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The Color of Algorithms: An Analysis and Proposed Research Agenda for Deterring Algorithmic Redlining

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THE COLOR OF ALGORITHMS: AN ANALYSIS AND PROPOSED RESEARCH AGENDA FOR DETERRING ALGORITHMIC REDLINING

*James A. Allen**

ABSTRACT

Modern algorithms are capable of processing gargantuan amounts of data — with them, decision-making is faster and more efficient than ever. This massive amount of data, termed “big data,” is compiled from innumerable sources, and due to decades of discrimination, often leads algorithms to arrive at biased results that disadvantage people of color and people from low- and moderate-income communities. Moreover, the decision-making procedures of modern algorithms are often structured by a homogenous group of people, who develop algorithms without transparency, auditing, or oversight.

This lack of accountability is particularly worrisome because algorithms are beginning to be deployed more rapidly and more expansively by public and private actors. Recent scholarship has raised concerns about how algorithms work to perpetuate discrimination and stereotypes in practically all areas, from casually searching the internet to criminal justice. This Article explores how algorithms in the housing arena operate, or have the potential to operate, in a manner that perpetuates previous eras of discrimination and segregation. By specifically concentrating on algorithms used in housing finance, marketing, and tenancy selection, this Article

* J.D., Brooklyn Law School; B.A., Howard University. I am indebted to Professor Christina Mulligan, for without her direction, this Article would not have been possible. Special thanks to Nadav Pearl and the staff of the *Fordham Urban Law Journal* for excellent editing assistance and finding a home for this piece. I am also grateful for the helpful comments of Sara Amri, Christopher Wallace, and Thebe Kgositsile. Finally, thanks are owed to Richard Rothstein, author of *The Color of Law*, which was the inspiration for this Article.

provides a research agenda for exploring whether housing stakeholders are creating an era of algorithmic redlining.

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After the lecture, when the judge said, “I’m going to give you boys another chance,” I don’t know why or what happened, but I heard myself say, “Man, you not givin’ us another chance. You givin’ us the same chance we had before.”

- Claude Brown, *MANCHILD IN THE PROMISED LAND*¹

Harlem, New York

INTRODUCTION

Algorithms, or automated decision systems, are being used by public and private entities to optimize efficiency, cut costs, and expand social welfare.² Although beneficial in many respects, algorithms deployed by public and private actors also make decisions that go against our better instinct.³ Algorithms are now being used in the affordable and fair housing arena — to ensure equitable results, these algorithms must be implemented with transparency, auditing, and oversight.⁴ This Article explores the potentially inequitable uses of big data and algorithms in the housing arena and suggests how different actors in the United States may be perpetuating a previous era of “redlining.”

In its most technical sense, the term “redlining” can be traced back to the 1933 practice of racial discrimination stewarded by the United States government’s Home Owners’ Loan Corporation (HOLC).⁵ At

1. CLAUDE BROWN, *MANCHILD IN THE PROMISED LAND* 118 (1965).

2. *See, e.g.*, VIKTOR MAYER-SCHÖNBERGER & KENNETH CUKIER, *BIG DATA: A REVOLUTION THAT WILL TRANSFORM HOW WE LIVE, WORK, AND THINK* 52–61 (2013); Kevin Slavin, *HOW ALGORITHMS SHAPE OUR WORLD* (TEDGLOBAL 2011), https://www.ted.com/talks/kevin_slavin_how_algorithms_shape_our_world [<https://perma.cc/R9ZY-Y2WY>]; THE SECRET RULES OF MODERN LIVING: ALGORITHMS (BBC Four 2015) (detailing algorithms built by private entities and deployed by the aviation administrators to assist in coordinating plane arrival and departure; detailing a matching algorithm created by academics to connect those in need of organs with organ donors).

3. *See, e.g.*, VIRGINIA EUBANKS, *AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR* 1–13 (2017); SAFTYA UMOJA NOBLE, *ALGORITHMS OF OPPRESSION: HOW SEARCH ENGINES REINFORCE RACISM* 12–14 (2018); CATHY O’NEIL, *WEAPONS OF MATH DESTRUCTION* 1–13 (2016).

4. Nestor M. Davidson, *Affordable Housing Law and Policy in an Era of Big Data*, 44 *FORDHAM URB. L.J.* 277, 278 (2017) (discussing how data is used to focus on outputs, such as the number of units that can be constructed from a given investment or management property jobs, but should instead focus on outcomes, “the actual short- and long-term consequences of policy interventions for those served by affordable housing programs and the communities at issue”).

5. *See generally* RICHARD ROTHSTEIN, *THE COLOR OF LAW: A FORGOTTEN HISTORY OF HOW OUR GOVERNMENT SEGREGATED AMERICA* viii (2017) (describing

the time, the HOLC was the nation's largest financier of federally-backed government loans, lending to individuals and families to buy homes.⁶ However, the HOLC did not disburse these government-backed loans equitably — the agency would literally draw red lines on maps around communities of color, which they identified as too risky to serve.⁷ This practice etymologized what became widely known as “redlining,” as underwriters across the country followed suit in an attempt to adhere to the federal government’s “risk-evaluation” standards.⁸

As the practice of redlining expanded, so did its meaning. The term “redlining” has since become more encompassing and is now commonly considered to describe the general practice of an institution’s refusal to provide resources and financial support to areas considered “high-risk.”⁹ Unfortunately, these “high-risk” areas remain disproportionately those with properties owned by people of color, due in large part to the previous era of technical redlining.¹⁰ Though the housing industry has moved away from maps and red pencils, “redlining” and its historical impact remain relevant today. This Article cautions that overreliance on automated, algorithmic decision-making systems may perpetuate housing segregation through “algorithmic redlining.” In line with the modern, broader understanding of redlining, this Article uses the term “algorithmic redlining” to encompass sets of instructions — simple or complex — which carry out procedures that prohibit or limit people of color from

how racial segregation became *de jure* policy of the federal government in the context of housing).

6. *Id.* at 63–67.

7. *Id.*

8. *Id.* at 65–67 (describing how the Federal Housing Administration’s Underwriter’s Manual required racially segregating procedures).

9. *Redlining*, BLACK’S LAW DICTIONARY (10th ed. 2014); see also OFFICE OF THE COMPTROLLER OF THE CURRENCY, COMMUNITY REINVESTMENT ACT FACT SHEET n.1 (2014), <https://www.occ.gov/topics/community-affairs/publications/fact-sheets/pub-fact-sheet-cra-reinvestment-act-mar-2014.pdf> [<https://perma.cc/9H8D-D4UY>] (“‘Redlining’ refers to the practice whereby lending institutions refused to offer home loans in certain neighborhoods, based on the income, racial or ethnic composition of the area. The term ‘redlining’ stems from some lenders’ practice of using a red pencil to outline such areas.”); Barbara A. Kleinman & Katherine Sloss Berger, *The Home Mortgage Disclosure Act of 1975: Will It Protect Urban Consumers from Redlining*, 12 NEW ENG. L. REV. 957, 957 (1977).

10. *Redlining*, BLACK’S LAW DICTIONARY, *supra* note 9. Unfortunately, this Article addresses redlining only as a backdrop to how it has informed and created the data that impacts modern algorithms. For a persuasive, detailed background on redlining’s perverse impact, see Richard Rothstein’s *The Color of Law: A Forgotten History of How Our Government Segregate America* is a tour de force. See generally ROTHSTEIN, *supra* note 5.

procuring housing or housing financing, particularly in non-minority neighborhoods.¹¹ Algorithmic redlining and the original era of pencil redlining are synchronized in a crucial way: both result in the exclusion of minority and low-income members of society from access to adequate housing.¹²

This Article explores the impact and potential harms of overreliance on automated decision systems, specifically in the housing equity context, and proceeds in three parts. Part I provides a brief history of algorithms, from their origins as a basic set of steps to complex, autonomous procedures. This includes a discussion of the rise of “big data” and an exploration of how machine learning has intensified the proliferation of automated decision systems. Part I also addresses some of the recent concerns about algorithms as expressed by community activists, academics, and lawmakers — as algorithms become more expansive, so too have concerns about their adverse impact on society. A discussion of this history is important in understanding how pencil redlining was, in a way, an algorithm: “area” plus “colored people” equals “do not lend.” It is also important to appreciate how redlining resulted in adverse consequences for people of color, consequences that make up the data modern algorithms use to generate decisions.

Part II begins with a brief discussion of the importance of access to housing equity, and then offers a research agenda to explore how algorithmic redlining has the potential to exacerbate existing segregation. This Part examines the use of algorithms in three particular areas of the housing market and explores the segregation that can result when algorithms themselves are discriminatory. The first, and perhaps most important, area is that of housing finance — because of biases built into automated credit evaluation and mortgage lending decisions, algorithms act as initial barriers for a subset of people attempting to access credit and housing finance.¹³ This initial barrier to financing comes in the form of scoring systems that rate the riskiness of credit and mortgage applicants, as well as algorithms used

11. “Algorithmic redlining” is left intentionally broad and generally means any computational process that operates to curtail a person or family’s access to housing based on race and/or socioeconomic status.

12. See *infra* Part II.

13. See, e.g., Aaron Glantz & Emmanuel Martinez, *Kept Out: For People of Color, Banks Are Shutting the Door to Homeownership*, REVEAL (Feb. 15, 2018), <https://www.revealnews.org/article/for-people-of-color-banks-are-shutting-the-door-to-homeownership/> [<https://perma.cc/L4M9-SMN5>].

to target minorities and low-income individuals for usurious loans.¹⁴ By reviewing initial reports of systems that rely on these kinds of algorithms, it is possible to see that they result in disproportionately negative lending practices towards people of color.¹⁵ The second area of potential biases is found in the algorithms that direct advertising or marketing towards different races. While present research concerning online advertising in the housing ownership and rental market is scant, bias in other areas of online discriminatory marketing is reason for concern.¹⁶ Finally, the third area of potential bias is in unfair algorithms that may be used in the housing selection process. This is exhibited by recent calls of housing advocates for reform in offline affordable housing lottery algorithms¹⁷ and in the algorithms used to evaluate private market rental applicants.¹⁸

Part III reviews previous reforms and discusses how these once beneficial policies are outdated in the modern, online housing economy. This Part borrows from previous policies to suggest various ways in which the adverse impacts of algorithmic redlining can be curbed: transparency, oversight, and greater human autonomy in automated decision-making. These suggestions draw on previous legislation in the United States and contemporary legislation in the European Union, while also advocating for reforms previously put forth by academics and stakeholders, who call for a modernization of laws impacting the areas mentioned above. While some of these reforms may seem improbable, particularly given America's political climate, this Part discusses why these laws are really commonsense and necessary to protect the modern consumer.

14. Linda E. Fisher, *Target Marketing of Subprime Loans: Racialized Consumer Fraud & Reverse Redlining*, 18 J.L. & POL'Y 121, 124 (2009); Andrea Freeman, *Racism in the Credit Card Industry*, 95 N.C. L. REV. 1071, 1078 (2017).

15. Cassandra Jones Havard, "On the Take": *The Black Box of Credit Scoring and Mortgage Discrimination*, 20 B.U. PUB. INT. L.J. 241, 241 (2011).

16. O'NEIL, *supra* note 3, at 68–83 (describing predatory and biased online marketing).

17. Ethan Geringer-Sameth, 'Community Preference' Lawsuit at Center of Affordable Housing, Segregation Debates, GOTHAM GAZETTE (Mar. 29, 2017), <http://www.gothamgazette.com/city/6838-community-preference-lawsuit-at-center-of-affordable-housing-segregation-debates> [https://perma.cc/4N4A-HGAE]; Keaton Norquist, *Local Preferences in Affordable Housing: Special Treatment for Those Who Live or Work in a Municipality*, 36 B.C. ENVTL. AFF. L. REV. 207, 207 (2009).

18. 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, 40 (2011).

I. “THIS IS THE PROCEDURE”: A BRIEF HISTORY OF ALGORITHMS, FROM BYZANTINE TO BOOLEAN

In their simplest form, “algorithms” are processes that rely on a specific set of steps to consistently produce the same result.¹⁹ When an entity with knowledge of how a given procedure functions conveys this information in a step-by-step formulation, it can reproduce the steps or particular method of analysis for the given criteria as an algorithm.²⁰ Once conveyed in this way, anyone can apply data to the algorithm, and the results remain predictable.²¹

In a sense, algorithms have always been an engine that drives societal advancement. Some of the earliest algorithms were used to advance community and economic development by conveying how to build infrastructure or how to determine the rate of carried interest on a potential investment.²² For example, early societies used algorithmic methods to manage the crucial practice of water management: if a person knew the length, width, and height of a certain area, with the appropriate algorithm, that person could use that data to build a cistern.²³ If a person knew they had capital commitments from potential investors for their cistern-building business, with the appropriate algorithm, they could take the investor’s pledged commitments and calculate their potential carried interest.²⁴ These basic examples are not too different from those used in recent history or even today.

While ancient algorithms are similar in their objective to today’s algorithms, the latter are obviously far more complex.²⁵ Modern

19. *Algorithm*, BLACK’S LAW DICTIONARY (10th ed. 2014) (defining “algorithm” as “[a] mathematical or logical process consisting of a series of steps, designed to solve a specific type of problem”); see also DAVID BERLINKSKI, *THE ADVENT OF THE ALGORITHM: THE IDEA THAT RULES THE WORLD* xvi (2000).

20. See, e.g., *THE SECRET RULES OF MODERN LIVING: ALGORITHMS*, *supra* note 2.

21. See DONALD E. KNUTH, *SELECTED PAPERS ON COMPUTER SCIENCE* 191–94 (1996).

22. See *id.* (describing the ancient Babylonian practice of using algorithms to convey methods of building infrastructure and calculating carried interest and rates of usury). These ancient algorithms frequently concluded with the same post-amble: “This is the procedure.” Knuth points out that the common use of the phrase, “This is the procedure,” is proof that these were algorithms — a way of denoting a particular process meant to produce the same result at a time when algorithms were yet to be defined. See *id.* at 188.

23. *Id.* at 187.

24. *Id.*

25. M.D. Atkinson, *The Complexity of Algorithms*, in *COMPUTING TOMORROW 1* (Ian Wand & Robin Miller eds., 1996); John F. McGowan, *Complex Algorithm Research and Development: Harder Than Many Think*, MATHBLOG.COM (July 20,

algorithms are tremendously intricate and take many forms. Most relevant to the discussion here are “machine learning” algorithms,²⁶ which are informed and powered by “big data.”²⁷ In a broad sense, big data is the process of aggregating massive amounts of information from various online platforms and data capturing entities for the purpose of identifying potential patterns; machine learning algorithms are a form of artificial intelligence, which operate to process big data, learn from it, and then perform tasks and analytics.²⁸ These are such well-known terms that they have become buzzwords, as popular as they are opaque and complicated.²⁹

In essence, increasingly invasive modern algorithms — deployed by private businesses and governmental actors alike — use sophisticated computer technology and aggregated sets of data to generate automated decisions and assumptions about individuals.³⁰ By

2009), <https://mathblog.com/complex-algorithm-research-and-development-harder-than-many-think/> [<https://perma.cc/GA5R-EMGB>] (discussing the complexity of modern algorithms).

26. Joshua A. Kroll et al., *Accountable Algorithms*, 165 U. PA. L. REV. 633, 638 (2017) (describing machine learning systems as those “that derive their decision rules from data rather than from code written by a programmer”).

27. See Kate Crawford & Jason Schultz, *Big Data and Due Process: Toward a Framework to Redress Predictive Privacy Harms*, 55 B.C. L. REV. 93, 96 (2014); see also Jack M. Balkin, *2016 Sidley Austin Distinguished Lecture on Big Data Law and Policy: The Three Laws of Robotics in the Age of Big Data*, 78 OHIO ST. L.J. 1217, 1219–20 (2017) (“Big Data, too, is just a feature of the Algorithmic Society. In fact, Big Data is just the flip side of a society organized around algorithmic decision-making. Big Data is the fuel that runs the Algorithmic Society; it is also the product of its operations. Collection and processing of data produces ever more data, which in turn, can be to improve the performance of algorithms. To vary Kant’s famous dictum, algorithms without data are empty; data without algorithms are blind.”).

28. For further reading concerning big data, see *The Big Data Conundrum: How to Define It?*, MIT TECH. REV. (Oct. 3, 2013), <https://www.technologyreview.com/s/519851/the-big-data-conundrum-how-to-define-it/> [<https://perma.cc/828Q-QDC7>]. For further reading concerning machine learning algorithms, see Nikki Castle, *An Introduction to Machine Learning Algorithms*, DATASCIENCE (June 29, 2017), <https://www.datascience.com/blog/introduction-to-machine-learning-algorithms> [<https://perma.cc/N7N3-2SB3>].

29. Jackie Snow, *An A.I. Glossary*, N.Y. TIMES (Oct. 18, 2018), <https://www.nytimes.com/2018/10/18/business/an-ai-glossary.html> [<https://nyti.ms/2AgdiSh>] (discussing and explaining many of these buzzwords).

30. Maurice E. Stucke & Ariel Ezrachi, *Looking Up in the Data-Driven Economy*, CPI ANTITRUST CHRON., May 2017, at 5, <https://www.competitionpolicyinternational.com/wp-content/uploads/2017/05/CPI-Stucke-Ezrachi.pdf> [<https://perma.cc/RA56-GLWL>] (quoting Tim Berners-Lee, a founder of the World Wide Web, who distinctively points out that “[t]hese sites make more money when we click on the links they show us. And, they choose what to show us based on algorithms which learn from our personal data that they are constantly harvesting.”).

gathering personally identifiable information and optimizing data aggregating techniques, big data is able to reform and refine algorithms, making them more efficient and producing more “rational” decisions.³¹ Modern machine learning algorithms are now being used for everyday purposes, making automated decisions about matters concerning everything from leisure to subsistence. For example, Netflix uses a machine learning algorithm to suggest what shows a viewer may wish to add to their queue,³² and New York City wants to use an algorithm to automatically enroll individuals in welfare benefits.³³

Though efficient and socially productive, the race to create and deploy algorithms may come at a cost.³⁴ For one, it is possible that enhancing efficiency through algorithms is coupled with overt invasions of privacy.³⁵ One popular example of such privacy invasion took place in 2012, when a Target algorithm inadvertently served as one woman’s publicized pregnancy announcement.³⁶ Target became the subject of public scorn when one of its automated decision-

31. MAYER-SCHÖNBERGER & CUKIER, *supra* note 2, at 52–61.

32. Tom Vanderbilt, *The Science Behind the Netflix Algorithms that Decide What You’ll Be Watching Next*, WIRED (Aug. 7, 2013), https://www.wired.com/2013/08/qq_netflix-algorithm/ [<https://perma.cc/2TFJ-MBDA>] (describing the algorithms that suggest movies and shows on Netflix).

33. NEW YORK CITY, N.Y., Int. 0855-B (2018) (a bill to use computer algorithms to auto-enroll New York City residents into eligible benefits plans).

34. Donald Knuth — considered the father of the modern algorithm and the “Yoda of Silicon Valley” — has warned that “premature optimization is the root of all evil,” and in discussing modern algorithms, said that he is “worried that algorithms are getting too prominent in the world.” Siobhan Roberts, *The Yoda of Silicon Valley*, N.Y. TIMES (Dec. 17, 2018), <https://www.nytimes.com/2018/12/17/science/donald-knuth-computers-algorithms-programming.html> [<https://nyti.ms/2GjaIjp>]. See also Davidson, *supra* note 4, at 279 (describing how data-driven policy, in examining outputs, is creating a “positive feedback loop”); Omer Tene & Jules Polonetsky, *Taming the Golem: Challenges of Ethical Algorithmic Decision-Making*, 19 N.C. J.L. & TECH. 125, 134–35 (2017) (summarizing the debate regarding “faulty algorithms”).

35. FRANK PASQUALE, *THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION* 3 (2015) (“Surveillance cameras, data brokers, sensor networks, and ‘supercookies’ record how fast we drive, what pills we take, what books we read, what websites we visit. The law, so aggressively protective of secrecy in the world of commerce, is increasingly silent when it comes to the privacy of persons.”); Daniel J. Steinbock, *Data Matching, Data Mining, and Due Process*, 40 GA. L. REV. 1, 6 (2005).

36. Kashmir Hill, *How Target Figured Out a Teen Girl Was Pregnant Before Her Father Did*, FORBES (Feb. 16, 2012), <https://www.forbes.com/sites/kashmirhill/2012/02/16/how-target-figured-out-a-teen-girl-was-pregnant-before-her-father-did/#6a9c5c3c6668> [<https://perma.cc/S8TL-STDD>].

making algorithms, which utilizes big data, concluded that a customer was pregnant.³⁷ The company sent her family promotional advertisements for pregnancy and baby products — before her father was aware that she was expecting.³⁸

Additionally, the lack of transparency in how various public or private actors utilize algorithms has been a major cause for concern among academics, legal advocates, and lawmakers.³⁹ Transparency issues are often bifurcated into two conceptually different types of algorithms. First are “source code algorithms”; developed by private entities and often deployed by public agencies, these algorithms are immune from disclosure because their code is protected under the harbors of trade secret laws.⁴⁰ Second are complex “machine-learning algorithms” or “neural-network algorithms,” which, while also enjoying trade secret protection, are opaque in a different sense; these algorithms are fed data and then arrive at decisions autonomously, making transparency difficult even if mandatory disclosure were required.⁴¹

In addition to being criticized for their invasiveness and opacity, algorithms are criticized for being racially biased.⁴² These criticisms

37. *Id.* Target’s marketers identified potentially pregnant women by mining buying patterns like cocoa butter, calcium tablets, and larger purses that could hold diapers. *Id.*

38. *Id.*

39. *See* Decision & Judgment at 1–5, Brennan Ctr. for Justice at N.Y.U. Law Sch. v. N.Y.C. Police Dep’t, No. 160541/2016, 2017 WL 6610414 (N.Y. Sup. Ct. Dec. 27, 2017) (finding that the New York Police Department had to produce documents about its predictive policing algorithms to the Brennan Center at New York University School of Law under a Freedom of Information Law (FOIL) request); *see also* Cliff Kuang, *Can A.I. Be Taught to Explain Itself?*, N.Y. TIMES MAG. (Nov. 21, 2017), <https://www.nytimes.com/2017/11/21/magazine/can-ai-be-taught-to-explain-itself.html> [<https://nyti.ms/2hR2weQ>].

40. *See generally* PASQUALE, *supra* note 35, at 1–18; *see also* Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249, 1292–93 (2008) (describing how Freedom of Information Act (FOIA) regulations exempt trade secrets).

41. David Grossman, *How Machine Learning Robots Teach Themselves*, POPULAR MECHANICS (Dec. 19, 2017), <https://www.popularmechanics.com/technology/robots/a14457503/how-machine-learning-lets-robots-teach-themselves/> [<https://perma.cc/ETR5-AFPS>]; Kroll et al., *supra* note 26, at 638 (reflecting on the difficulty of regulating machine learning algorithms and the decisions they produce).

42. *See, e.g.*, EXEC. OFFICE OF THE PRESIDENT, *BIG DATA: SEIZING OPPORTUNITIES, PRESERVING VALUES* 7–8 (May 2014), https://obamawhitehouse.archives.gov/sites/default/files/docs/big_data_privacy_report_may_1_2014.pdf [<https://perma.cc/7TEB-UCXJ>] [hereinafter *BIG DATA: SEIZING OPPORTUNITIES*]; Megan L. Brown et al., *ACLU Suit Attacks Computer Fraud and Abuse Act to Investigate Website Discrimination Using Controversial Online*

are largely advanced under two theories — that modern algorithms are built using decades of discriminatory data, and that they are created by a homogenous fraction of persons with inherent biases.⁴³ Ample research has shown that by using biased data and potentially biased code, algorithms are creating a funneling effect that perpetuates discrimination and stereotypes.⁴⁴ Understanding the importance of bias in algorithms is crucial as we shift to what internet law scholars have dubbed the “scored society” — a culture driven by evaluating people based on shadowy metrics and ratings.⁴⁵ Complainants have recently started alleging that biased algorithms are generating biased scores, which are then used to influence or make decisions in a range of important matters such as criminal justice, distribution of social services, evaluation of public employees, and even influencing democratic elections.⁴⁶ Like so many of these

Tactics, BLOOMBERG BNA; ELECTRONIC COMM. & L. REP. (July 13, 2016) (discussing an ACLU suit that alleges discriminatory practices in “scraping” data and using digital “bots”); Tene & Polonetsky, *supra* note 34, at 133–35.

43. Bryce W. Goodman, *Economic Models of (Algorithmic) Discrimination* 1–2 (29th Conference on Neural Information Processing Systems) (2016), <http://www.mlandthelaw.org/papers/goodman2.pdf> [<https://perma.cc/9HV4-PTRZ>]; Solon Barocas & Andrew D. Selbst, *Big Data’s Disparate Impact*, 104 CALIF. L. REV. 671, 684 (2016); Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 4 (2014) (“Because human-beings program predictive algorithms, their biases and values are embedded into the software’s instructions, known as the source code and predictive algorithms. Scoring systems mine datasets containing inaccurate and biased information provided by people.”); Mary Madden et al., *Privacy, Poverty, and Big Data: A Matrix of Vulnerabilities for Poor Americans*, 95 WASH. U. L. REV. 53, 86 (2017) (“While data analytics is touted for its ability to reduce human biases, it often merely replicates them.”); Kate Crawford, Opinion, *Artificial Intelligence’s White Guy Problem*, N.Y. TIMES (June 25, 2016), <https://www.nytimes.com/2016/06/26/opinion/sunday/artificial-intelligences-white-guy-problem.html> [<https://nyti.ms/28YaKg7>] (describing how coders building algorithms are often white males).

44. Davidson, *supra* note 4, at 279–80; Madden et al., *supra* note 43, at 64–67; Jahna Otterbacher, *New Evidence Shows Search Engines Reinforce Social Stereotypes*, HARV. BUS. REV. (Oct. 20, 2016), <https://hbr.org/2016/10/new-evidence-shows-search-engines-reinforce-social-stereotypes> [<https://perma.cc/8NQQ-SMQW>].

45. Citron & Pasquale, *supra* note 43, at 4.

46. See generally EUBANKS, *supra* note 3 (conducting an analysis of how automated decisions perpetuate inequality); Tanvi Misra, *When Welfare Decisions Are Left to Algorithms*, ATLANTIC (Feb. 15, 2018), <https://www.theatlantic.com/business/archive/2018/02/virginia-eubanks-automating-inequality/553460/> [<http://perma.cc/KB7S-BW2B>] (reviewing Eubanks’s book); see also *Filtering Practices of Social Media Platforms, Before the H. Comm. on the Judiciary*, 114th Cong. (Apr. 26, 2018), <https://docs.house.gov/meetings/JU/JU00/20180426/108231/HHRG-115-JU00-Wstate-BlackburnM-20180426.pdf> [<https://perma.cc/4HNC-CKPT>] (statement of Chairman Rep. Marsha Blackburn); Amanda Taub & Max Fisher, *Where Countries Are Tinderboxes and Facebook Is a Match*, N.Y. TIMES (Apr. 21, 2018),

other areas, automated decisions in the housing arena are not immune to the biases found in big data processing.⁴⁷

As we begin to rely more frequently on algorithms to make decisions in sensitive areas of public policy, including the increasingly important area of housing, it is important that those algorithms are not only efficient and accurate, but also equitable.⁴⁸ Beginning with a brief overview of the importance of housing and homeownership, the next Part of this Article suggests a research agenda focusing on how cryptic algorithms may be used at various levels in housing procurement to perpetuate deep physical segregation within society — this is algorithmic redlining.

II. ALGORITHMIC REDLINING: THE THREAT OF AUTOGENERATING SEGREGATION

Housing and homeownership are important to the American public for several reasons.⁴⁹ For one, owning a home is considered a reliable asset, and home equity is often cited as an important factor in helping families enter the middle class.⁵⁰ Additionally, housing and

<https://www.nytimes.com/2018/04/21/world/asia/facebook-sri-lanka-riots.html> [<https://perma.cc/EKL8-7WCB>] (examining how Facebook can influence elections and cause public unrest); *see, e.g.*, *Pitch v. Lightbourne*, 221 Cal. App. 4th 480, 484 (Cal. Ct. App. 2013) (plaintiff challenged a computerized benefit platform that allegedly produced erroneous benefit terminations); *Hous. Fed'n of Teachers v. Hous. Indep. Sch. Dist.*, 251 F. Supp. 3d 1168, 1171 (S.D. Tex. 2017) (teachers alleging they were inappropriately fired due to an algorithm that evaluated performance).

47. *See* Davidson, *supra* note 4, at 279–80; Lee Anne Fennell, *Searching for Fair Housing*, 97 B.U. L. REV. 349, 361 (2017).

48. BIG DATA: SEIZING OPPORTUNITIES, *supra* note 42, at iii (“... [b]ig data analytics have the potential to eclipse longstanding civil rights protections in how personal information is used in housing, credit, employment, health, education, and the marketplace. Americans’ relationship with data should expand, not diminish, their opportunities and potential.”).

49. William M. Rohe & Mark Lindblad, *Reexamining the Social Benefits of Homeownership After the Housing Crisis*, JOINT CTR. FOR HOUSING STUD., HARV. UNIV. 6–9 (Aug. 2013), <http://www.jchs.harvard.edu/sites/default/files/hbtl-04.pdf> [<https://perma.cc/3KTR-LZ5D>]; *Beneficial Impacts of Homeownership: A Research Summary*, HABITAT FOR HUMANITY 1 (2016), <http://www.habitatbuilds.com/wp-content/uploads/2016/04/Benefits-of-Homeownership-Research-Summary.pdf> [<https://perma.cc/ZL3U-7ATK>]; Michelle Higgins, *Homeownership, the Key to Happiness?*, N.Y. TIMES (July 12, 2013), <https://www.nytimes.com/2013/07/14/realestate/homeownership-the-key-to-happiness.html> [<https://nyti.ms/1dr7q3j>].

50. Pamela M. Blumenthal & John R. McGinty, *Housing Policy Levers to Promote Economic Mobility*, URB. INST. 2015, at 5, https://www.urban.org/sites/default/files/publication/71496/2000428-housing-policy-levers-to-promote-economic-mobility_0.pdf [<https://perma.cc/T5GH-BHE8>]; U.S.

homeownership determine where one lives, which often correlates with a host of other factors such as where one goes to school (thus significantly impacting on the quality of one's education⁵¹), the quality of health, and overall quality of life.⁵² Nevertheless, both owning and renting property can be prohibitively expensive.⁵³ This creates a problematic dichotomy: affordable housing and homeownership are simultaneously vital and out of reach for most Americans.⁵⁴ Recognizing this, lawmakers have attempted to facilitate greater homeownership in the United States by introducing policies that make home financing, home marketing, and affordable housing procurement accessible to a larger portion of the American public.⁵⁵ Though commendable in theory, many of these policies

Dep't of Housing and Urban Dev., *Paths to Homeownership for Low-Income and Minority Households*, EVIDENCE MATTERS (Fall 2012), <https://www.huduser.gov/portal/periodicals/em/fall12/highlight1.html> [<https://perma.cc/BW4A-Z7B7>].

51. U.S. Dep't of Housing & Urban Dev., *How Housing Mobility Affects Education Outcomes for Low-Income Children*, EVIDENCE MATTERS (Fall 2014), <https://www.huduser.gov/portal/periodicals/em/fall14/highlight2.html> [<https://perma.cc/G9HG-GMXF>]; Mary Cunningham & Graham MacDonald, *Housing as a Platform for Improving Outcomes Among Low-Income Children*, URB. INST. 1–2 (2012), <https://www.urban.org/sites/default/files/publication/25331/412554-Housing-as-a-Platform-for-Improving-Education-Outcomes-among-Low-Income-Children.PDF> [<https://perma.cc/C3ZH-J72D>]; Jonathan Rothwell, *Housing Costs, Zoning, and Access to High-Scoring Schools*, BROOKINGS INSTITUTION (Apr. 19, 2012), <https://www.brookings.edu/research/housing-costs-zoning-and-access-to-high-scoring-schools/> [<https://perma.cc/BB8U-BHDC>]; Ben Chapman, *Kids from Poorest Neighborhoods Left Out of City's Elite Schools*, N.Y. DAILY NEWS (Apr. 3, 2018), <http://www.nydailynews.com/new-york/education/kids-poorest-neighborhoods-left-city-elite-schools-article-1.3911218> [<https://perma.cc/FT5X-7Q4B>] (describing how students from the poorest schools in New York rarely make it into the City's elite schools).

52. Dalia Streimikiene, *Quality of Life and Housing*, 5 INT'L J. INFO. & EDUC. TECH. 140, 140 (2015); Rohe & Lindblad, *supra* note 49, at 8; *Beneficial Impacts of Homeownership*, *supra* note 49, at 1.

53. A. Mechele Dickerson, *The Myth of Home Ownership and Why Home Ownership Is Not Always a Good Thing*, 84 IND. L.J. 189, 196, 207 (2009); Maria La Ganga, *Ordinary People Can't Afford a Home in San Francisco. How Did It Come to This?*, GUARDIAN (Aug. 5, 2016), <https://www.theguardian.com/business/2016/aug/05/high-house-prices-san-francisco-tech-boom-inequality> [<https://perma.cc/85W6-9XFJ>]; Kyle Munzenrieder, *81 Percent of Miami Millennials Think Home Ownership Is Too Expensive*, MIAMI NEW TIMES (Apr. 15, 2016), <http://www.miaminewtimes.com/news/81-percent-of-miami-millennials-think-home-ownership-is-too-expensive-8393251> [<https://perma.cc/5XYV-LGGK>].

54. Dickerson, *supra* note 53, at 189.

55. *See* Home Mortgage Disclosure Act, 12 U.S.C. § 2801 (2012); Community Reinvestment Act, 12 U.S.C. § 2901 (2012); Equal Credit Opportunity Act, 15 U.S.C. § 1691 (2012); Fair Housing Act, 42 U.S.C. § 3601 (2012).

have had a deleterious impact, directly segregating neighborhoods in two ways: by making the benefits of these policies available to only a select few, and by concentrating investments and the infrastructure of these policies according to demographic.⁵⁶

Consider, for example, the Fair Housing Act (FHA), which was established with the goal of promoting homeownership for a greater, more diverse group of people.⁵⁷ The FHA undoubtedly identified an important hurdle for minorities attempting to access housing,⁵⁸ but scholars have argued that by not accounting for the impact that prior racial discrimination and segregation had on income inequality, the FHA did not go far enough in expanding housing access for minorities, thus benefiting only the select few who were lucky enough to accumulate wealth during the era of pencil redlining.⁵⁹

Moreover, as Caucasian-American families migrated to the suburbs — often after accumulating wealth from home equity unavailable to minorities during the era of pencil redlining — public

56. See ROTHSTEIN, *supra* note 5, at 65; Philip Tegeler & Michael Hilton, *Disrupting the Reciprocal Relationship Between Housing and School Segregation*, JOINT CTR. FOR HOUSING STUD., HARV. UNIV., 2017, at 4–6, http://www.jchs.harvard.edu/sites/default/files/a_shared_future_disrupting_reciprocal_relationship.pdf [<https://perma.cc/6HRG-HT62>]; see also Kleinman & Berger, *supra* note 9, at 958 n.7; Ira Rheingold et al., *From Redlining to Reverse Redlining: A History of Obstacles for Minority Homeownership in America*, 34 CLEARINGHOUSE REV. 642, 645–47 (2001); Adam Gordon, Note, *The Creation of Homeownership: How New Deal Changes in Banking Regulation Simultaneously Made Homeownership Accessible to Whites and Out of Reach for Blacks*, 115 YALE L.J. 186, 189–90 (2005) (examining how the wealth-building opportunity of the Fair Housing Act was not shared with African Americans during the FHA’s first three decades); Connor Dougherty, *Tax Overhaul Is a Blow to Affordable Housing Efforts*, N.Y. TIMES (Jan. 18, 2018), <https://www.nytimes.com/2018/01/18/business/economy/tax-housing.html> [<https://nyti.ms/2DIPsna>] (discussing how the tax overhaul will more likely benefit developers rather than affordable housing tenants and advocates); Adam Looney, *The Early Results of States’ Opportunity Zones Are Promising, but There’s Still Room for Improvement*, BROOKINGS INSTITUTION (Apr. 18, 2018), <https://www.brookings.edu/research/the-early-results-of-states-opportunity-zones-are-promising-but-theres-still-room-for-improvement/> [<https://perma.cc/4B9F-6GSW>] (discussing how the designation of “Opportunity Zones” galvanizes gentrification).

57. 42 U.S.C. § 3604 (2012).

58. *Id.* §§ 3604(a), (b), (c).

59. Gordon, *supra* note 56, at 189–90; Walter F. Mondale, Opinion, *Walter Mondale: The Civil Rights Law We Ignored*, N.Y. TIMES (Apr. 10, 2018), <https://www.nytimes.com/2018/04/10/opinion/walter-mondale-fair-housing-act.html?rref=collection%2Ftimestopic%2FAffordable%20Housing> [<https://nyti.ms/2v3uF8n>] (one of the co-authors of the FHA reflecting on how the government failed to use it for the benefit of those most neglected by society — low-income communities and communities of color).

and private investment migrated with them.⁶⁰ Public infrastructure projects, including the development of residential subdivisions that often enacted racially-restrictive covenants, were concentrated in predominantly Caucasian-American neighborhoods.⁶¹ Additionally, private lenders, though legally prohibited from discriminating based on race in credit evaluations, still used race as a factor for mortgage applicants. For example, consider the Equal Credit Opportunity Act (ECOA) — legislation enacted following the era of pencil redlining that fostered a series of regulations designed to curb racial discrimination in lending.⁶² One of those regulations, 12 C.F.R. § 1002.6,⁶³ specifically prohibits lenders from using race as a metric in evaluating credit applicants, yet section 1002.13, titled “Information for monitoring purposes,” specifically *requires* mortgage lenders to account for race:

(a) Information to be requested. (1) A creditor that receives an application for credit primarily for the purchase or refinancing of a dwelling . . . shall request as part of the application the following information regarding the applicant(s): (i) Ethnicity, using the categories Hispanic or Latino, and not Hispanic or Latino; and for race, the aggregate categories American Indian or Alaska Native, Asian, Black or African American, Native Hawaiian or Other Pacific Islander, and White⁶⁴

Consequently, over the last several decades, segregating housing policies, particularly those that deal with housing finance, have greatly tilted the playing field by systematically disenfranchising communities of color.⁶⁵ Racially isolating housing policies have also exacerbated segregation according to socioeconomic status, forcing low-income families and individuals into inadequate living conditions

60. ROTHSTEIN, *supra* note 5, at 115–37.

61. *Id.*

62. 15 U.S.C. § 1691 (2012).

63. Equal Credit Opportunity Act, Regulation B, 12 C.F.R. § 1002.6 (2017).

64. *Id.* § 1002.13.

65. See ROTHSTEIN, *supra* note 5, at 65; see also DANIEL IMMERGLUCK, CREDIT TO THE COMMUNITY: COMMUNITY REINVESTMENT AND FAIR LENDING POLICY IN THE UNITED STATES 87–108 (2015) (discussing segregating policies and discriminatory lending practices); OFFICE OF THE COMPTROLLER OF THE CURRENCY, *supra* note 9, at 1 n.1; Gordon, *supra* note 56, at 206–07 (describing regulations that denied most African Americans the opportunity to buy homes); Matthew Desmond, *How Homeownership Became the Engine of American Inequality*, N.Y. TIMES MAG. (May 9, 2017), <https://www.nytimes.com/2017/05/09/magazine/how-homeownership-became-the-engine-of-american-inequality.html> [https://nyti.ms/2pZnWIB].

such as slums, areas with poorly performing schools, deteriorating recreational facilities, and underfunded hospitals.⁶⁶

The segregating policies discussed, one of which was pencil redlining, have greatly influenced modern algorithms because they generated massive data sets that consist of decades of information built on exclusion and discrimination. When modern algorithms rely on these databases to make automated decisions, they engage in algorithmic redlining — reproducing, reinforcing, and perpetuating preexisting segregation.⁶⁷ The coming subsections examine precisely these algorithms, which make determinations in housing finance, marketing, and housing selection. This Article describes how these automated decision-making systems operate and explains their potential to operate in today's scored society in a manner that furthers segregation.

First is an overview of perhaps the most important form of algorithmic redlining: algorithms operating in the sphere of housing finance.⁶⁸ Algorithms that determine an applicant's creditworthiness are of utmost importance, as they serve as a functional gatekeeper to the funds necessary to procure housing. Second is a discussion of algorithms used in online housing marketing.⁶⁹ As mentioned, with the increased use of internet advertising to find housing, it is important that the algorithms that act as editors of what options consumers view are not corrupted by biased search characteristics.⁷⁰ Finally, there is a subsection analyzing housing selection algorithms, which can act as barriers to available housing and are a key part of anyone's access to affordable and inclusive housing.⁷¹ Unfortunately, many algorithms that assess and determine housing procurement are tainted by biased data and segregating weighting techniques.⁷² These three issues — finance, marketing, and selection — are not meant to be an exhaustive list of the forms of algorithmic redlining that may perpetuate segregation. Rather, this Article aims to show that

66. REINHOLD MARTIN ET AL., THE ART OF INEQUALITY: ARCHITECTURE, HOUSING, AND REAL ESTATE—A PROVISIONAL REPORT 30 (2016).

67. See *supra* note 11 and accompanying text.

68. See *infra* Section II.A.

69. See *infra* Section II.A.3.

70. See *infra* Section II.A.3.

71. See *infra* Section II.B.

72. See *infra* Sections II.A and II.B.

research into, and monitoring of, each is critical to fostering truly integrated communities across America.⁷³

A. Potential Harms of Discriminatory Credit and Lending Algorithms

Banks have relied on “consumer data” to determine an applicant’s creditworthiness as a guise to discriminate based on race for decades.⁷⁴ As previously mentioned, the United States pioneered the practice of race-based credit evaluations as early as 1933, when the federal government’s HOLC would draw red lines around African-American neighborhoods and communities of color that were identified as “too-risky to serve.”⁷⁵ The government’s overtly racist practice of redlining became commonplace in America, as underwriters across the country drew lines on their maps to follow the U.S. government’s “risk-evaluation” standards.⁷⁶

73. For example, tax appraisal algorithms may serve to perpetuate segregation and unfair housing policy. See Scott M. Stringer, *Growing Unfairness the Rising Burden of Property Taxes on Low-Income Households*, OFF. OF THE N.Y.C. COMPTROLLER (Sept. 6, 2018), <https://comptroller.nyc.gov/reports/growing-unfairness-the-rising-burden-of-property-taxes-on-low-income-households/> [<https://perma.cc/4VHA-APBJ>]; Rebecca Diamond & Tim McQuade, *Who Wants Affordable Housing in Their Backyard? An Equilibrium Analysis of Low Income Property Development*, J. POL. ECON. 5, 5 (forthcoming 2017), https://web.stanford.edu/~diamondr/LIHTC_spillovers.pdf. [<https://perma.cc/CHW6-UXD8>]. Similarly, gerrymandering algorithms may identify households by race in an attempt to predict voters who have the ability to elect policymakers that could, once in office, change discriminatory housing policies. See MICAH ALTMAN & MICHAEL McDONALD, *AMERICAN GRIDLOCK* 55, 59 (James A. Thurber & Antoine Yoshinaka eds., 2015); Bernard Grofman & Lisa Handley, *Identifying and Remediating Racial Gerrymandering*, 8 J.L. & POL. 345, 354 (1992). Zoning algorithms, though only briefly discussed in this Article, may be used in ways that perpetuate segregation by encouraging single-family developments rather than multi-family developments. See S. McCauley & S.J. Goetz, *Mapping Residential Density Patterns Using Multi-Temporal Landsat Data and a Decision-Tree Classifier*, 25 INT. J. REMOTE SENSING 1077, 1084 (2014). Algorithms that perpetuate segregation should be considered a form of algorithmic redlining and must be scrutinized accordingly — this work focuses on a particularly salient subset of these kinds of algorithms.

74. See DAVID MURAKAMI WOOD, *UNDERSTANDING SPATIAL MEDIA* 226–32 (Rob Kitchin et al. eds., 2015); Kenny Malone & Robert Smith, *Episode 798: The Bad Credit Bureau*, PLANET MONEY, NAT’L PUB. RADIO (Oct. 6, 2017), <https://www.npr.org/sections/money/2017/10/06/556212654/episode-798-bad-credit-bureau> [<https://perma.cc/C7UV-3E5F>] (“In 1874, if you wanted to buy groceries on store credit, the cashier would reach under the counter and pull out a little blue book. Inside would be your name, profession and whether you paid your debts on time. It was the beginning of the Equifax business model.”).

75. ROTHSTEIN, *supra* note 5, at 63–67.

76. *Id.*

Redlined neighborhoods were usually urban areas housing people of color.⁷⁷ In these neighborhoods, financially qualified community members were denied consideration for credit or mortgages because of their skin color, or even because they lived near a person of color.⁷⁸ Construed as an objective model to determine efficient lending, the U.S. Federal Housing Administration openly used redlined maps to inform computational evaluation algorithms for risk-rating calculations, racist cartography, and discriminatory tax appraisals.⁷⁹ Building upon these discriminatory evaluations, government funded public works and institutional investors were encouraged to direct their investments in white areas and disinvest from black communities.⁸⁰ Eventually, these race-based investment decisions became self-actualizing: by making it nearly impossible for black communities to obtain access to equitable housing finance, people and neighborhoods of color were forced into adverse financial circumstances and adverse living conditions.⁸¹

Today, the consequences of the era of redlining have stained the “big data” that determines conditions for housing financing. For example, scholars have recently made persuasive arguments that there have been racist practices in the credit reporting industry, which produces metrics that evaluate a person’s ever-important credit score.⁸² Similarly, academics have raised concerns that race-based evaluations play a role in determining mortgage rates for borrowers-of-color, an industry that heavily relies on credit scores.⁸³ Algorithms making biased choices regarding housing are also exhibited in analyses of the Great Recession, which saw an era of “reverse

77. Alex Rosenblat et al., *Data & Civil Rights: Consumer Finance Primer*, DATA & SOC’Y RESEARCH INST. & OPEN TECH. INST., 2014, at 1, <http://www.datacivilrights.org/pubs/2014-1030/Finance.pdf> [https://perma.cc/84N3-G9R9].

78. ROTHSTEIN, *supra* note 5, at 65 (“The [Federal Housing Authority] judged that properties would probably be too risky for insurance if they were in racially mixed neighborhoods or even in white neighborhoods near black ones that might possibly integrate in the future.”).

79. *Id.* at 169–72; see generally Jennifer Light, *Discriminating Appraisals: Cartography, Computation, and Access to Federal Mortgage Insurance in the 1930s*, 52 TECH. & CULTURE 485, 485–522 (2011).

80. ROTHSTEIN, *supra* note 5, at 93–137 (discussing the impact that redlining had on communities of color).

81. *Id.* at 109–13, 153–75 (discussing the impact redlining had on obtaining affordable housing, economic inequality, and intergenerational mobility).

82. MAYER-SCHÖNBERGER & CUKIER, *supra* note 2, at 92; Freeman, *supra* note 14, at 1071–72; Havard, *supra* note 15, at 241.

83. Madden et al., *supra* note 43, at 81; Rosenblat et al., *supra* note 77, at 3; Oren Bar-Gill & Elizabeth Warren, *Making Credit Safer*, 157 U. PA. L. REV. 1, 38 (2008).

redlining” — a shorthand for the practice of targeting African Americans for the hyper-lending of subprime mortgages.⁸⁴ Finally, consumer protection scholars and advocates have also alleged that algorithms have been used as a tool to predatorily target low-income people of color for the solicitation of highly usurious “payday loans,” adding to the barriers of financial hardship.⁸⁵ Importantly, each of the abovementioned practices relies on algorithms to limit access to desperately needed housing financing for communities of color.

1. *Credit Card Scoring and Algorithms Giving Access to Loans*

A credit score is a metric that lenders use to evaluate a person’s creditworthiness — a determination of whether it is safe to grant a loan to an applicant because she can be trusted to fulfill the obligations of that loan.⁸⁶ Traditionally, credit scores are compiled

84. Bar-Gill & Warren, *supra* note 83, at 66–67; Raymond H. Brescia, *Subprime Communities: Reverse Redlining, the Fair Housing Act and Emerging Issues in Litigation Regarding the Subprime Mortgage Crisis*, 2 ALB. GOV’T L. REV. 164, 173 (2009) (“Indeed more than half of the mortgages taken out by African-American families in 2005 had subprime features (as compared to the industry average of 20%), and 40% of Latino families taking out mortgages in 2005 were also subprime borrowers.”); Fisher, *supra* note 14, at 123–24.

85. See Bar-Gill & Warren, *supra* note 83, at 44 (“Payday loans provide another example of a credit product that can impose substantial costs on imperfectly informed and imperfectly rational borrowers. This consumer credit product is designed as a short-term cash advance offered at a fee. In a typical transaction, a consumer might pay a \$30 fee for a two-week \$200 cash advance. The fee structure of payday loans makes it difficult for consumers to compare directly the costs associated with a payday loan to the costs associated with other consumer credit products. In the typical payday loan described above, the \$30 fee corresponds to an annual interest rate of almost 400%.”). See generally UPTURN, LED ASTRAY: ONLINE LEAD GENERATION AND PAYDAY LOANS 8 (2015), https://www.upturn.org/static/reports/2015/led-astray/files/Upturn_-_Led_Astray_v.1.01.pdf [<https://perma.cc/27VK-XYW7>] [hereinafter LED ASTRAY].

86. See generally *Credit Card Redlining: Hearings Before the Subcommittee on Consumer Affairs of the Committee on Banking, Housing, and Urban Affairs, United States Senate, 96th Cong.* 189, 244 (1979), <https://archive.org/details/creditcardredlin00unit> [<https://perma.cc/4FEV-9EC4>] (statement of Gail S. Rubino, National Retail Merchants Association, arguing that credit scoring based on geographical location is not considered redlining); Danielle Keats Citron, *Reservoirs of Danger: The Evolution of Public and Private Law at the Dawn of the Information Age*, 80 S. CAL. L. REV. 241, 295 (2007) (exploring how an individual’s creditworthiness is critical to market identity and being a full, free person in the modern age); Havard, *supra* note 15, at 241; Brenda Reddix-Small, *Credit Scoring and Trade Secrecy: An Algorithmic Quagmire or How the Lack of Transparency in Complex Financial Models Scuttled the Finance Market*, 12 U.C. DAVIS BUS. L.J. 87, 88–89 (2011); ROBINSON + YU, KNOWING THE SCORE: NEW DATA, UNDERWRITING, AND MARKETING IN THE CONSUMER CREDIT MARKETPLACE 1, 4 (2014).

using sets of data mainly pertaining to a person's financial transactions.⁸⁷ However, like many other modern algorithms, credit scoring algorithms are beginning to include data points that go beyond personal financial transactions.⁸⁸ Using "big data," credit scoring firms claim that they will be able to make more accurate assessments of creditworthiness.⁸⁹ Unfortunately, like the redlined maps of the 1930s, many of the data points that algorithms use to generate credit scores have a disproportionately adverse impact on low-income communities of color, and, in some instances, even on those who patronize establishments in those communities.⁹⁰ For example, American Express came under scorn when customers complained that, even though they had successfully made credit payments, their scores were tarnished for shopping at establishments where other patrons are considered less "creditworthy."⁹¹

Such biased miscalculations are particularly worrisome because many industries use credit scores to assess whether someone qualifies for crucial needs such as housing financing. In the mortgage industry, lenders frequently rely on credit scores to determine whether to approve mortgages to home seekers, and to determine what rates of interest to charge when making loans.⁹² If credit scores are being generated using suspect, race-related data, such scoring operates to the disadvantage of communities of color by restricting access to equitable lending. This is particularly true as computer algorithms begin to heavily rely on zip codes to score society, because zip codes are often tied to race and socioeconomic status.⁹³

https://www.upturn.org/static/files/Knowing_the_Score_Oct_2014_v1_1.pdf
[<https://perma.cc/SX5Q-WLUQ>].

87. See Julius Adebayo & Mikella Hurley, *Credit Scoring in the Era of Big Data*, 18 YALE J.L. & TECH. 148, 159, 179 (2016).

88. See *id.* at 160.

89. See *id.* at 163.

90. See *id.* at 151.

91. See *id.*; O'NEIL, *supra* note 3, at 156–57.

92. See generally Jason Scott Johnston, *The Freedom to Fail: Market Access as the Path to Overcoming Poverty and Inequality*, 40 HARV. J.L. & PUB. POL'Y 41, 44 (2017); Jonelle Marte, *Here's How Much Your Credit Score Affects Your Mortgage Rate*, WASH. POST (Nov. 17, 2016), https://www.washingtonpost.com/news/get-there/wp/2016/11/17/heres-how-much-your-credit-score-affects-your-mortgagerate/?noredirect=on&utm_term=.dab31a344b39 [<https://perma.cc/84N3-G9R9>]; Rosenblat et al., *supra* note 77, at 3, 6.

93. See Matthew Adam Bruckner, *The Promise and Perils of Algorithmic Lenders' Use of Big Data*, 93 CHI.-KENT L. REV. 3, 3–4 (2018); Emily Badger & Quoc Trung Bui, *Detailed Maps Show How Neighborhoods Shape Children for Life*, N.Y. TIMES (Oct. 1, 2018), <https://www.nytimes.com/2018/10/01/upshot/maps-neighborhoods-shape-child-poverty.html> [<https://nyti.ms/2OrqCLI>].

Without access to housing finance, communities of color are restricted to rental options, diminishing (if not eviscerating) their opportunity to build equity through homeownership.⁹⁴ Even if biasedly-scored applicants are able to obtain mortgages, their interest rates will be higher — thus, they will likely be restricted to purchasable properties in low-value and low-income areas, which are often isolated from booming job markets and other desirable characteristics.⁹⁵ Ironically, as evidenced by post-mortems of the Great Recession, lenders use modern algorithms as a tool to target people of color whom lenders had determined to be more susceptible to high-interest loans. Thus, although credit scoring algorithms are a potentially biased barrier in accessing housing finance, other algorithms are used to target minority, disproportionately low-income applicants with financially burdensome loans. The ways in which algorithms have been used to burden minorities through reverse redlining, subprime mortgages, and payday loans is discussed in further detail in the coming section.

2. *Algorithms Used in Reverse Redlining, Subprime Mortgages, and Payday Loans*

As academics and consumer advocates started to diagnose the causes of the Great Recession, many began to suggest that part of the problem was the emergence of “reverse redlining.”⁹⁶ Reverse redlining is the practice of targeting minorities with home loans that have steep interest rates and complicated compliance provisions.⁹⁷ Irrespective of the biased metrics that generate poor creditworthiness ratings, in the leadup to the Great Recession, algorithms were used by lenders to target African Americans chasing the dream of homeownership; in reality, however, these lenders were burdening

94. See ROTHSTEIN, *supra* note 5, at 182; Sarah Molseed, *An Ownership Society for All: Community Development Financial Institutions as the Bridge Between Wealth Inequality and Asset-Building Policies*, 13 GEO. J. ON POVERTY L. & POL’Y 489, 490 (2006); Thomas M. Shapiro, *Race, Homeownership and Wealth*, 20 WASH. U. J.L. & POL’Y 53, 67–68 (2006).

95. See ROTHSTEIN, *supra* note 5, at 110–11.

96. See RAYMOND BRESCIA, *HOW CITIES WILL SAVE THE WORLD: URBAN INNOVATION IN THE FACE OF POPULATION FLOWS, CLIMATE CHANGE, AND INEQUALITY* 20 (2016); O’NEIL, *supra* note 3, at 40; Brescia, *supra* note 84, at 173; Fisher, *supra* note 14, at 126–27.

97. See Fisher, *supra* note 14, at 126–27; Bryce Goodman, *Discrimination, Data Sanitisation and Auditing in the European Union’s General Data Protection Regulation*, 2 EUR. DATA PROT. L. REV. 493, 501 (2016); Rheingold et al., *supra* note 56, at 651.

them with nightmare loans.⁹⁸ These minority individuals and families were often more willing to accept subprime loans because they were less familiar with lending practices and more desperate for housing finance, factors that are repercussions from the previous era of redlining and biased creditworthiness evaluations.⁹⁹ Moreover, because of the extremely high premiums attached to these loans, chances of default were more likely — defaults led to foreclosure, foreclosures led to evictions and vacancies, which created slums riddled with poverty, crime, and a general worsening of the quality of life.¹⁰⁰ Worryingly, these predatory lending practices have not ceased since the Great Recession.¹⁰¹ Rather, they have taken new form in algorithms used to target vulnerable populations through the solicitation of highly usurious “payday loans.”¹⁰²

Like subprime mortgages, payday loans are usually targeted at low-income, less educated American populations, who are often unable to understand the complicated interest rates and hidden fees attached to payday loans.¹⁰³ In a sense, the disproportionate disbursement of payday loans to low-income communities of color is the premier example of the ills of redlining, both pencil and algorithmic. Like subprime mortgages, targeted communities accept payday loans because of the desperation for financing, as indicated by the exorbitantly high interest rates they are willing to accept — this desperation is a product of pencil redlining, when no financing whatsoever was available.¹⁰⁴ Algorithms only exacerbate this problem because they target and market payday loans specifically to low-income communities of color, learning from preexisting data that residents in those communities will be more willing to subscribe to their usurious disbursements.¹⁰⁵ Unfortunately, because these communities are often underfunded and neglected, schools tend to

98. See IMMERGLUCK, *supra* note 65, at 89–90, 106; Fisher, *supra* note 14, at 126–27.

99. See IMMERGLUCK, *supra* note 65, at 107.

100. See ROTHSTEIN, *supra* note 5, at 186–87; Rheingold et al., *supra* note 56, at 651–52.

101. See Jack Smith IV, *This Is How Payday Lenders Dodge Google, Target the Vulnerable and Exploit the Poor*, MIC (Nov. 6, 2015), <https://mic.com/articles/128057/this-is-how-payday-lenders-dodge-google-target-the-vulnerable-and-exploit-the-poor#.vfMIKly0W> [<https://perma.cc/J72S-VSUD>].

102. See *id.*

103. See Bar-Gill & Warren, *supra* note 83, at 44; LED ASTRAY, *supra* note 85, at 3; Smith, *supra* note 101.

104. O’NEIL, *supra* note 3, at 81–82; *Dirty Money: Payday* (Netflix, Jan. 26, 2018).

105. Rheingold et al., *supra* note 56, at 651, 651 n.61.

perform poorly, leading to a less educated populous that is often less likely to be aware of a payday loan's usurious impact.¹⁰⁶

In sum, when the lending industry relies on automated, algorithmic decision-making systems, it also relies on biased technologies that disproportionately target and score minority individuals and their families more negatively.¹⁰⁷ Biased targeting and scoring technologies thus limit access to housing finance, which in turn narrows the scope of where minority individuals and families can search for housing. Moreover, because biased algorithms disproportionately target minorities and low-income individuals, these already marginalized populations are forced to limit their housing searches to properties in communities that have homes of lesser value — communities, as it often turns out, already populated by minorities and other low-income families.¹⁰⁸ These communities are continually neglected, leading to a lack of wealth and investment, which results in living conditions that are inadequate and unstable. Consequently, persons of means — composed primarily of non-minorities — avoid searching for housing in these areas, further exacerbating preexisting segregation.¹⁰⁹

3. *Discriminatory Algorithms in Housing Advertisements and Marketing*

The previous section detailed a basic agenda for researching algorithmic redlining in the context of access to housing finance. This section discusses another form of algorithmic redlining, home searching algorithms, and details the importance of why further research and scrutiny is also needed in this area. The online housing-search process for communities and individuals of color is another potential cause of perpetuating segregation.¹¹⁰

As University of Chicago Law Professor Lee Anne Fennell explains in her 2017 article, *Searching for Housing*, some online home-seeker biases may come from user-generated preferences, causing what is popularly known as *de facto* segregation.¹¹¹ For example, many online housing marketers allow users to establish their

106. See O'NEIL, *supra* note 3, at 202–03; Bar-Gill & Warren, *supra* note 83, at 44–45.

107. Citron & Pasquale, *supra* note 43, at 5 (“There is nothing unbiased about scoring systems.”).

108. Fennell, *supra* note 47, at 361.

109. *See id.*

110. *See id.*

111. *See id.*

own search characteristics and, therefore, biases can be attributed to the preferences of the searchers rather than the algorithms.¹¹² However, as Fennell suggests, some biases may be built into third-party algorithms in assumptions coded directly into search engine or home marketing website algorithms.¹¹³ This hypothesis regarding biased search results is increasingly troubling as more people utilize the internet to search for housing.¹¹⁴ As more and more home seekers turn to online portals to find where to live, it is important to understand that internet marketers and search engine operators use algorithms to provide users with a more personalized experience¹¹⁵ by cataloging user search histories, conducting geographical filtering, and using “bots” that “scrape” webpages to compile user information.¹¹⁶

By incorporating an internet user’s “scraped” information and utilizing other aggregated data, algorithms can generate personalized advertising based on a user’s “latent trait inferences.”¹¹⁷ Latent trait inferences are assumptions about users that algorithms generate by analyzing their digital footprint.¹¹⁸ Online advertising platforms use latent trait inferences to target consumers and promote products they believe will lead to consumption.¹¹⁹ In theory, the attempt by online marketers and search engine providers to create more personalized ads based on latent trait inferences is merely an extension of

112. *See id.*

113. *See id.* at 362.

114. JESSICA LAUTZ ET AL., NAT’L ASS’N OF REALTORS, REAL ESTATE IN A DIGITAL AGE: REPORT 2017 2 (2017), <https://www.nar.realtor/sites/default/files/reports/2017/2017-real-estate-in-a-digital-age-03-10-2017.pdf> [<https://perma.cc/MV2M-U5UV>] (“In 1981, 22 percent of home buyers read newspaper ads to find a home and eight percent used friends as an information source. In 2016, 44 percent looked for properties online first.”); THE DIGITAL HOUSE HUNT: CONSUMER AND MARKET TRENDS IN REAL ESTATE, NAT’L ASSOC. OF REALTORS & GOOGLE 2–3 (2013), https://www.nar.realtor/sites/default/files/documents/Study-Digital-House-Hunt-2013-01_1.pdf. [<https://perma.cc/F69P-ZSTA>].

115. *See* PASQUALE, *supra* note 35, at 20.

116. *See* Jack M. Balkin, *Free Speech in the Algorithmic Society: Big Data, Private Governance, and New School Speech Regulation*, 51 U.C. DAVIS L. REV. 1149, 1204 (2018); Alice E. Marwick, *How Your Data Are Being Deeply Mined*, N.Y. REV. BOOKS (Oct. 30, 2013), <https://www.nybooks.com/articles/2014/01/09/how-your-data-are-being-deeply-mined/> [<https://perma.cc/WK7Z-N82R>]; Paris Martineau, *How the Bathing Suit You Looked at Online Once Follows You Around for Two Months*, OUTLINE (Apr. 20, 2018), <https://theoutline.com/post/4224/how-that-ad-follows-you-all-around-the-internet> [<https://perma.cc/HK4F-H7T4>].

117. *See* O’NEIL, *supra* note 3, at 70; Balkin, *supra* note 116, at 1204; Tim Wu, *Blind Spot: The Attention Economy and the Law*, ANTITRUST L.J. 1, 20 (2017).

118. *See* PASQUALE, *supra* note 35, at 39.

119. Wu, *supra* note 117, at 13–14.

traditional marketing practices, which attempted to do the same with larger demographics.¹²⁰ But in practice, as the algorithms that inform the process of personalization become more sophisticated, advertisers are able to target consumers more and more precisely, leading to predatory and discriminatory marketing practices.¹²¹

When internet marketers and search engine providers deploy algorithms that capture and analyze user data, and then generate decisions based on that data, they serve as functional “gatekeepers” and “editors.” As gatekeepers, advertising and search engine algorithms determine what information is displayed to any particular consumer.¹²² As editors, they determine how information already displayed is prioritized.¹²³ In the housing arena, online marketing and search platforms potentially create algorithmic redlining if they are serving as biased gatekeepers or editors. For example, as discussed

120. Ken Auletta, *How the Math Men Overthrew the Mad Men*, NEW YORKER (May 21, 2018), <https://www.newyorker.com/news/annals-of-communications/how-the-math-men-overthrew-the-mad-men> [<https://perma.cc/FLD9-PFNP>]; *Planet Money, Episode 678: This Ad's for You*, NAT'L PUB. RADIO (May 29, 2015), <https://www.npr.org/templates/transcript/transcript.php?storyId=410589806> [<https://perma.cc/JYY5-D996>].

121. See generally MAJORITY STAFF, OFFICE OF OVERSIGHT & INVESTIGATIONS, SENATE COMM. ON COMMERCE, SCI., & TRANSP., A REVIEW OF THE DATA BROKER INDUSTRY: COLLECTION AND SALE OF CONSUMER DATA FOR MARKETING PURPOSES 12, 24–25 (2013), http://www.commerce.senate.gov/public/?a=Files.Serve&File_id=bd5dad8b-a9e8-4fe9-a2a7-b17f4798ee5a [<https://perma.cc/UXP8-QULC>]; Edith Ramirez, Chairwoman, Fed. Trade Comm'n, Opening Remarks at FTC Fall Technology Series: Ransomware, at 3, 4 (Sept. 7, 2016), https://www.ftc.gov/system/files/documents/public_statements/983593/ramirez_-_ransomware_remarks_9-7-16.pdf [<https://perma.cc/4H97-FR34>] (referencing FED. TRADE COMM'N, DATA BROKERS: A CALL FOR TRANSPARENCY AND ACCOUNTABILITY 26 (2014), <http://www.ftc.gov/system/files/documents/reports/data-brokers-call-transparency-accountability-report-federal-trade-commission-may-2014/140527databrokerreport.pdf> [<https://perma.cc/R9PY-7BSN>]) (noting that this narrowed focus gives internet platforms the ability to target a consumer based on personally identifiable data that is usually gathered by a shadowy “data broker” and then sold to the advertising platform); O'NEIL, *supra* note 3, at 78–80 (discussing modern marketing algorithms); Zeynep Tufekci, *Algorithmic Harms Beyond Facebook and Google: Emergent Challenges of Computational Agency*, 13 J. ON TELECOMM. & HIGH TECH. L. 203, 209 (2015); Charles Duhigg, *Bilking the Elderly with a Corporate Assist*, N.Y. TIMES: BUS. DAY (May 20, 2007), <http://www.nytimes.com/2007/05/20/business/20tele.html?pagewanted=all> [<https://nyti.ms/2m4hOgU>]; Michael Kosinski, Opinion, *Congress May Have Fallen for Facebook's Trap, but You Don't Have to*, N.Y. TIMES (Dec. 12, 2018), <https://www.nytimes.com/2018/12/12/opinion/facebook-data-privacy-advertising.html> [<https://nyti.ms/2zV3ih0>] (discussing Facebook's methods of utilizing user data for targeted advertising).

122. See Tufekci, *supra* note 121, at 206, 208.

123. See *id.* at 206; Wu, *supra* note 117, at 20.

further below, by using “big data” and making accurate latent trait inferences about users, platforms can accurately identify users through race-correlative data points like zip code, name, profile picture, or various other data points in a user’s digital footprint.¹²⁴ When internet home marketing and search engines use these segregating scoring systems to stereotype and make assumptions about consumers, they nudge seekers of color towards houses available in communities and neighborhoods predominantly comprised of minorities, while simultaneously nudging white home seekers toward options in predominantly white and wealthy communities, thereby perpetuating preexisting segregation.¹²⁵

To be sure, this is only one of many *potential* harms in online home marketing that could result from automated decision-making, and should be studied further.¹²⁶ Currently, there is little data on how websites like Trulia, Craigslist, or Facebook prioritize their millions of listings, because these massive databases have utilized intellectual property laws to incorporate a veil of secrecy in an effort to protect their code.¹²⁷ In 2018, however, a lawsuit was filed against social-media juggernaut Facebook, alleging that the abovementioned discriminatory marketing practices occurred on its website.¹²⁸ Fair-housing advocates brought the challenge, stating that Facebook had been “encourage[ing] its paid advertisers to discriminate using its vast trove of personal data.”¹²⁹ Though alarming, the litigation filed

124. See MAYER-SCHÖNBERGER & CUKIER, *supra* note 2, at 90; Balkin, *supra* note 116, at 1164.

125. See Fennell, *supra* note 47, 361–63.

126. EXEC. OFFICE OF THE PRESIDENT, BIG DATA: A REPORT ON ALGORITHMIC SYSTEMS, OPPORTUNITY, AND CIVIL RIGHTS 5 (2016), https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/2016_0504_data_discrimination.pdf [<https://perma.cc/ZZ9Q-JZ2Z>] (detailing several areas of potential harm but focusing mainly on criminal justice, employment, higher education, marketing and lending, particularly access to credit, and mentioning housing only in brief); Fennell, *supra* note 47, at 361.

127. Frank Pasquale, *Internet Nondiscrimination Principles: Commercial Ethics for Carriers and Search Engines*, 2008 U. CHI. LEGAL F. 263, 282, 284.

128. Complaint, Nat’l Fair Hous. All. et al. v. Facebook Inc., No. 18 Civ. 2689 (S.D.N.Y. Mar. 27, 2018).

129. Samantha Schmidt, *Facebook Sued for Allegedly Allowing Housing Advertisers to Discriminate*, CHI. TRIB. (Mar. 28, 2018), <https://www.chicagotribune.com/business/ct-biz-facebook-sued-housing-discrimination-20180328-story.html> [<https://perma.cc/HZJ5-NN3C>]. This lawsuit was settled on March 19, 2019. See Opinion, *Facebook Faces a Reckoning for Redlining*, N.Y. TIMES (Mar. 29, 2019), <https://www.nytimes.com/2019/03/29/opinion/facebook-discrimination-civil-rights.html> [<https://nyti.ms/2CJmFL2>]; *Facebook Settlement*, NAT’L FAIR HOUSING ALLIANCE, <https://nationalfairhousing.org/facebook-settlement/> [<https://perma.cc/JZ8P-TM3M>].

against Facebook’s alleged marketing practices should come as no surprise. While research on how algorithms impact the marketing of *housing* is scant, there is abundant data showing that other areas of online advertising — while not specifically incorporating race — have incorporated race-compatible data points that produce race-oriented results.¹³⁰ The use of race-compatible data points in online algorithms has drawn the ire of scholars and policymakers alike, who have reported that algorithms can come to biased conclusions that assume a person’s race based on factors like name, geographical region, record of consumer purchases, public records, and myriad other sources.¹³¹ These scholars and policymakers argue that by allowing advertisers to use race-compatible data points, we also allow them to harmfully stereotype consumers.¹³²

One stark example of this is found in a 2012 study commissioned by the Obama administration, which was tasked with assessing the impact and use of big data in targeted online advertisements.¹³³ The study showed that search-engine inquiries for typically African-American names lead to “negative” advertisements, such as those that contained the word “arrest.”¹³⁴ Accordingly, a hypothetical person named Jerome who lives in a high-crime neighborhood, buys a pack of cigarettes a week, and has had a prior eviction, may be directed to options that would be considered “negative.”¹³⁵ By contrast, typically Caucasian-American names lead to “neutral” advertisements.¹³⁶ Anecdotes from other recent experiments concerning automated decisions indicate similarly biased results.¹³⁷ One study showed that artificial intelligence algorithms overwhelmingly responded to queries with the term, “beauty,” by producing results that leaned toward favoring white (or at least lighter) skin tones.¹³⁸

130. BIG DATA: SEIZING OPPORTUNITIES, *supra* note 42, at 8; PASQUALE, *supra* note 35, at 20.

131. PASQUALE, *supra* note 35, at 39.

132. *Id.*

133. BIG DATA: SEIZING OPPORTUNITIES, *supra* note 42, at 3.

134. *Id.* at 7.

135. PASQUALE, *supra* note 35, at 39.

136. *See id.*; BIG DATA: SEIZING OPPORTUNITIES, *supra* note 42, at 7.

137. *See generally* NOBLE, *supra* note 3, at 25 (discussing the trend of auto-predictions in search engines queries that begin with “why are black girls . . .” ending with predictions such as “. . . always angry,” and similar results).

138. Sam Levin, *A Beauty Contest Was Judged by AI and the Robots Didn’t Like Dark Skin*, GUARDIAN (Sept. 8, 2016), <https://www.theguardian.com/technology/2016/sep/08/artificial-intelligence-beauty-contest-doesnt-like-black-people> [https://perma.cc/C825-WJQP]; Natasha Lomas,

Consequently, it seems that winning the uphill battle of fair and sufficient housing finance may be, to this day, a Sisyphean chore, as people of color may still be subjected to internet search and marketing algorithms that discriminatorily segregate communities based on race. By acting as biased gatekeepers and editors, and by considering biased and discriminatory data points in their algorithms, online lending and housing search platforms are potentially prioritizing user-specific advertising at the expense of equitable marketing. Such algorithmic redlining is harmful to the welfare of consumers from minority communities and only serves to reinforce cascading segregation.¹³⁹

B. When You Can't Buy, Rent: Affordable Housing and Rental Housing Selection Algorithms

Unfortunately, as a result of the many impediments discussed above, low-income, predominantly minority individuals living in communities of color, are often unable to purchase housing.¹⁴⁰ Once purchasing is not a viable option, seekers-of-color are left to fend for themselves in competitive and pricey rental housing markets.¹⁴¹

FaceApp Apologizes for Building Racist AI, TECHCRUNCH (Apr. 25, 2017), <https://techcrunch.com/2017/04/25/faceapp-apologises-for-building-a-racist-ai/> [<https://perma.cc/DU38-XSNV>]; Fiona Rutherford & Alan White, *This Is Why Some People Think Google's Results Are "Racist,"* BUZZFEED (Apr. 12, 2016), <https://www.buzzfeed.com/fionarutherford/heres-why-some-people-think-googles-results-are-racist> [<https://perma.cc/DU38-XSNV>] (discussing how Google's search engine brings up mainly white people when users search for "beauty," though Google has denied this is any intentional bias on their part, claiming that this is just the way society thinks); see also DENISE MURRELL, *POSING MODERNITY: THE BLACK MODEL FROM MANET AND MATISSE TO TODAY* 116–18 (2018) (discussing how artists during the Harlem Renaissance sought to change the stigma of African Americans, particularly those from inner cities such as Harlem); Margaret Talbot, *The Myth of Whiteness in Classical Structure*, NEW YORKER (Oct. 29, 2018), <https://www.newyorker.com/magazine/2018/10/29/the-myth-of-whiteness-in-classical-sculpture> [<https://perma.cc/T7HM-4NAS>] (discussing how, through our false awareness of color in ancient art, we associate positive things with whiteness and negative things with color, and that we have "a tendency to equate whiteness with beauty, taste, and classical ideals, and to see color as alien, sensual, and garish").

139. PASQUALE, *supra* note 35, at 56; Rory Van Loo, *Rise of the Digital Regulator*, 66 DUKE L.J. 1267, 1269 (2017) (discussing how digital intermediaries influence the behavior of public actors and cause suboptimal decisions).

140. MARTIN ET AL., *supra* note 66, at 30.

141. Justin Fox, *New York's Have and Have-Not Housing Market*, BLOOMBERG (Feb. 22, 2018), <https://www.bloomberg.com/view/articles/2018-02-22/new-york-s-housing-market-favors-wealthier-renters> [<https://perma.cc/8399-DW4B>]; La Ganga, *supra* note 53; David Schaper, *Houston's Tight Rental Market Makes It Tough for Low-Income Hurricane Victims*, NAT'L PUB. RADIO (Sept. 18, 2017),

While rental and subsidized markets do not provide the same equity value and cost-benefits of homeownership, these options are still important to overall quality of life.¹⁴² Fortunately, affordable housing development has been on the rise, and creative policies to expand affordable housing have recently been advanced.¹⁴³ But even if a seeker-of-color resigns herself to renting rather than purchasing, a hurdle remains: algorithms that determine rental tenancy can fall prey to the same biases as algorithms in the housing purchase realm, thereby exacerbating and furthering the harms of algorithmic redlining.

Affordable housing plays a pivotal role in the public's overall well-being,¹⁴⁴ but, because of its low cost, access to affordable housing is extremely competitive.¹⁴⁵ Undoubtedly, algorithms are a powerful tool to assign affordable rental housing as efficiently as possible.¹⁴⁶

<https://www.npr.org/2017/09/18/551726491/houstons-tight-rental-market-makes-it-tough-for-low-income-hurricane-victims> [<https://perma.cc/PF8P-CYQ7>].

142. MARTIN ET AL., *supra* note 66, at 30.

143. Saraf Ahmed, *5 Cities Taking Steps to Improve Affordable Housing Access and Availability*, FORBES (June 21, 2017), <https://www.forbes.com/sites/bisnow/2017/06/21/5-cities-taking-steps-to-improve-affordable-housing-access-and-availability/#496429363f9f> [<https://perma.cc/BEW3-HJV5>]; Henry Grabar, *Minneapolis Confronts Its History of Housing Segregation*, SLATE (Dec. 7, 2018), <https://slate.com/business/2018/12/minneapolis-single-family-zoning-housing-racism.html> [<https://perma.cc/6P6Z-2ENJ>]; Jillian Weinberger, *Leaving Baltimore Behind*, VOX (Nov. 30, 2018), <https://www.vox.com/the-impact/2018/11/30/18116513/baltimore-the-impact-income-inequality-race-housing-segregation> [<https://perma.cc/D37X-HWS8>].

144. *See, e.g.*, National Affordable Housing Act, 42 U.S.C. § 12702 (2012) (stating that the objective of the National Affordable Housing Act is to introduce policies that “reaffirm the long-established national commitment to decent, safe, and sanitary housing for every American”).

145. *See, e.g.*, Tanya Warekar, *Essex Crossing's First Affordable Housing Lottery Nets Over 93,000 Applicants*, CURBED (June 8, 2017), <https://ny.curbed.com/2017/6/8/15761716/essex-crossing-affordable-housing-applications> [<https://perma.cc/R5XH-3U57>] (demonstrating the disproportionality of the solution to the problem: over 93,000 applicants for only 104 available affordable units).

146. Caitlin Dewey, *Creepy Startup Will Help Landlords, Employers and Online Dates Strip-Mine Intimate Data from Your Facebook Page*, WASH. POST (June 9, 2016), <https://www.washingtonpost.com/news/the-intersect/wp/2016/06/09/creepy-startup-will-help-landlords-employers-and-online-dates-strip-mine-intimate-data-from-your-facebook-page/?noredirect=on> [<https://perma.cc/R5L6-7C3J>]; Dia Kayyali, *Big Data and Hidden Cameras Are Emerging as Dangerous Weapons in the Gentrification Wars*, QUARTZ (Aug. 23, 2016), <https://qz.com/763900/surveillance-and-gentrification/> [<https://perma.cc/7LQZ-J8PQ>] (discussing big data and tenant screening firms); David Silverberg, *Landlords Are Using a New Digital Tool to Dig Up Dirt on Potential Tenants*, MOTHERBOARD (Sept. 12, 2016), https://motherboard.vice.com/en_us/article/yp35ev/landlords-naborly-tenants-toronto-vancouver-rentals [<https://perma.cc/Z6J4-CLH6>].

As beneficial as some these algorithms may be,¹⁴⁷ some have nonetheless been the subject of scrutiny from both legal observers and housing advocates.¹⁴⁸ As examined below, fair housing advocates and watchdog groups have asserted that the algorithms used in affordable housing lotteries rely on improper, biased preferences.¹⁴⁹ Further, algorithms are playing an increasingly important role in deciding who qualifies for private-market rental units, often tilting the playing field against individuals from low-income, minority neighborhoods.¹⁵⁰

1. *Improper Preferences in Affordable Housing Algorithms*

Recognizing the importance of housing affordability, federal, state, and local governments have enacted legislation encouraging and, at times, requiring available affordable housing — that is, housing provided below market rate and available on an income-driven basis.¹⁵¹ These heavier government requirements, coupled with rising market demand for affordable housing, have prompted housing authorities, as well as the landlords and developers they work with, to assess how to most efficiently administer and disburse affordable housing units to tenants.¹⁵² As already mentioned, algorithms are a powerful tool to enhance efficiency, and so have unsurprisingly become heavily intertwined in the administration of affordable

147. HALIL TOROS & DANIEL FLAMING, PRIORITIZING WHICH HOMELESS PEOPLE GET HOUSING USING PREDICTIVE ALGORITHMS, ECONOMIC ROUNDTABLE 1 (2017), <https://economicrt.org/wp-content/uploads/2017/04/Prioritizing-Which-Homeless-People-Get-Housing-Using-Predictive-Algorithms.pdf> [<https://perma.cc/SEJ8-NQKC>].

148. Fennell, *supra* note 47, at 362.

149. Schmidt, *supra* note 129.

150. Dunn & Ehman, *supra* note 18, at 36–38.

151. See 42 U.S.C. § 12702 (2012); see also A BRIEF HISTORICAL OVERVIEW OF AFFORDABLE RENTAL HOUSING, NATIONAL LOW INCOME HOUSING COALITION 8–9 (2015), https://nlihc.org/sites/default/files/Sec1.03_Historical-Overview_2015.pdf [<https://perma.cc/T3MQ-FGZE>]; David Roberts, *The Future of Housing Policy Is Being Decided in California*, VOX (Apr. 4, 2018), <https://www.vox.com/cities-and-urbanism/2018/2/23/17011154/sb827-california-housing-crisis> [<https://perma.cc/3E3E-4FYB>] (describing a series of reforms passed by the California legislature and signed into law by then governor Jerry Brown); *Mandatory Housing Inclusion, How It Works*, N.Y.C. DEPT OF HOUSING (2018), <http://www1.nyc.gov/assets/housing/downloads/pdf/mih-fact-sheet.pdf> [<https://perma.cc/U4D2-DR2M>].

152. David Thacher, *The Rise of Criminal Background Screening in Rental Housing*, 33 L. & SOC. INQUIRY 5, 11–18 (2008); Dunn & Ehman, *supra* note 18, at 36–38.

housing.¹⁵³ While enhancing the efficient production and distribution of affordable housing, many of these algorithms have also been labelled discriminatory.

In New York City, for example, Mayor Bill de Blasio's administration introduced — and the city council passed — policies requiring that approximately twenty percent of all new housing development be reserved as “affordable housing.”¹⁵⁴ To be recognized as “affordable,” units must satisfy two conditions: first, they have to be rented at a rate below market value, typically thirty percent less than other comparable units in the same building; second, they must be available only to applicants that earn a certain percentage below the building's area median income.¹⁵⁵ With this approach in place, individuals and families are able to apply to an “affordable housing lottery” that randomly selects applicants pending a screening process to assess whether they qualify for one of the affordable housing units.¹⁵⁶ Though designating a block of units for low-income individuals and families may help integrate neighborhoods, these efforts are often insufficient, particularly when the algorithms used to generate such decisions remain faulty.¹⁵⁷

For instance, while New York's approach is lauded as progressive, the algorithm used to select lottery applicants for screening also allegedly has a built-in bias: a preference for members of the surrounding community.¹⁵⁸ Advocates and lawmakers have challenged this preferential treatment and argue that it gives an unfair advantage to individuals that already live in the area.¹⁵⁹ These critics

153. See *supra* note 73 and accompanying text.

154. See N.Y.C. DEP'T OF HOUSING, *supra* note 151.

155. See *Affordability and Area Median Income (AMI)*, N.Y.C. DEP'T OF HOUSING PRESERVATION & DEV. (2018), <https://www1.nyc.gov/site/hpd/renters/area-median-income.page> [<https://perma.cc/L46U-9WNS>]; *Income Eligibility*, N.Y.C. HOUSING DEV. CORP. (2018), <http://www.nychdc.com/pages/Income-Eligibility.html> [<https://perma.cc/QKQ8-XRNS>].

156. See Mariela Quintana, *How the NYC Affordable Housing Lottery Works*, STREETEASY.COM (Apr. 17, 2018), <https://streeteasy.com/blog/nyc-affordable-housing-lottery/> [<https://perma.cc/GW34-86Y8>].

157. See Kathryn Brenzel, *New York City Is Still Segregated 50 Years After Fair Housing Act*, THEREALDEAL (Apr. 23, 2018), <https://therealdeal.com/2018/04/23/city-is-still-segregated-50-years-after-fair-housing-act/> [<https://perma.cc/B3MD-ZXEZ>]; Warekar, *supra* note 145.

158. See Quintana, *supra* note 156. It is worth mentioning that while selection algorithms have drawn scorn from across the country, they are addressed only briefly here.

159. See Sally Goldenberg, *50 Years After Fair Housing Act, New York City Still Struggles with Residential Segregation*, POLITICO (Apr. 23, 2018), <https://www.politico.com/states/new-york/albany/story/2018/04/23/50-years-after-fair->

often suggest that the preference policy keeps neighborhoods demographically homogeneous.¹⁶⁰ Even though affordable housing algorithms are the product of government policy, they face the same challenges that corporate algorithms must contend with — they are obtuse, overly relied upon, and built using questionable data.¹⁶¹

The obtuseness of government affordable housing algorithms is similar to the veil of secrecy surrounding the aforementioned internet marketing websites.¹⁶² Some municipalities disclose the details of their affordable housing lottery preferences, but for most of the tens of thousands of applicants jockeying for a few hundred units, the lottery and selection process remain a mystery.¹⁶³ Moreover, city and state governments are turning to algorithms to make choices concerning affordable housing and, with increasing frequency, algorithmic decisions are having the last word.¹⁶⁴ Of course, algorithms can be shortcuts to efficiently administering remedial decisions and approving a balanced pool of applicants, but reliance on these automated decisions without the prudence of human intuition may be costly and exacerbate segregation.

Even if the veil of secrecy was lifted and the details of algorithms were known, applicants and fair housing advocates have raised concerns that some factors introduced by municipalities or affordable unit landlords are biased and antithetical to integration.¹⁶⁵ Consider the 2010 dispute between the Department of Justice and the wealthy

housing-act-new-york-city-still-struggles-with-residential-segregation-376170 [https://perma.cc/7LDZ-K53K].

160. See Ethan Geringer-Sameth, *'Community Preference' Lawsuit at Center of Affordable Housing, Segregation Debates*, GOTHAM GAZETTE (Mar. 29, 2017), <http://www.gothamgazette.com/city/6838-community-preference-lawsuit-at-center-of-affordable-housing-segregation-debates> [https://perma.cc/4N4A-HGAE]; Mireya Navarro, *New York City Is Sued Over Lotteries Used for Subsidized Housing*, N.Y. TIMES (July 7, 2015), <https://www.nytimes.com/2015/07/08/nyregion/new-york-city-is-sued-over-lotteries-used-for-subsidized-housing.html> [https://nyti.ms/1NMMHtU].

161. See generally Dunn & Ehman, *supra* note 18, at 36–38.

162. See *id.*

163. See Lauren Cook, *How NYC's Affordable Housing Lottery Works: NYCurious*, AM N.Y. (June 20, 2018), <https://www.amny.com/real-estate/nyc-affordable-housing-lottery-explained-1.12691144> [https://perma.cc/8KSN-CT53].

164. See *id.*

165. See Jessica Lerner, *Developer Heads to Court over Denial of Branford Affordable Housing Project*, NEW HAVEN REGISTER (Feb. 26, 2018), <https://www.nhregister.com/metro/article/Developer-heads-to-court-over-denial-of-Branford-12710499.php> [https://perma.cc/26J7-HTKP]; Hiram Sasser, *How Zoning Can Be a Subtle Kind of Bigotry*, N.Y. POST (Dec. 14, 2018), <https://nypost.com/2018/12/14/how-zoning-can-be-a-subtle-kind-of-bigotry/> [https://perma.cc/N4PQ-6E5X].

Connecticut township of Darien, an idyllic town about midway between New York City and New Haven, Connecticut, with high-performing public schools and an overall high quality of life.¹⁶⁶ In 2010, Darien's population was 94 percent white,¹⁶⁷ and when a developer purchased a plot of land with the goal of providing affordable housing, Darien's affordable housing algorithmic weighing system came under scrutiny.¹⁶⁸ Darien's municipal algorithm distributed affordable housing based on a "priority population" preference system, which provided that available affordable units "shall be offered for sale or rent to income eligible households in accordance with [a set of seven] priority designations."¹⁶⁹ The first six priority categories gave preference to Darien residents or former Darien residents, with the lowest priority category explicitly relegating "[a]ll other individuals or families" to an afterthought.¹⁷⁰ Darien's process would obviously work to the disadvantage of housing applicants from nearby Norwalk or Bridgeport, Connecticut towns with substantial minority populations and far less opportunity.¹⁷¹ Indeed, Darien's suspect procedure was going to be investigated by the Department of Justice,¹⁷² and, fortunately, Darien withdrew its policy after the Department of Justice intervened.¹⁷³ Unfortunately, however, such preference systems still exist elsewhere,

166. See Renee Williams, *Recent Developments in Challenges to Residency Preferences*, 43 HOUSING L. BULL. 129, 131 (2013).

167. See *id.*

168. See Lisa Prevost, *Snob Zones: Fear, Money, and Real Estate*, SALON (July 20, 2013), https://www.salon.com/2013/07/20/snob_zones_fear_money_and_real_estate/ [<https://perma.cc/HQ5Q-SUSY>].

169. TOWN OF DARIEN AFFORDABLE HOUSING PLAN 50–51 (approved August 24, 2009) (detailing seven priority designations, from highest to lowest, as follows: "(a) Individuals or families who live and work in the Town of Darien who provide volunteer emergency/life-saving services for residents of the Town. (b) Individuals or families who are employed by the Town of Darien or Darien Public School system. (c) Individuals or families who live and work in the Town of Darien. (d) Individuals or families who live in the Town of Darien. (e) Individuals who work in the Town of Darien. (f) Individuals or families who previously lived for a minimum of one (1) year in the Town and wish to return. (g) All other individuals or families.").

170. See *id.*

171. See Erin Boggs, *Testimony of Open Communities Alliance in Support of HB 7297, An Act Establishing a Private Right of Action in the Duty to Promote Fair Housing and Requiring a Study of Connecticut's Housing Inventory and Current and Future Housing Needs*, Sess. Year 2017 (Mar. 22, 2017), <https://www.cga.ct.gov/2017/PDdata/Tmy/2017HB-07297-R000322-Boggs,%20Erin,%20Executive%20Director%20Open%20Communities%20Alliance%20-TMY.PDF> [<https://perma.cc/L26Y-GZ7J>].

172. See Williams, *supra* note 166, at 131.

173. See Prevost, *supra* note 168.

in urban areas such as New York City and in affluent suburbs like Cheshire, Connecticut.¹⁷⁴

2. Rental Housing Algorithms

Issues similar to those of publicly administered affordable housing algorithms have been raised about tenancy selection application algorithms utilized by the private rental sector.¹⁷⁵ Under the FHA, landlords with rental units on the private market must adhere to a federal standard of nondiscrimination — they cannot refuse to rent a unit for reasons that rely on protected-class characteristics such as race.¹⁷⁶ Though the algorithms that evaluate modern rental applications do not explicitly incorporate race, they often take account of a massive amount of statistics (through big data) that closely correlate with race, such as credit score, eviction records, arrest records, levels of education, employment backgrounds, and previous addresses.¹⁷⁷ In another example of the “scored society,” because rental markets are so closely competitive, landlords often employ “tenant-screening firms” to “score” rental applicants and determine the applicant’s likely performance as a tenant.¹⁷⁸

174. See CHESHIRE COUNTY ZONING REGULATIONS § 44.5 (as amended 2016), <http://www.cheshirect.org/media/93458/amended-zoning-regs-2016.pdf> [<https://perma.cc/7SAN-UQQN>]; J. David Goodman, *From Former De Blasio Official, an Admission on Segregation*, N.Y. TIMES (May 2, 2018), <https://www.nytimes.com/2018/05/02/nyregion/nyc-segregation-affordable-housing.html> [<https://nyti.ms/2FCIghoh>].

175. See generally Dunn & Ehman, *supra* note 18, at 36–38; see also Jonathan Mahler & Steve Eder, *‘No Vacancies’ for Blacks: How Donald Trump Got His Start, and Was First Accused of Bias*, N.Y. TIMES (Aug. 27, 2016), <https://www.nytimes.com/2016/08/28/us/politics/donald-trump-housing-race.html> [<https://nyti.ms/2bOYUVI>] (noting that in its most straightforward and pernicious form, one method of “algorithmic redlining” is simply never reviewing applications from people of color).

176. See, e.g., 42 U.S.C. § 3601 (“It is the policy of the United States to provide, within constitutional limitations, for fair housing throughout the United States.”); see also *Ohana v. 180 Prospect Place Realty Corp.*, 996 F. Supp. 238, 240 (E.D.N.Y. 1998) (“[The FHA] is intended to promote ‘open, integrated residential housing patterns and to prevent the increase of segregation, in ghettos, of racial groups whose lack of opportunities the Act was designed to combat.’”) (citing *Otero v. N.Y.C. Hous. Auth.*, 484 F.2d 1122, 1134 (2d Cir. 1973)).

177. See Thacher, *supra* note 152, at 11, 12; Dunn & Ehman, *supra* note 18, at 35, 36; Devon Thorsby, *Are Online Applications Making Renting an Apartment Easier or Harder?*, U.S. NEWS (Aug. 10, 2016), <https://realestate.usnews.com/real-estate/articles/are-online-applications-making-renting-an-apartment-easier-or-harder> [<https://perma.cc/6Z45-U4YV>].

178. See Dunn & Ehman, *supra* note 18, at 35–36.

Unfortunately, like the scoring systems in housing finance, these scores are sometimes generated using biased or bad data.¹⁷⁹

As was the case with increasing transparency in housing finance to provide more equitable lending opportunities for borrowers-of-color, increasing transparency in renting will make a significant impact. Transparency in decisions regarding who has access to rental housing, who sees marketed units for rent, and who gets selected for those units is crucial to a fair rental housing process that promotes community integration. It is evident that without appropriate reform people of color will continue to bear much of the brunt of biased data and discriminatory algorithms. So what are some of the solutions to correct bad data and corrupt automated decisions? This next Part explores prior reforms to the era of pencil redlining and potential reforms needed to bring those policies into the modern age.

III. POLICIES AND SOLUTIONS: LOOKING BACK AND LOOKING AHEAD

During the previous era of pencil redlining, many progressive policies such as the FHA, the Community Reinvestment Act (CRA), and the Fair Credit Reporting Act (FCRA) were passed in reaction to the improprieties and inequalities in access to fair and adequate housing. The FHA introduced prohibitions against housing discrimination on the basis of enumerated protected categories, including race, color, and national origin, and established strict guidelines for the fair marketing of affordable housing to a range of potential applicants.¹⁸⁰ The CRA was enacted in direct response to pencil redlining, establishing lending test policies that required banks to adhere to disclosure requirements, which federal regulators could then use to determine whether banks were fulfilling the needs of low-income areas and individuals.¹⁸¹ Similarly, the FCRA was introduced

179. In fact, TransUnion, a company that produces credit scores, has branched out and begun to offer “tenant scoring” through a subsidiary company, SmartMove. See Andrea Collatz, *SmartMove’s ResidentScore vs. A Typical Credit Score: Which Is Better?*, TRANSUNION: BLOG (June 14, 2016), <https://www.mysmartmove.com/SmartMove/blog/residentscore-tailored-tenant-screening.page> [https://perma.cc/F2AZ-2EEZ]; see also Dunn & Ehman, *supra* note 18, at 38–39.

180. See 42 U.S.C. § 3604(c) (2012).

181. See 12 C.F.R. §§ 25.22, 195.22, 228.22, and 345.22 (detailing the lending tests initiated by the CRA and enforced through four federal banking agencies: the Federal Reserve System, the Federal Deposit Insurance Corporation, the Office of the Comptroller of the Currency, and the Federal Financial Institutions Examination Council, respectively); see also ROBERTO QUERCIA & JANNEKE RATCLIFFE, THE

to ensure banks and credit reporting bureaus were not using incorrect or biased information in creditworthiness evaluations.¹⁸²

Though well-intended, because of misapplication and modern technological advancements, these policies are no longer able to protect the public from the current era of algorithmic redlining. Take, for example, the CRA's lending test requirements, which allow the government to monitor how banks are lending to individuals specifically in low-income areas where the banks operate a brick-and-mortar branch.¹⁸³ This may have been effective as a direct response to pencil redlining.¹⁸⁴ But today, as more banks move lending practices online and close brick-and-mortar branches, and as more and more modern financial technology institutions operate strictly online, it is far harder to monitor whether banks are providing investment and loan opportunities to the communities they are encouraged to serve.¹⁸⁵ Similarly, as suggested by the plaintiffs in the litigation against Facebook, modern algorithms, though not specifically incorporating race, may be using race-correlative data to skirt the FHA's provisions that prohibit landlords from

COMMUNITY REINVESTMENT ACT: OUTSTANDING, AND NEEDS TO IMPROVE, THE UNC CENTER FOR COMMUNITY CAPITAL 47–49 (2010), https://www.frbsf.org/community-development/files/cra_outstanding_needs_improve1.pdf [<https://perma.cc/4XC9-JLQE>].

182. See Fair Credit Reporting Act, 15 U.S.C. § 1681 (2012); see also CONSUMER FIN. PROT. BUREAU, A SUMMARY OF YOUR RIGHTS UNDER THE FAIR CREDIT REPORTING ACT, <https://www.consumer.ftc.gov/articles/pdf-0096-fair-credit-reporting-act.pdf> [<https://perma.cc/YGB4-695C>].

183. 12 U.S.C. § 2901 (2012) (stating, “[i]t is the purpose of this chapter to require each appropriate Federal financial supervisory agency to use its authority when examining financial institutions, to encourage such institutions to help meet the credit needs of the local communities in which they are chartered consistent with the safe and sound operation of such institutions.”); John Taylor & Josh Silver, *The Community Reinvestment Act at 30: Looking Back and Looking to the Future*, 53 N.Y.L. SCH. L. REV. 203, 204–05 (2008); Ruth Simon & Coulter Jones, *Goodbye, George Bailey: Decline of Rural Lending Crimps Small-Town Business*, WALL ST. J. (Dec. 25, 2017), <https://www.wsj.com/articles/goodbye-george-bailey-decline-of-rural-lending-crimps-small-town-business-1514219515> [<https://perma.cc/D7VP-AVFD>].

184. See Keith N. Hylton & Vincent D. Rougeau, *Lending Discrimination: Economic Theory, Econometric Evidence, and the Community Reinvestment Act*, 85 GEO. L.J. 237, 241 (1996).

185. See Quercia & Ratcliffe, *supra* note 181, at 53–54; Thomas W. Beetham, *The Community Reinvestment Act and Internet Banks: Redefining the Community*, 39 B.C. L. REV. 911, 912–13 (1998); Kathleen C. Engel & Patricia A. McCoy, *The CRA Implications of Predatory Lending*, 29 FORDHAM URB. L.J. 1571, 1596–97 (2002); Krista Shonk, *Brainard: Fed Fully Engaged in CRA Reform Process*, AM. B. ASS'N. BANKING J. (Oct. 15, 2018), <https://bankingjournal.aba.com/2018/10/brainard-fed-fully-engaged-in-cra-reform-process/> [<https://perma.cc/HPM8-LZBP>].

discriminatory marketing and from rejecting housing applicants based on their belonging to a suspect class.¹⁸⁶

With an eye toward modernization, the final Part of this Article suggests reforms to these policies and others — upgrades to the web of intersecting guidelines that impact fair housing so they seamlessly interact with policies that promote transparency and auditing. Some of these upgrades demand human oversight over automated decisions — because without this oversight, current automated decision systems will continue their patterns of algorithmic redlining. Some of the reforms proposed here are presently considered more out-of-the-box, but, as argued herein, are critical to promote community integration and desegregation in a modern society.

Broadly speaking, many scholars who have studied how to prevent algorithms from furthering discrimination and producing disparate impacts have called for more accountability in algorithms that generate automated decisions, specifically by increasing transparency, auditing or oversight, and involving human autonomy.¹⁸⁷ Without transparency, those impacted by algorithmic redlining in housing finance, home marketing, and tenancy selection will remain unaware of how enigmatic algorithms and big data reduce their opportunities for fair and affordable housing or how they worsen community segregation.¹⁸⁸ Without auditing, biased data inputs and disparate outcomes may continue to perpetuate race-based results, like nudging minority home seekers towards housing in minority areas while pushing non-minority home seekers to more affluent areas.¹⁸⁹ Finally, without human oversight and autonomous decision-making in fair and affordable housing, gatekeepers such as management companies and lenders may continue to rely on algorithms that are

186. Complaint, Assistant Secretary for Fair Hous. & Equal Opportunity v. Facebook, Inc. (Aug. 13, 2018), https://www.hud.gov/sites/dfiles/PIH/documents/HUD_01-18-0323_Complaint.pdf [<https://perma.cc/UVD6-VACR>] [hereinafter Housing Discrimination Complaint]; Brakkton Booker, *HUD Hits Facebook for Allowing Housing Discrimination*, NAT'L PUB. RADIO (Aug. 19, 2018), <https://www.npr.org/2018/08/19/640002304/hud-hits-facebook-for-allowing-housing-discrimination> [<https://perma.cc/T3KH-UGVB>].

187. See Pauline T. Kim, *Auditing Algorithms for Discrimination*, 166 U. PA. L. REV. ONLINE 189, 190 (2017) (arguing that trade secrets can be adequately protected even if we police algorithms by analyzing their results or their inputs); see also BRUCE SCHNEIER, *DATA AND GOLIATH: THE HIDDEN BATTLES TO COLLECT YOUR DATA AND CONTROL YOUR WORLD* 155–66 (2017).

188. See Housing Discrimination Complaint, *supra* note 186; Fennell, *supra* note 47, at 351; Goodman, *supra* note 97, at 501.

189. See Fennell, *supra* note 47, at 355–56, 361–62.

perilous to minorities and advantageous for non-minorities.¹⁹⁰ In the following section, each of these arguments — transparency, auditing, and autonomy — is analyzed to assess how future policies ought to combat this new era of algorithmic redlining.

A. Transparency: Promoting Choice and Accountability Through an Understanding of Automated Decisions

Automated decisions that impact housing procurement should become more transparent. In reaction to the previous era of pencil redlining, many fair housing advocates combatted segregation through legislative advocacy, pushing for laws such as the ECOA and the Home Mortgage Disclosure Act (HMDA) — both of which required banks to disclose certain scoring and rating techniques they use in credit evaluations.¹⁹¹ Also, as previously mentioned, the CRA was passed in response to redlining and required banks to report their efforts of lending in low- and moderate-income communities to federal regulators.¹⁹² To make these laws relevant to modern technologies, they must be updated to incorporate similar disclosure and lending requirements for new types of internet financial outlets and online lending institutions. Further, the laws must be amended to establish greater disclosure requirements for banks and online marketers that rely on automated decision systems.

Consider the CRA, which presently does not apply to increasingly popular internet banking institutions and popular financial technology outlets. CRA Section 2901 requires federally insured banks to demonstrate that they “serve the convenience and needs of the communities in which they are chartered to do business,” and demands that they evidence a “continuing and affirmative obligation to help meet the credit needs of the local communities in which they are chartered,” consistent with their safe and sound operation.¹⁹³ Also relevant is Section 2903 of the CRA, which provides that the bank’s designated regulatory agency shall “assess the [community banking] institution’s record of meeting the credit needs of its entire community, including low- and moderate-income

190. *See id.* at 351.

191. *See* Equal Credit Opportunity Act, Regulation B, 12 C.F.R. § 1002.6 (2012); Kleinman & Berger, *supra* note 9, at 958.

192. *See* Fair Credit Reporting Act (FCRA), 15 U.S.C. § 1681 (2012); Community Reinvestment Act (CRA), Pub. L. No. 95-128, 91 Stat. 1147 (2012) (requiring minimum amount of investment for FDIC-backed banks that have a physical presence in a community).

193. 12 U.S.C. § 2901 (2012).

neighborhoods”¹⁹⁴ Undoubtedly, these provisions were a step in the right direction towards combatting the ills of the pencil redlining era. However, the CRA should be updated so that it applies beyond banks and the “local communities in which they are chartered.” Rather, amendments to the act should focus on applying to all (or at least to a large share) of online lending institutions, and should not be tied to brick-and-mortar branches. Consider, also, the provisions of the ECOA that require mortgage lenders to collect information for “monitoring” when accepting mortgage applications for home financing.¹⁹⁵ It should be evident that ethnicity ought not be a requirement (or, at the very least, should be a permissive category), but the Act should also be amended to include a provision that requires lenders to disclose the exact metrics or data points they use to generate scores or determine borrower interest rates.

Aside from revising antiquated language in laws to make them current, transparency can be facilitated by requiring disclosure from public agencies that utilize privately-owned algorithmic decision-making systems. When contracting and partnering with businesses, federal, state, and local governments should be required to disclose the background information, such as the various data sources, of the algorithms they use. For example, legal advocates from the Brennan Center at New York University School of Law recently sued the New York Police Department (NYPD) after it refused to comply with the Center’s Freedom of Information Law (FOIL) request, asking for and receiving some NYPD documents about its predictive policing algorithms.¹⁹⁶ Rather than requiring lawsuits and FOIL requests to invoke transparency, governments at all levels should use their contracting power to require disclosure, making transparency the rule rather than the exception. A bill introduced by the New York City Council is a model for legislation that is a step in this direction. The bill, though not requiring public disclosure, would create a governmental “task force” to review algorithms being used by public entities and actors.¹⁹⁷

194. Community Reinvestment Act, 12 U.S.C. § 2903 (2012).

195. See Equal Credit Opportunity Act, 15 U.S.C. § 1691 (2012).

196. See Decision & Judgment at 1–5, Brennan Center for Justice at N.Y.U. Law Sch. v. NYC Police Dept., No. 160541/2016, 2017 WL 6610414 (N.Y. Sup. Ct. Dec. 27, 2017).

197. See Julia Powles, *New York City’s Bold, Flawed Attempt to Make Algorithms Accountable*, NEW YORKER (Dec. 20, 2017), <https://www.newyorker.com/tech/annals-of-technology/new-york-citys-bold-flawed-attempt-to-make-algorithms-accountable> [<https://perma.cc/V29Q-RXYB>] (describing

Aside from the above proposed legislative amendments and contractual changes, lawmakers should require advanced disclosure from the credit bureaus that generate credit scores or from the lenders that make decisions using these algorithms — this is a change that would directly address the aforementioned hurdles in the housing arena. Further, governments should require disclosure from the online marketers that act as gatekeepers and editors in disseminating home marketing information, otherwise seekers would not be able to determine whether they are viewing truly unbiased results. Finally, when algorithms operate to screen affordable and rental tenancy applicants, those administering the algorithms should clearly and expressly inform lottery entrants and rental applicants about the process by, for example, disclosing what factors are weighed and naming any third-party screening consultancies that are involved.

Lawmakers have a responsibility to ensure that seekers, particularly those from minority neighborhoods, have the ability to assess whether scores are biased, search characteristics are skewed, or factors are perpetuating segregation by limiting access for people of color to move into non-minority neighborhoods. A powerful way to do this is by increasing public transparency, empowering seekers and renters by giving them more knowledge of the details of otherwise opaque algorithms that make potentially life-changing decisions for them. However, disclosure alone is not enough; to ensure a level playing field, lawmakers must also audit the information algorithms are being fed and the outcomes they generate.

B. Auditing Algorithms for Fairness

In addition to disclosure, legislation should focus on auditing algorithmic inputs and outputs. Inputs are the troves of data that artificial intelligence algorithms learn from to arrive at outputs, the actual autonomous decisions and scores that algorithms generate.¹⁹⁸ Algorithmic auditing is increasingly important as algorithms become more complex and autonomous.¹⁹⁹ Transparency will go a long way in requiring disclosure for identifiable source code information in an algorithm, like what preferences are already built into an affordable

legislation introduced in New York City that creates a task force to analyze and report on the use of algorithms used by City agencies).

198. See Kim, *supra* note 187, at 190; Madden et al., *supra* note 43, at 66; Kuang, *supra* note 39.

199. See James Guszczka et al., *Why We Need to Audit Algorithms*, HARV. BUS. REV. (Nov. 28, 2018), <https://hbr.org/2018/11/why-we-need-to-audit-algorithms> [<https://perma.cc/3XXQ-RN8Y>].

housing lottery's policy. However, as recently explained in an article by a group of leading internet scholars, transparency alone is necessary but not sufficient:

Machine learning, one increasingly popular approach to automated decisionmaking, is particularly ill-suited to source code analysis [i.e., through transparency] because it involves situations where the decisional rule itself emerges automatically from the specific data under analysis, sometimes in ways that no human can explain. In this case, source code alone teaches a reviewer very little, since the code only exposes the machine learning method used and not the data-driven decision rule.²⁰⁰

In other words, the code in machine learning algorithms is not necessarily where biases generate, rather, they come from the data with which the algorithm is “taught.” Accordingly, regulators advocating for transparency would struggle to understand disclosures made for complex machine learning algorithms, because they crunch gargantuan amounts of data, learn from it, and then make autonomous decisions.²⁰¹ For such algorithms, it is important to monitor the types of data inputs they use, and then correct any biased information they are being fed.²⁰² In that regard, where algorithms operate to influence key public welfare decisions, such as those in affordable housing, operators should be required to disclose what data sets they used to “train” the artificial intelligence algorithm. Simultaneously, the outputs produced by these algorithms should be audited to assess whether there is a constant bias that repeats time and again, and whether they produce results otherwise adverse to the public interest.²⁰³

As applied to the aforementioned areas of algorithmic redlining, credit card companies, credit reporting bureaus, and mortgage lenders should be required to disclose the data inputs they use to formulate credit scores and mortgage rates. Simultaneously, those entities ought to be audited to determine whether the scores and rates they are producing are disproportionately higher for lenders-of-color, or whether they produce other disparate impacts on marginalized populations. Internet marketers, search engine operators, affordable

200. Kroll et al., *supra* note 26, at 638.

201. *See id.*

202. Kroll et al., *supra* note 26, at 639, 699–705; Roy D. Simon, *Artificial Intelligence, Real Ethics*, N.Y. ST. B. ASSOC. (Apr. 2018), http://www.nysba.org/Journal/2018/Apr/Artificial_Intelligence,_Real_Ethics/ [<https://perma.cc/D972-PU8Z>].

203. Kroll et al., *supra* note 26, at 640 n.14; Simon, *supra* note 202.

housing lottery administrators, and landlords that utilize algorithms should be similarly audited to ensure they rely on non-discriminatory data for their inputs, and that they correct any outputs that produce adverse results for disenfranchised groups.

C. Human Oversight and Autonomy: Algorithms as a Method of Retaining Free Will

Increased transparency and oversight are especially necessary in decisions regarding fundamental needs as crucial as housing. But such a basic right also demands human autonomy, so that we can ensure affordable units are fairly administered.²⁰⁴ As expressed previously, housing is an element of American life that closely binds individuals to what society has frequently considered of utmost importance: education, health, job opportunity, economic prosperity, community development, and community integration.²⁰⁵ Thus, while both transparency and auditing are required to break down the barriers that currently prohibit access to housing, neither will solve the problems of algorithmic hubris, particularly because of automation bias — the human tendency to believe without question algorithmic results.²⁰⁶ To temper our overreliance of algorithms, automated decision making must be coupled with an accountable level of human autonomy. Take, for example, a 2016 exchange between Tom Woods, the Chairman of the National Association of Home Builders, and then U.S. Senator Heidi Heitkamp, which took place at a Congressional hearing concerning access to mortgage credit.²⁰⁷ Senator Heitkamp asked Mr. Woods directly about the “trend to try and analyze creditworthiness looking at big data and algorithms and different kinds of inputs.”²⁰⁸ Implying that such a

204. O'NEIL, *supra* note 3, at 155.

205. *See supra* note 49 and accompanying text.

206. Citron, *supra* note 40, at 1271–72; *see also* Sandra Faucett, *Tenant Screening: Finding a Great Renter*, ZILLOW, <https://www.zillow.com/rental-manager/resources/multiple-qualified-rental-applications/> [https://perma.cc/3TRX-VZAG] (advising agents against going with their “gut,” stating that landlords should not go with their intuitive choice but should rely on tenant screening tool: “When you’re faced with multiple qualified renter applications, it’s tempting to start looking at their personal, nonfinancial qualities to help you select your resident. Don’t.”).

207. *Exploring Regulatory Burdens that Are Restricting Mortgage Credit, Including Recommendations to Alleviate the Burden: Hearing Before the Committee on Banking, Housing, and Urban Affairs, United States Senate*, 114th Cong. 38–40 (2016), <https://www.govinfo.gov/content/pkg/CHRG-114shrg95735/pdf/CHRG-114shrg95735.pdf> [https://perma.cc/DJ27-3DZP] [hereinafter *Hearing on Obtaining Mortgage Credit*].

208. *Id.*

trend may lead to the overreliance of algorithmically generated scores and decisions, Senator Heitkamp wanted to know if this was a present problem or “a 10-year-out problem.”²⁰⁹ Mr. Woods responded indicating that it was likely a “10-year-out problem,” but that he was “intrigued” by that kind of data.²¹⁰ He also indicated that, at least in the early stages of this “trend,” such scoring did limit the autonomy of the community banker, steering them away from making an intuitive decision:

You could have a banker, a client or customer comes in and you look at the financial statement. It checks all the boxes. There is no way you are going to give them a loan. The guy who owns the body shop down the street who you know has always paid his bills, because you know his community reputation, you want to give him the loan and you do not want to be dinged for it in an examination, or you want to be able to do what you have always done in your communities.²¹¹

Mr. Woods’s description of the “guy who owns a body shop” epitomizes the risk of the community banker strictly adhering to algorithmic scoring and decisions. A banker must be willing to consider the validity a loan that his or her intuition tells them might be valid, regardless of automaton. This is especially vital when algorithms operate to perpetuate adverse lending practices by failing to serve individuals and families that have been discriminately scored and ruled uncreditworthy. Accordingly, regulations in the housing arena should seek to implement a structure where decisions are ultimately made or reviewed by a human decision-maker who can think about justice, fairness, and equity.²¹²

Procedures should be put in place to allow community bankers and other lenders to approve loans that depart from algorithmic decisions if they feel that the algorithms failed to consider, or adversely considered, “intangibles” that ought to point towards approval. The same should be applied to housing authorities and landlords that use algorithms for affordable housing lotteries and rental tenancy. Moreover, as discussed in detail in the following section, internet marketers and search engine operators should be held accountable for knowingly using algorithms that operate as biased gatekeepers

209. *Id.*

210. *Id.*

211. *Id.*

212. PASQUALE, *supra* note 35, at 1–18 (discussing how the rise of algorithms has become so perfuse that it has substituted the judgement of the community banker).

and editors, rather than being shielded from liability under the safe harbors of internet advertising legislation.

D. Other Reforms and Modernizations

As is often the case with reforms, implementing procedures that increase transparency, auditing, and human oversight will be an uphill battle. For one, as noted by the exchange between Mr. Woods and Senator Heitkamp, many key stakeholders see these issues as a “10-year-out problem,” leading them to sweep the issue under the rug or become more reactionary than proactive.²¹³ Moreover, as briefly addressed above, disclosure requirements through transparency and auditing are difficult to demand from private actors that act in completely private spheres, as these entities are protected by intellectual property laws and other safe harbors.²¹⁴ The opacity of automated decision-making in the private sector will remain a burden to the “scored society” as long as intellectual property law and bank regulations maintain favorable safe harbors, which protect the interests of powerful corporate entities at the expense of consumers.²¹⁵ The following section identifies and expands upon reforms that several legal scholars have recently advocated for in areas like intellectual property, data protection, internet law, and public administration, which reflect the ways consumers operate in the modern economy.

1. *Improvements to Intellectual Property, Data Protection, and Internet Law*

In the area of intellectual property, trade secret laws protect many algorithms from disclosure, allowing private actors to veil automated decisions behind a wall of business interests.²¹⁶ Banks, credit outlets, mortgage evaluators, online marketers, and tenant-screening firms can use trade secret protections to guard their valuable code.²¹⁷ In

213. *Hearing on Obtaining Mortgage Credit*, *supra* note 207, at 39.

214. Pasquale, *supra* note 127, at 282.

215. PASQUALE, *supra* note 35, at 14.

216. *Id.* at 6–14.

217. *See id.*; Christian Sandvig et al., *An Algorithm Audit*, in DATA AND DISCRIMINATION: COLLECTED ESSAYS, OPEN TECHNOLOGY INSTITUTE & NEW AMERICA 7 (Seeta Peña Gangadharan et al. eds., 2014), <https://static.newamerica.org/attachments/403-data-and-discrimination/OTI-Data-and-Discrimination-FINAL-small.pdf> [<https://perma.cc/F484-KSXW>]; Darren Stevenson, *Locating Discrimination in Data-Based Systems*, in DATA AND DISCRIMINATION: COLLECTED ESSAYS, OPEN TECHNOLOGY INSTITUTE & NEW AMERICA 16,

the future, such business interests should be weighed against notions of public welfare, and courts ought to come to more favorable decisions for plaintiffs bringing appeals against algorithmic decisions. Such reforms have been promoted by internet law scholars like Professor Frank Pasquale, author of *The Black Box Society* as well as a number of other articles concerning internet law reform. Professor Pasquale, along with other legal scholars, has suggested that internet juggernauts provide services so critical to the public that they ought to be viewed by courts and the public as utility companies, which are typically subject to transparency requirements and reviews of decision-making procedures.²¹⁸

Additionally, as evidenced by legislation introduced abroad, transparency of algorithmic decisions can be accomplished through legislation meant to police automated decisions.²¹⁹ In that regard, the United States should consider introducing legislation similar to the European Union's comprehensive General Data Protection Regulation (GDPR). The GDPR took effect in 2018, replacing the European Data Protection Directive (EDPD) that, in essence, regulated the processing of personal data and brokerage of such data.²²⁰ The E.U. enacted the GDPR to cope with the slew of issues that arise from rapid technological advancements, including data privacy, algorithmic decision-making, and antitrust problems.²²¹

While the GDPR focuses heavily on data privacy and protection, a key provision of the regulation, Article 22, specifically addresses

<https://static.newamerica.org/attachments/403-data-and-discrimination/OTI-Data-and-Discrimination-FINAL-small.pdf> [<https://perma.cc/F484-KSXW>].

218. Pasquale, *supra* note 127, at 298; *see also* K. Sabeel Rahman, *Infrastructural Regulation and the New Utilities*, 35 YALE J. ON REG. 911, 914 (2018); K. Sabeel Rahman, *The New Utilities: Private Power, Social Infrastructure, and the Revival of the Public Utility Concept*, 39 CARDOZO L. REV. 1621, 1689–90 (2018).

219. Craig McAllister, Note, *What About Small Businesses: The GDPR and Its Consequences for Small, U.S.-Based Companies*, 12 BROOK. J. CORP. FIN. & COM. L. 187, 189 (2017); Margot Kaminski, *The GDPR's Version of Algorithmic Accountability*, 2018 JOTWELL, at 1–2 (2018); Julian Wagner & Alexander Benecke, *National Legislation Within the Framework of the GDPR*, 2 EUR. DATA PROT. L. REV. 353, 353 (2016); Minke D. Reijneveld, *Quantified Self, Freedom, and the GDPR*, 14 SCRIPTED 285, 287–88 (2017); Lilian Edwards & Michael Veale, *Slave to the Algorithm: Why a 'Right to an Explanation' Is Probably Not the Remedy You Are Looking for*, 16 DUKE L. & TECH. REV. 18, 21 (2017); Robert van den Hoven van Genderen, *Privacy and Data Protection in the Age of Pervasive Technologies in AI and Robotics*, 3 EUR. DATA PROT. L. REV. 338, 346 (2017).

220. Reijneveld, *supra* note 219, at 287.

221. McCallister, *supra* note 219, at 193.

decisions based *solely* on automated decisions systems.²²² Article 22, titled “Automated individual decision-making, including profiling,” explicitly limits the reliance of auto-generated decisions involving an individual’s legal rights.²²³ Additionally, Article 22 allows individuals a right to intervene and dispute algorithmically generated decisions they feel adversely impact them.²²⁴ To make sure that entities making algorithmically generated decisions are held accountable, the GDPR also introduced provisions implementing fines for non-compliance, adding teeth to the oversight mechanisms put in place.²²⁵

The United States should follow in the European Union’s footsteps by pursuing a policy similar to that enacted in Article 22. This policy should not limit oversight to algorithmically generated decisions pertaining to legal rights, but should also expand oversight to those decisions that concern fundamental moral rights such as those that impact housing. This type of oversight would place the ultimate autonomy back into the hands of the community banker, which will level the playing field in online marketing and promote rational, empathetic, human decision-making regarding housing finance and rental options, even if it goes against outcomes calculated by

222. Regulation 2016/679, of Apr. 27, 2016, on the Protection of Natural Persons with Regard to the Processing of Personal Data and on the Free Movement of Such Data, and Repealing Directive 95/46/EC (General Data Protection Regulation), art. 22, 2016 O.J. (L 119) 46 (EU), <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:L:2016:119:TOC> [https://perma.cc/S5P7-6BZY] [hereinafter *GDPR*]; *Automated Decision Making: In Brief – What Does the Data Protection Act Say About Automated Decision Making?*, U.K. INFO. COMM’R’S OFF. (2018) <https://ico.org.uk/for-organisations/guide-to-data-protection/guide-to-the-general-data-protection-regulation-gdpr/individual-rights/rights-related-to-automated-decision-making-including-profiling/> [https://perma.cc/S7YL-RG6D]; Emily Pehrsson, *The Meaning of the GDPR Article 22 2* (Stanford – Vienna Transatlantic Tech. Law Forum, European Union Law Working Papers, No. 31, 2018), https://www-cdn.law.stanford.edu/wp-content/uploads/2018/05/pehrsson_eulawwp31.pdf [https://perma.cc/E4YG-QJVT].

223. *GDPR*, *supra* note 222, art. 22(1) (stating, a person “shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her”).

224. *Id.* art. 22(3) (“[T]he data controller shall implement suitable measures to safeguard the data subject’s rights and freedoms and legitimate interests, at least the right to obtain human intervention on the part of the controller, to express his or her point of view and to contest the decision.”).

225. Sam Pfeifle, *WP29 Releases Guidelines on Administrative Fines Under the GDPR*, INT’L ASSOC. PRIVACY PROFS. (Oct. 23, 2017), <https://iapp.org/news/a/a29wp-releases-guidelines-on-administrative-fines-under-the-gdpr/> [https://perma.cc/6CLS-HCYJ].

algorithms.²²⁶ Undoubtedly, humans are also biased and imperfect, but without any responsibility from a human actor, overreliance on machine algorithms will leave housing decision-makers asleep at the wheel, with limited recourse for housing advocates and seekers.

2. *Adjustments to Internet Law*

In addition to adopting provisions similar to Article 22 of the GDPR, the United States should emulate the E.U.'s general philosophy and begin to consider a more comprehensive overhaul of its antiquated regulations. Currently, a web of legislation impacts how modern algorithmic decisions are regulated, but many of the component pieces of legislation have been rendered ineffective by technological advancements, or may even be antithetical to one another.²²⁷

One example of how the laws are now antiquated and ineffective is illustrated by a principle provision of the FHA — the prohibition against marketing housing on the basis of an enumerated protected category, like race, color, or national origin.²²⁸ Although this provision is still in place, it can be easily skirted by algorithms that make accurate latent trait inferences after analyzing data that is race-correlative but not per se inclusive of race, color, or national origin.²²⁹ This seems like a paradoxical approach: advertisements for housing that discriminate based on a protected class, such as race, are not legal, but advertisements for housing that use assumptions based on a digital footprint that *imply* race (but exclude its direct incorporation) seem entirely lawful.

That the laws governing algorithmic decision-making can sometimes act in opposition to one another is a serious problem. For example, when advertisements that rely on *implied* race are generated by computer-automated decisions and not curated by humans, many of the marketers dispersing the ads are shielded from liability — precisely because of various safe harbor provisions in

226. Christina M. Mulligan, *Perfect Enforcement of Law: When to Limit and When to Use Technology*, 14 RICH. J.L. & TECH. 1, 2–3 (2007) (providing a framework that can be used to determine the wisdom of using a technology to enforce law by explaining the several types of perfect enforcement and analyzing the concerns raised by their use).

227. Christina Mulligan, *Technology Intermediaries and Freedom of Press*, 66 S.M.U. L. REV. 157, 169–70 (2013).

228. Fair Housing Act, 42 U.S.C. § 3601 (2012).

229. See discussion *supra* Section II.B.2.

other parts of piecemeal legislation.²³⁰ Specifically, safe harbor provisions in the Digital Millennium Copy Right Act (DMCA) and the Communications Decency Act (CDA) shield internet service providers, online marketers, and search engine platforms from liability for any content algorithmically generated on their platforms.²³¹ Thus, online marketers and search engine platforms like Facebook and Google are not liable for advertisements and other gatekeeper decisions generated by algorithms.²³²

Some internet advocates and users argue that these kinds of legislative shields are foundational to facilitating internet free speech.²³³ This may certainly be true, and this work does not discount the importance of free speech protections — but considering the current state of affairs and the increasingly monopolistic tendencies of internet firms, it seems the pendulum may have swung too far. Internet-based corporations are so massive, inherently powerful, and enjoy such significant protections from liability that Professor Pasquale has called them “functional sovereigns” but “absentee owners.”²³⁴ Pasquale uses the term “functional sovereign” as a way of describing “the level of power a private firm reaches when it is no longer one of many market participants, but instead the main supervisor and organizer of actual market participants.”²³⁵ At the same time, these massive firms operate as “absentee owners,” “neglect[ing] traditional functions [firms] had previously served, in order to maximize revenue in accordance with its . . . demands.”²³⁶

230. PASQUALE, *supra* note 35, at 25; Balkin, *supra* note 116, at 1178; Adam Weintraub, “Landlords Needed, Tolerance Preferred”: A Clash of Fairness and Freedom in *Fair Housing Council v. Roommates.com*, 54 VILL. L. REV. 337, 338–39 (2009) (describing situations where discriminatory ads were posted but the webhosting platform was not liable).

231. Digital Millennium Copy Right Act, 17 U.S.C. § 512 (a)–(d) (2012); Communications Decency Act, 47 U.S.C. § 230(c)(1) (2012); Mulligan, *supra* note 226, at 169–70.

232. Frank Pasquale, *Asterisk Revisited: Debating a Right of Reply on Search Results*, 3 J. BUS. & TECH. L. 61, 69 (2008) (“Perhaps the bevy of immunities Congress has granted to search engines via the Digital Millennium Copyright Act and Communications Decency Act should be conditioned on something like the asterisk proposal—or at least their adoption of some self-regulating internal processes designed to give those hurt by search results a fair hearing.”).

233. Mulligan, *supra* note 227, at 169–70.

234. Frank Pasquale, *Tech Platforms and the Knowledge Problem*, AM. AFF., Summer 2018, <https://americanaffairsjournal.org/2018/05/tech-platforms-and-the-knowledge-problem/> [<https://perma.cc/7L43-BHZ6>].

235. *Id.*

236. *Id.*

Consider an example of this kind of contradiction — the safe harbor provisions in the DMCA and CDA mean that if an advertisement reflecting discriminatory housing marketing was displayed in a print publication such as the Wall Street Journal or the New York Times, the *Journal* or the *Times* would be liable for the dissemination of the ad.²³⁷ By contrast, if Facebook’s algorithms were to display the same discriminatory advertisement on its platform, Facebook would be immune from any liability as long as the advertisement was a product of its algorithmic marketing system.²³⁸

3. *Modernizing Public Administration*

Appreciating the necessity for transparency, auditing, and human oversight, as well as the need for comprehensive reform, some scholars have suggested that a central government agency with expertise in the area could be created to oversee and apply these principles. In 2008, for example, Professors Oren Bracha and Frank Pasquale suggested the need for a “Federal Search Commission,” which would supervise search engine manipulation and algorithmic discrimination.²³⁹ In 2016, Professors Paul Ohm and Blake Reid introduced a similar centralized authority concept.²⁴⁰ Certainly, this kind of centralized agency is needed, but it can go beyond supervision. This agency should not only make search engine algorithms and methods more transparent and accountable, but also expand its reach into other areas of the internet, such as policing big data brokers and private actors that rely on automated decisions to make choices crucial to the public interest.²⁴¹ This agency should also

237. Oren Bracha & Frank Pasquale, *Federal Search Commission? Access, Fairness, and Accountability in the Law of Search*, 93 CORNELL L. REV. 1149, 1192–93 (2008); Weintraub, *supra* note 230, at 364 (describing, situations where discriminatory ads were posted but the webhosting platform was not liable).

238. Mulligan, *supra* note 227, at 169–70.

239. Bracha & Pasquale, *supra* note 237, at 1208–09; *see also* Pasquale, *supra* note 127, at 298.

240. Paul Ohm & Blake Reid, *Regulating Software When Everything Has Software*, 84 GEO. WASH. L. REV. 1672, 1700 (2016).

241. Pasquale, *supra* note 127, at 298 (“If search engines are to be accountable at all, if their interest is to be balanced against those of the various other claimants involved in search-related disputes, and if social values are to be given any weight, some governmental agent should be able to peer into the black box of search and determine whether or not illegitimate manipulation has occurred.”); *see also* BIG DATA: SEIZING OPPORTUNITIES, *supra* note 42, at iii (“[B]ig data analytics have the potential to eclipse longstanding civil rights protections in how personal information is used in housing, credit, employment, health, education, and the marketplace. Americans’ relationship with data should expand, not diminish, their opportunities and potential.”).

borrow successful components from other agencies, such as the Consumer Financial Protection Bureau (CFPB), an agency that works with other government actors like the Federal Trade Commission (FTC) and the Department of Justice (DOJ) to police and prosecute industry practices harmful to American consumers.²⁴² The new internet oversight agency should also use expertise from industry and academic leaders to think of new, creative reforms to create an internet accountable to consumers.²⁴³

Further, this centralized internet agency could work with other governmental actors to specifically combat algorithmic redlining. For example, the agency could work with the Department of Housing and Urban Development (HUD), as well as state and local housing agencies, to ensure that algorithms in affordable housing lotteries and rental tenancy applications are being administered fairly. Similarly, the centralized agency could work with banking regulators like the Federal Deposit Insurance Commission (FDIC) and Federal Trade Commission (FTC) to spearhead reforms for “algorithmic compliance,” so that the algorithms used in credit ratings and lending evaluations satisfy the protections of the CRA.²⁴⁴

4. *Changes by Private Actors*

Governmental action in the form of legislation, oversight or a specific legislative agency, will not be enough to tackle the myriad problems with algorithmic accountability. This is particularly so considering how rapidly technology changes, how slowly government operates, and the fact that the Federal Government has recently rolled back progressive reforms. Ultimately, some changes have to be made in the private sector. Indeed, private actors have begun to initiate reforms to combat algorithmic discrimination and should do more to police algorithmic redlining. For example, when addressing European Union policymakers in 2018, Tim Cook, CEO of technology juggernaut Apple, discussed the “weaponization” of personal data and the need for reform.²⁴⁵ Cook’s sentiment directly

242. See Bar-Gill & Warren, *supra* note 83, at 33.

243. See Mark Penn, Opinion, *How to Make Facebook More Accountable*, N.Y. TIMES (Apr. 10, 2018), <https://www.nytimes.com/2018/04/10/opinion/facebook-zuckerberg-privacy.html> [<https://nyti.ms/2v1KTid>] (proposing a system of regulation more similar to those applied to television and radio).

244. Community Reinvestment Act, 12 U.S.C. §§ 2901, 2904 (2012).

245. Sam Schechner & Emre Peker, *Apple CEO Condemns ‘Data Industrial Complex’*, WALL ST. J. (Oct. 24, 2018), <https://www.wsj.com/articles/apple-ceo-tim->

aligned with reforms internet law scholars have advocated for, particularly their suggestions of creating “information fiduciaries.”²⁴⁶ Similar to doctors, lawyers, or financial advisors, information fiduciaries would have a primary duty of care to individuals whose data they are collecting and brokering.²⁴⁷

In addition to information fiduciaries, there are reforms that private actors should introduce specifically to combat algorithmic redlining and improve algorithmic equity in the housing arena. For example, some scholars have highlighted the benefits of encouraging an era of “greenlining.” As described by law professor Mary Stzo, greenlining “directs investment into communities to encourage individual behaviors that will maximize net social benefits directly within the constraints of available resources [with a] main goal [of] neutralizing disinvestment with investment.”²⁴⁸ Other instances of private actors taking proactive steps to combat segregation can be seen from modern lending institutions like SoFi.²⁴⁹ After pressure from regulators, SoFi, a strictly online financial institution, adopted a policy to adhere to the reporting components of the CRA and thus has a much stronger incentive to serve low- and moderate-income communities.²⁵⁰

CONCLUSION

Ultimately, no single approach will be a silver bullet, and many reforms are needed in both private and public practice to remedy the harmful results of algorithmic redlining. The solutions suggested above, tough as they may be to pursue, are critical to protect home seekers from discriminatory algorithms and to advance community integration.

cook-calls-for-comprehensive-u-s-privacy-law-1540375675 [https://perma.cc/HHV4-7MZR].

246. SCHNEIER, *supra* note 187, at 204–05; Balkin, *supra* note 27, at 1227–32.

247. SCHNEIER, *supra* note 187, at 204–05; Balkin, *supra* note 27, at 1227–32.

248. Mary Stzo, *Real Estate Agents as Agents of Social Change: Redlining, Reverse Redlining, and Greenlining*, 12 SEATTLE J. SOC. JUST. 1, 43–52 (2013).

249. Josh Silver, *SoFi, Not So Good: Is This Virtual Redlining?*, SHELTERFORCE.ORG (July 27, 2017), <https://shelterforce.org/2017/07/27/sofi-not-good-virtual-redlining/> [https://perma.cc/LTF3-SER3].

250. Kate Garber et al., *SoFi Bank Charter Could Test CRA Status Quo*, BANKING EXCHANGE (Aug. 16, 2017), <http://www.bankingexchange.com/news-feed/item/7000-sofi-bank-charter-could-test-cra-status-quo> [https://perma.cc/A4TN-QKPJ] (arguing that other popular financial technology institutions like RobinHood, Lending Club, and Fundbox, each one a corporation with encouraging social purposes, should follow a model similar to SoFi).

The harms of the original era of redlining have had a profound, often unendurable adverse impact on communities and individuals of color. As public and private actors begin to rely more heavily on automated decisions, society is at risk of perpetuating the deleterious impacts of pencil redlining through algorithms in housing finance, marketing, and tenancy selection. This Article suggested three discrete areas where algorithmic redlining may further segregation. First, in housing finance, where decision-makers rely on algorithms that generate biased credit scores and predatory marketing targets. Second, in online home marketing and housing searches, where operators may nudge seekers toward homogenous, self-integrating housing options, as they seem to be doing in other areas of online marketing and internet searching. Finally, in housing selection, where authorities that determine tenancy for affordable housing and rental units are using biased calculations and selection characteristics to inform their tenancy selections. Even a cursory inspection of these three areas shows that further transparency, auditing, and human oversight over algorithmic redlining are absolutely necessary. However, resolving the problems in these areas alone is not enough — to truly combat algorithmic discrimination more fundamental reforms are required. Without sweeping, large-scale reforms in the modern housing procurement process, algorithmic redlining is likely to become more prevalent, only serving to exacerbate preexisting discrimination and segregation.