<https://perma.cc/5W7W-6HWE>].

191. Ed Yong, *A Popular Algorithm Is No Better at Predicting Crimes Than Random People*, ATLANTIC (Jan. 17, 2018), <https://www.theatlantic.com/technology/archive/2018/01/equivant-compas-algorithm/550646/> [<https://perma.cc/GK8K-RBUM>] (“[J]udges in the real world have access to far more information . . . Paradoxically, that informational overload can lead to worse results by allowing human biases to kick in.”).

192. Fuchs, *supra* note 185, at 8; see also Julia Angwin et al., *Machine Bias*, PROPUBLICA (May 23, 2016), <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing> [<https://perma.cc/8JGJ-L5TJ>] (describing pervasive machine bias in predicting future criminal offenders); Cofone, *supra* note 15, at 1396–97 (stating that “the algorithm mistakenly identified as high risk

disparities in the outputs from COMPAS by profiling two individuals—one Black and one white—arrested for petty theft.¹⁹³ The COMPAS system predicted that the Black defendant would reoffend and the white one would not; two years after arrest it was clear that the algorithm got it wrong—the white defendant was rearrested and convicted while the Black defendant was not charged with any new crimes.¹⁹⁴

Relying on crime reports which are fraught with racial bias as training data, COMPAS “learned” to double down on that bias. First, COMPAS relied on re-arrests to predict rates of recidivism without compensating for biased police practices.¹⁹⁵ Additionally, COMPAS used data from other biased algorithms (e.g., algorithms that use data to predict crime locations and deploy police accordingly, which often leads to the over-policing of minority neighborhoods and results in more crime reports from those areas).¹⁹⁶ One proposal to “retrain” COMPAS suggested that it simply remove racial information from the training data; however, machine learning algorithms often implicitly reconstruct missing data and “use these probabilistically inferred proxy variables for discriminatory classification.”¹⁹⁷ Given that programmers created machine learning algorithms to find relationships across data, they are astute at inferring missing or deleted data.¹⁹⁸

When simply deleting data about race did not lead to more accurate results for the COMPAS system, a team of researchers suggested adding false training data to improve COMPAS’s performance and correct the underlying racial bias. In this study, the more frequently a group was classified incorrectly by COMPAS, the more false data was generated for that group to “undo” the bias.¹⁹⁹

twice as many black individuals than it did white individuals, and mistakenly identified as low risk more white individuals than it did black individuals”).

193. Angwin et al., *supra* note 192, at ¶ 4.

194. *Id.*

195. *Id.*

196. Fuchs, *supra* note 185, at 1 (“Learned biases formed on human-related data frequently resemble *human-like* biases towards race, sex, religion, and many other common forms of discrimination.”).

197. *Id.* at 9.

198. Sapiezynski et al., *supra* note 173, at 1 (“If an algorithm is not provided with a demographic feature, one might think, then its outputs should not discriminate with respect to that feature. This may not be true, however, when there are other features that are correlated with that demographic feature.”).

199. Fuchs, *supra* note 185, at 10.

For example, if subjects with a particular type of criminal record that was more frequently committed by African Americans were frequently misclassified as repeat offenders despite not reoffending, the algorithm was exposed to falsified data in proportion to the rate of the misclassification—i.e., falsified reports would be generated showing that subjects with that type of criminal record were not repeat offenders.²⁰⁰ When applied to COMPAS, this type of corrective antibias action was relatively successful: misclassification rates for African Americans dropped from 45% to 26%, while white misclassifications remained at 23%.²⁰¹

Corrective antibias “training” for artificial intelligence systems has been applied in contexts outside of criminal law.²⁰² For example, researchers noted that artificial intelligence algorithms used to identify successful business managers often use “training data” sets that reflect current inequities between women and men or between whites and racial/ethnic minorities.²⁰³ Data sets might reveal that the most successful managers in the past were white men

200. *Id.*

201. *Id.*; see also Cofone, *supra* note 15, at 1422 (“COMPAS was not biased as a measure of re-arrest; it was biased as a measure of re-offense. COMPAS used its prediction of re-arrest as a proxy for re-offense. In doing so, it picked up the social biases that distort the relationship between offending and being arrested.”).

202. Some scholars warn against this type of corrective antibias training. Compare Tene & Polonetsky, *supra* note 12, at 7, 29 (arguing that when companies “employ an editorial hand” in changing the results of algorithms to combat bias, they must do so with transparency and accountability, and that “[b]laming the algorithm for existing social inequity and requiring back office tweaking to cleanse its results is myopic. Instead of solving societal problems, it would bury them under a glass of political correctness and sanitized accounting.”), with MacCarthy, *supra* note 14, at 70, 72 (2018) (noting that Supreme Court decisions permit designing or modifying algorithms to “mov[e] toward statistical parity” in some instances. For example, without discussing algorithms in particular, in *Texas Dep’t of Hous. and Cmty. Affs. v. Inclusive Cmty. Project, Inc.*, 135 S. Ct. 2507 (2015), the Supreme Court held that “remodel efforts are not precluded by equal protection even they are race conscious, but stronger measures such as racial targets or quotas might not be consistent with equal protection.”). Note that, in response to lawsuits asserting claims based on bias in algorithms, there are now companies that specialize in identifying and remediating bias in algorithms. The O’Neil Risk Consulting & Algorithmic Auditing Company (ORCAA), for example, offers to audit algorithms for “accuracy, bias, consistency, transparency, fairness and legal compliance.” *O’Neil Risk Consulting & Algorithmic Auditing*, ORCAA, <https://orcaarisk.com/> [<https://perma.cc/PC25-69JP>].

203. LaBrie & Steinke, *supra* note 26, at 4.

(because women and racial or ethnic minorities faced sexism and racism), and thus the algorithm would suggest that hiring white men to fill manager positions will yield the best results.²⁰⁴ Similarly, a data set might show a correlation between number of hours worked in a given year and success as a manager, and the algorithm again might favor men in workplaces where it is more likely for women to take parental leave than men.²⁰⁵ Simply removing demographic data from data sets is unlikely to remedy such algorithmic discrimination, but creating false datasets that pairs traits associated with women and minorities on equal footing with white men could produce better results. To reduce algorithmic discrimination, sometimes we must “lie’ to the algorithm, pretending that we live in the kind of society that we want to live in.”²⁰⁶

There is sometimes tension between anti-discrimination principles, which prohibit classifications based on protected categories, and anti-subordination principles, which prohibit disadvantaging historically vulnerable groups; the Fair Housing Act jurisprudence speaks to both principles.²⁰⁷ The Fair Housing Act prohibits actors from making housing-related decisions “because of” race—an anti-discrimination principle.²⁰⁸ At the same time, the Fair

204. *Id.* at 3–4; see also Cofone, *supra* note 15, at 1397–98 (analyzing a machine learning system that Amazon developed to rank job candidates, which “to the surprise of the algorithm’s programmers, ended up being sexist.” The reason the “system displayed a significant bias against female candidates” is “[b]ecause the algorithm was trained using Amazon’s existing hiring data under the idea that Amazon’s current employee choices are a good proxy for Amazon’s desired employee choices, the algorithm reflected existing hiring practices.”)

205. LaBrie and Steinke, *supra* note 26, at 4.

206. Cofone, *supra* note 15, at 1421–22 (“[T]o conform with antidiscrimination law, [companies and government agencies] could be required to consider that, even though groups are not equal in the real world, they must be treated equally for the purposes of the decision-making process, and could be asked to train their models to conform to such belief.”). For a discussion of how a disparate impact assessment in machine learning could operate, see MacCarthy, *supra* note 14, at 67.

207. Cofone, *supra* note 15, at 1431; see also MacCarthy, *supra* note 14, at 68 (discussing the “dispute between those who think the anti-discrimination laws aim at group disadvantaging practices and those who think they target arbitrary misclassification of individuals”). For a discussion of the nuanced differences between the anti-discrimination principle, involving individual discriminatory harms, and the anti-subordination principle, focusing generally on social change “necessary to eliminate group-based inequality,” see Schneider, *supra* note 37, at 582.

208. FHA, *supra* note 30, at §§ 3601–3619.

Housing Act's stated purpose—"to provide, within constitutional limitations, for fair housing throughout the United States"²⁰⁹—and over fifty years of disparate impact jurisprudence embodies the anti-subordination principle: that "decisions should not worsen *or* perpetuate protected groups' subordinate status" without a sufficient business justification.²¹⁰ Training algorithms to recognize bias and correct for it relies on both anti-discrimination principles (in some cases, by disallowing the algorithm to rely on data that relates to protected classes) and anti-subordination principles (by using race-conscious data to correct for algorithmic bias). The purpose of disparate impact analysis is "not to freeze inequality in an unjust situation but rather to correct the state of affairs and achieve a more just state of the world."²¹¹ Using corrective training data, or, as another scholar put it, "lying" to the algorithm so that training data resembles "the more equal world that the law dictates we should live in" enables us to "tak[e] the anti-subordination principle seriously in the context of algorithmic discrimination."²¹²

C. In Some Circumstances, Put the Human Back into the Equation

Sometimes there is an even simpler fix to bias in algorithms: using the data produced by algorithms in only limited capacities and allowing for human intervention when bias is revealed. For example, in 2013, the City of Boston introduced an application that used the motion-sensing capabilities of smartphones to automatically report information on potholes to the municipal government.²¹³ Users could download the app, and then, whenever their smartphones sensed the deep bump from a pothole, the location information was automatically transmitted to the relevant governmental authority.²¹⁴ Not surprisingly, the app reported more potholes in wealthy areas of the city than poor ones because wealthier residents were more likely to have smart phones and to download the application.²¹⁵ If the city had relied only on the data from the application, it would have

209. *Id.* at § 3601.

210. Cofone, *supra* note 15, at 1432.

211. *Id.* at 1432–33.

212. *Id.* at 1442–43.

213. Tene & Polonetsky, *supra* note 12, at 26.

214. *Street Bump*, CITY OF BOS. (last updated July 1, 2019), <https://www.boston.gov/transportation/street-bump> [<https://perma.cc/93Q7-6K7E>].

215. Tene & Polonetsky, *supra* note 12, at 26.

regressively diverted city resources from poor communities to rich communities.²¹⁶ Instead of relying on data that was likely to be infected with bias, the City of Boston deployed the application to its city road inspectors who serviced all parts of the city equally and then used the citizen-generated data just to supplement what came in from the city employees.²¹⁷

We may not always need machines to correct biased algorithms; for example, allowing users to input or correct data may lead to better results.²¹⁸ In a 2016 report, the Executive Office of the President suggested that allowing subjects “to correct inaccurate data and appeal algorithmic-based decisions” was a key element of algorithmic fairness.²¹⁹ The data analytics firm Axicom accomplishes this by inviting members of the public “to search for their names and profiles on a public interface, and update or correct information that is outmoded or shows errors.”²²⁰ User input improves the efficacy and efficiency of the algorithm while encouraging members of the public to help correct biases.²²¹ On the other hand, it puts the burden of confronting bias on those who may be most likely to suffer from the

216. *Id.*

217. EXEC. OFF. OF THE PRESIDENT, BIG DATA: SEIZING OPPORTUNITIES, PRESERVING VALUES 52 (2014) (noting that the Street Bump app has to date recorded tens of thousands of “bumps,” helping Boston identify road castings like manholes and utility covers, not potholes, as the biggest obstacle for drivers).

218. Matthew Adam Bruckner, *The Promise and Perils of Algorithmic Lenders’ Use of Big Data*, 93 CHI.-KENT L. REV. 3, 53 (2018) (“Data obtained through consumer consent is likely to be better quality (i.e. more accurate and reliable), thus presenting fewer compliance risks for algorithmic lenders.” (footnote omitted)).

219. EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 23; *see also* Lee et al., *supra* note 2, at ¶ 74 (“The subjects of automated decisions deserve to know when bias negatively affects them, and how to respond when it occurs.”).

220. Bruckner, *supra* note 218, at 53–54 (citing EVA WOLKOWITZ & SARAH PARKER, CTR. FOR FIN. SERVS. INNOVATION, BIG DATA, BIG POTENTIAL: HARNESSING DATA TECHNOLOGY FOR THE UNDERSERVED MARKET 12 (2015), http://www.morganstanley.com/sustainableinvesting/pdf/Big_Data_Big_Potential.pdf [<https://perma.cc/9WY8-WZMG>]).

221. EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 9 (noting that when there is a lack of transparency, individuals are unable to “detect and seek correction of any errors or bias”); *see also* Lee et al., *supra* note 2, at 16 (“People will continue to play a role in identifying and correcting biased outcomes long after an algorithm is developed, tested, and launched. While more data can inform automated decision-making, this process should complement rather than fully replace human judgement.”).

effects of discrimination and who are least likely to have the time and resources necessary to make corrections.²²²

Employment scholars have urged employers to utilize human decision-makers to carefully monitor algorithmic outputs to ensure that algorithms do not cause impermissible disparate impacts based on protected classes when it comes to hiring, promotion, and firing decisions. For example, one scholar advises training in-house personnel to “make sure that both the people using this data and the people creating the algorithm understand that they need to be aware of potential bias and have methods for checking for bias.”²²³ Employees should be trained to “review datasets and algorithms to ensure that hidden biases are not having an unintended impact on [protected] populations.”²²⁴ Certainly, there are opportunities for these types of user inputs in the rental housing context. Tenants should be given a clear reason anytime an algorithm rejects a rental application and tenants should have ample opportunities to correct the record or provide mitigating evidence.

D. Increased Transparency

In addition to “training” algorithms to be less discriminatory by providing them with false data sets that combat the racial disparities that infect existing data sets, algorithms may be less discriminatory if the algorithms themselves are less opaque. Algorithms, particularly those used in “machine learning,” are often a “black box”—an “opaque machine that takes inputs, carries out some inscrutable process, and delivers unexplained outputs based on that that process.”²²⁵ There is a push across industries to make companies “dramatically more transparent about the predictive tools they build and use.”²²⁶

222. Dana Floberg, *The Racial Digital Divide Persists*, FREE PRESS (Dec. 13, 2018), <https://www.freepress.net/our-response/expert-analysis/insights-opinions/racial-digital-divide-persists> [<https://perma.cc/TF3E-CENT>].

223. Reinsch & Goltz, *supra* note 11, at 60.

224. *Id.* at 60–61.

225. EXEC. OFF. OF THE PRESIDENT, *supra* note 1, at 8; *see also* Cofone, *supra* note 15, at 1436–1437 (“[T]he most accurate methods of machine learning, and thus the ones for which there is greater incentive to adopt, seem to be the least explainable ones.”).

226. Bogen & Rieke, *supra* note 25, at 2; *see also* Lehr & Ohm, *supra* note 103, at 692–93 (noting that “there are ways to make algorithms more explainable. For one, a simpler class of models can be chosen—one with a less complex

The opacity of algorithms can obfuscate intentional discrimination by hiding whether algorithms improperly rely on data about protected classes; this can make disparate impact claims impossible to prove by hiding how combinations of data points might be used as proxies for race. Potential plaintiffs need “some level of transparency in order to substantiate their claims.”²²⁷ On the other hand, those using algorithms may have valid trade secret or privacy concerns. To balance these interests, some scholars have argued that algorithms used in certain contexts should be regulated by a government agency which could set disclosure requirements similar to the SEC’s that do not reveal trade secrets but nonetheless provide meaningful notice about how the algorithm functions and whether it may result in discrimination.²²⁸

Predictive tools such as algorithms can give those who rely on them “the opportunity to look inward and adjust their own past behavior and assumptions.”²²⁹ This is not possible, of course, without transparency. Increased transparency, while helpful to those aggrieved by algorithmic discrimination, cannot, alone, eradicate algorithmic discrimination because even if there is more transparency, “[m]achine-learning algorithms do not learn nor reason like humans do, and that can make their outputs difficult to predict and difficult to explain.”²³⁰ While increasing transparency, researchers must stay informed of the changing nature of algorithms and work to anticipate issues that will come up.

optimization process.”); Andrew Tutt, *An FDA for Algorithms*, 69 ADMIN. L. REV. 83, 109 (2017) (“[T]here appears to be a growing consensus among scholars that the ability to require transparency should be one of the first tools used to regulate . . .”).

227. Cofone, *supra* note 15, at 1439.

228. Tutt, *supra* note 226, at 110; *see also* NYC, ALGORITHMS MANAGEMENT AND POLICY OFFICER, <https://www1.nyc.gov/site/amp/index.page> [<https://perma.cc/CUY5-M3LM>] (referencing a hiring notice for an “Algorithms Management and Policy Officer” for New York City).

229. Bogen & Rieke, *supra* note 25, at 9.

230. Tutt, *supra* note 226, at 87–88 (“The result is that in some of the most important applications to which they might one day be placed, we will be entrusting our fates to machines we do not, and perhaps even cannot, understand.”).

E. Update Nondiscrimination Laws to Address Algorithmic Discrimination

As described above, HUD has recently proposed a rule that would immunize housing providers from liability under the Fair Housing Act if a discriminatory algorithm is approved or used by a third party.²³¹ This head-in-the-sand approach to a technology that is taking over much of the decision-making in the rental housing market will encourage housing providers to turn a blind eye to the potentially discriminatory effects of using algorithms.²³² Instead of taking such a large part of the marketplace out from under the prohibitions included in the Fair Housing Act, regulations should be updated to specifically address algorithmic discrimination and provide guidance to housing providers on how to use algorithmic tools in ways that do not violate both the anti-discrimination and anti-subordination principles of the Fair Housing Act.²³³ Such regulations have the potential to spare housing providers from litigation and liability by clarifying for programmers how to avoid algorithmic discrimination in the design and training of housing-related algorithms.²³⁴ As one author put it:

It is increasingly clear that this framework [of nondiscrimination laws] must be adapted for regulating the growing number of questions— involving hiring, credit, admissions, criminal justice— where algorithms are now involved in how public and private institutions decide. . . . Getting the proper regulatory system in place does not simply limit the possibility of discrimination from algorithms; it has the potential to turn algorithms into a powerful

231. FHA, *supra* note 30, at §§ 3601–3619.

232. See Stephen M. Dane, *Fair Housing Policy Under the Trump Administration*, 44 HUM. RTS. 18 (2019) (“[T]he proposed Rule disincentivizes businesses to collect important data that can reveal discrimination.”).

233. See generally Lee et al., *supra* note 2 (suggesting that nondiscrimination and other civil rights laws should be updated to interpret and redress disparate impacts caused by algorithmic decision-making).

234. *Id.* at 11–12 (“[W]hen creators and operators of algorithms understand that these may be more or less non-negotiable factors, the technical design will be more thoughtful in moving away from models that may trigger and exacerbate explicit discrimination, such as design frames that exclude . . . certain inputs or are not checked for bias.”).

counterweight to human discrimination and a positive force for social good of multiple kinds.²³⁵

The updating of Fair Housing Act regulations to address algorithmic discrimination could include requirements of transparency, requirements that those who use algorithms audit them for bias, and requirements that housing providers ensure that the training data fed to algorithms will produce nondiscriminatory results. This would, of course, require the federal government to reverse course from the recently proposed HUD rule that specifically immunizes housing providers who use algorithms.²³⁶ Acknowledging both the potential and pitfalls of the use of technology and adapting legislation and regulations accordingly has the potential to ensure that the protections of the Fair Housing Act remain intact even as technology advances beyond what the drafters of the Fair Housing Act imagined.

CONCLUSION

As one author put it, “[d]ata and technology are the new frontier in the struggle for civil rights, and out on the frontier, a lot can go wrong.”²³⁷ That said, with increased transparency and a focus on ensuring that the use of technology does not undermine the efficacy of Civil Rights laws, there is potential for a lot to go right. The coming eviction crisis resulting from the COVID-19 pandemic serves as an illustrative example. As has been widely reported, COVID-19 has disproportionately affected Black individuals, both in terms of health impacts and in terms of financial impacts.²³⁸ It is

235. Jon Kleinberg et. al., *Discrimination in the Age of Algorithms*, 10 J. LEGAL ANALYSIS 113, 115 (2018) (footnote omitted).

236. The rule does not need to be finalized, especially given that “there is no support in the case law for the draconian changes being proposed.” Dane, *supra* note 232, at 20.

237. Aaron Rieke & Corrine Yu, *Discrimination’s Digital Frontier*, ATLANTIC (Apr. 15, 2019), <https://www.theatlantic.com/ideas/archive/2019/04/facebook-targeted-marketing-perpetuates-discrimination/587059/> [<https://perma.cc/6UJ9-SKKX>].

238. Centers for Disease Control and Prevention, *Health Equity Considerations & Racial & Ethnic Minority Groups*, CDC.GOV (last updated July 24, 2020), <https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/racial-ethnic-minorities.html> [<https://perma.cc/YQ77-LFGC>]; see also Linda Poon, *CityLab Daily: Covid-19 Evictions Will Wipe Out Black Renters*, BLOOMBERG (July 2, 2020), <https://www.bloomberg.com/news/newsletters/2020-07-02/citylab-daily-covid-19-evictions-will-wipe-out-black-renters>

almost certain that Black people will experience evictions at disproportionate rates and that data, when fed into algorithms, will result in increased barriers to housing for the individuals and communities that the Fair Housing Act aims to protect. As the final section of this article argues, transparency, intentionality, and creativity can ensure that algorithms do not calcify or worsen existing inequities.

Just as when housing providers who use human decision-makers are obliged to ensure that those decision-makers comply with the principles of the Fair Housing Act—they must train staff, include nondiscrimination language in leases, and ensure that advertising does not include discriminatory language—so must housing providers who rely on algorithms ensure that those algorithms do not cause or result in discrimination. HUD's regulations must shore up the Fair Housing Act's protections, not immunize vast swaths of the market from liability when algorithms are employed to make decisions that were traditionally left to individuals. It can be easy to assume that, because algorithms employ mathematical principles, they somehow do not reinforce racial realities; the opposite is true.

As big data grows and artificial intelligence capabilities become more complex and efficient (while becoming less expensive), it is likely that most rental housing decisions will be left to machines. Let's ensure that those machines are subject to and controlled by our most basic and most important civil rights laws.

[<https://perma.cc/7DU9-NUES>] (describing the likely disproportionate impact of the COVID-19 crisis on Black renters).