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Expanding Civil Rights to Combat Digital Discrimination on the Basis of Poverty

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EXPANDING CIVIL RIGHTS TO COMBAT DIGITAL DISCRIMINATION ON THE BASIS OF POVERTY

Michele Estrin Gilman*

ABSTRACT

Low-income people suffer from digital discrimination on the basis of their socio-economic status. Automated decision-making systems, often powered by machine learning and artificial intelligence, shape the opportunities of those experiencing poverty because they serve as gatekeepers to the necessities of modern life. Yet in the existing legal regime, it is perfectly legal to discriminate against people because they are poor. Poverty is not a protected characteristic, unlike race, gender, disability, religion or certain other identities. This lack of legal protection has accelerated digital discrimination against the poor, fueled by the scope, speed, and scale of big data networks. This Article highlights four areas where data-centric technologies adversely impact low-income people by excluding them from opportunities or targeting them for exploitation: tenant screening, credit scoring, higher education, and targeted advertising. Currently, there are numerous proposals to combat algorithmic bias by updating analog-era civil rights laws for our datafied society, as well as to bolster civil rights within comprehensive data privacy protections and algorithmic accountability standards. On this precipice for legislative reform, it is time to include socio-economic status as a protected characteristic in antidiscrimination laws for the digital age. This Article explains how protecting low-income people within emerging legal frameworks would provide a valuable counterweight against opaque and unaccountable digital discrimination, which undermines any vision of economic justice.

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I. INTRODUCTION

WE live in a “datafied” society in which a vast network of public and private entities collects and combines our personal data.¹ The digital exhaust people emit as they search and shop online, beam geolocation data from their smartphones, move through spaces under digital surveillance, and engage on social media is algorithmically combined with thousands of other data points into digital profiles.² In turn, these digital profiles “serve as gatekeepers to life’s necessities,” such as jobs, housing, healthcare, and education.³ Algorithms determine your credit score, affect your access to housing and employment, set the price of your insurance, and even decide whether the police will consider you a suspect.⁴ Numerous scholars and civil rights organizations have high-

1. See CARISSA VÉLIZ, *PRIVACY IS POWER: WHY AND HOW YOU SHOULD TAKE BACK CONTROL OF YOUR DATA* 1–3 (2020).

2. See SARAH E. IGO, *THE KNOWN CITIZEN: A HISTORY OF PRIVACY IN MODERN AMERICA* 355–57 (2018); Geoffrey A. Fowler, *It’s the Middle of the Night. Do You Know Who Your iPhone Is Talking To?*, WASH. POST (May 28, 2019), <https://www.washingtonpost.com/technology/2019/05/28/its-middle-night-do-you-know-who-your-iphone-is-talking/> [<https://perma.cc/3JZE-AV4Z>]; WOLFIE CHRISTL, *CRACKED LABS CORPORATE SURVEILLANCE IN EVERYDAY LIFE* 4–19 (June 2017), <https://crackedlabs.org/en/corporate-surveillance/> [<https://perma.cc/U8TT-3JE2>].

3. See MICHELE GILMAN, *DATA & SOC’Y RSCH. INST., POVERTY LAWGORITHMS: A POVERTY LAWYER’S GUIDE TO FIGHTING AUTOMATED DECISION-MAKING HARMS ON LOW-INCOME COMMUNITIES* 1 (2020), <https://datasociety.net/library/poverty-lawgorithms/> [<https://perma.cc/ZA8L-VZ3V>].

4. Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1–4 (2014).

lighted the potential for algorithmic bias in these profiling systems, and real-life examples of digital discrimination are ubiquitous—algorithms have administered lower quality health care to Black patients, learned to prefer male job applicants over females, excluded minorities from seeing certain housing advertisements, and more.⁵ As a result, numerous legislative proposals and emerging litigation strategies for countering algorithmic biases exist.⁶ These civil rights initiatives, however, have excluded a group of Americans who are particularly vulnerable to digital discrimination—people experiencing poverty.

American law generally does not protect people from discrimination based on their socioeconomic status (SES).⁷ As a constitutional matter, the Supreme Court has ruled that poverty is not an immutable characteristic and thus does not deserve heightened constitutional protection.⁸ As a result, any law discriminating against the poor with a rational basis will survive constitutional review.⁹ As a statutory matter, federal and state civil rights laws protect against discrimination based on race, gender, disability, age, national origin, religion, sexual orientation, and genetic history, but they do not protect the poor.¹⁰ There are numerous reasons for this exclusion, including the American belief in the myth of meritocracy, which assumes a far greater capacity for social mobility than actually exists.¹¹ This lack of legal protection has accelerated digital discrimination against the poor, fueled by the scope, speed, and scale of big data networks.

5. See *infra* Sections II.A., II.B.4.

6. See *infra* Section III.C.

7. Danieli Evans Peterman, *Socioeconomic Status Discrimination*, 104 VA. L. REV. 1283, 1286–87 (2018).

8. Suspect classes receive greater constitutional protections. These are groups of people who have an immutable trait, who suffer from a history of prejudice and stereotyping, and who lack a political voice. This framework was set forth in the famous footnote four of *United States v. Carolene Products Co.*, 304 U.S. 144, 152 n.4 (1938) (“[P]rejudice against discrete and insular minorities may be a special condition, which tends seriously to curtail the operation of those political processes ordinarily to be relied upon to protect minorities, and which may call for a correspondingly more searching judicial inquiry.”). The Court has long recognized that race, national origin, alienage, and gender are suspect classes, and as a result, legislation that draws lines on these bases is assessed with heightened scrutiny. See, e.g., *Strauder v. W. Va.*, 100 U.S. 303 (1879); *Graham v. Richardson*, 403 U.S. 365 (1971); *Miss. Univ. for Women v. Hogan*, 458 U.S. 718 (1982). Poor people are not a suspect class. See *San Antonio Indep. Sch. Dist. v. Rodriguez*, 411 U.S. 1, 28–29 (1973) (holding that strict scrutiny is inappropriate in a class action involving poor families’ claim to equal education funding).

9. See, e.g., *Harris v. McRae*, 448 U.S. 297, 322–25 (1980); *Maher v. Roe*, 432 U.S. 464, 470–72 (1977); *Rodriguez*, 411 U.S. at 28–29; *Lindsey v. Normet*, 405 U.S. 56, 74 (1972); *Dandridge v. Williams*, 397 U.S. 471, 487 (1970).

10. See *infra* Section II.A.

11. See JOEL F. HANDLER & YEHESEKEL HASENFELD, *BLAME WELFARE, IGNORE POVERTY AND INEQUALITY* 70 (2007); James Jennings, *Persistent Poverty in the United States: Review of Theories and Explanations*, in *A NEW INTRODUCTION TO POVERTY: THE ROLE OF RACE, POWER, AND POLITICS* 13, 14–21 (Louis Kushnick & James Jennings eds., 1999) (summarizing behavioral theories); Frank Munger, *Identity as a Weapon in the Moral Politics of Work and Poverty*, in *LABORING BELOW THE LINE: THE NEW ETHNOGRAPHY OF POVERTY, LOW-WAGE WORK, AND SURVIVAL IN THE GLOBAL ECONOMY* 1, 3 (Frank Munger ed., 2002).

In the meantime, while low-income people are suffering in a datafied society, businesses amass large profits at their expense, and governments digitally deny them social safety-net supports.¹² Algorithmic systems determine who will see online advertisements for desirable jobs and who will be tracked into low-wage work,¹³ who will obtain an affordable mortgage and who will be redlined into predatory loans,¹⁴ and who will obtain a college degree leading to a job and who will be targeted for high-interest loans to attend a for-profit school.¹⁵ Low-income people are usually on the losing end of these classification systems.¹⁶ Without their knowledge, they are sorted out of categories of credit-worthiness, tenant-worthiness, worker-worthiness, and more.¹⁷ At the same time, they are relentlessly targeted on the internet with offers for subprime financial products and services. Indeed, an entire sector of the consumer reporting industry exists to sell vulnerable consumers' data to interested businesses.¹⁸ To obtain public benefits, low-income people must navigate complex and often inaccessible online platforms that are not designed to meet their needs.¹⁹ These automated decision-making systems often deny or reduce benefits without transparency or due process, leaving thousands of people adrift without state support and not knowing why.²⁰ Layered on top of this data profiling are surveillance tools, such as facial recognition technology, which are increasingly deployed in workplaces, schools, and public housing to control poor and minority populations.²¹ Digital surveillance of student computers feeds the school-to-prison pipeline; predictive policing algorithms reinforce and expand policies of over

12. See generally Mary Madden, Michele Gilman, Karen Levy & Alice Marwick, *Privacy, Poverty and Big Data: A Matrix of Vulnerabilities for Poor Americans*, 95 WASH. U. L. REV. 53, 61–64 (2017).

13. MIRANDA BOGEN & AARON RIEKE, UPTURN, HELP WANTED: AN EXAMINATION OF HIRING ALGORITHMS, EQUITY, AND BIAS 14–25 (2018), <https://apo.org.au/sites/default/files/resource-files/2018-12/apo-nid210071.pdf> [<https://perma.cc/RNC5-PQUB>].

14. Emmanuel Martinez & Lauren Kirchner, *The Secret Bias Hidden in Mortgage-Approval Algorithms*, MARKUP (Aug. 25, 2021, 6:50 AM), <https://themarkup.org/denied/2021/08/25/the-secret-bias-hidden-in-mortgage-approval-algorithms> [<https://perma.cc/FTH2-5ZDJ>].

15. See generally Maura Dundon, *Students or Consumers? For-Profit Colleges and the Practical and Theoretical Role of Consumer Protection*, 9 HARV. L. & POL'Y REV. 375 (2015).

16. See CATHY O'NEIL, WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY 3–4 (2016).

17. See generally *id.*

18. See CONSUMER FIN. PROT. BUREAU, LIST OF CONSUMER REPORTING COMPANIES 31–33 (2022), https://files.consumerfinance.gov/f/documents/cfpb_consumer-reporting-companies-list_2022-01.pdf [<https://perma.cc/BNL7-2B8T>].

19. Michele Estrin Gilman, *Me, Myself, and My Digital Double: Extending Sara Greene's Stealing (Identity) From the Poor to the Challenges of Identity Verification*, 106 MINN. L. REV. HEADNOTES 301, 310–11 (2022).

20. See generally VIRGINIA EUBANKS, AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR (2018); Sarah Valentine, *Impoverished Algorithms: Misguided Governments, Flawed Technologies, and Social Control*, 46 FORDHAM URB. L.J. 364 (2019).

21. See Michele E. Gilman, *Five Privacy Principles (from the GDPR) the United States Should Adopt to Advance Economic Justice*, 52 ARIZ. ST. L.J. 368, 394–99 (2020) [hereinafter *Five Privacy Principles*].

policing and mass incarceration; and workplace algorithms monitor low-wage workers, shaping their performance in ways that cause physical and psychological injuries.²² In short, low-SES people disproportionately bear the brunt of harm in the datafied society.

As society makes greater efforts to rein in digital discrimination, the time is right to consider expanding the categories of protected groups under digital discrimination laws to include people of low SES. For this Article's purposes, digital discrimination laws include statutes addressing digital civil rights, data privacy, and algorithmic accountability. Part I of this Article describes the causes of algorithmic biases and maps the range of harms facing low-income people as a result of digital profiling, automated decision-making systems, and surveillance systems. Part II sets forth the landscape of existing antidiscrimination and data privacy laws and explains how the law currently provides no protection against SES discrimination in the digital context. It then provides an overview of proposed legislative reforms to enhance civil rights in digital privacy and algorithmic accountability. If enacted and enforced, these bills would certainly provide important new tools for combatting digital discrimination but not directly address harmful practices that target, exclude, or surveil people experiencing poverty. Part III thus proposes that any new laws prohibiting digital discrimination include low SES as a protected characteristic. It considers arguments for and against legal recognition of SES in data-centric regimes and concludes that it would provide a valuable counterweight against the opaque and unaccountable digital exploitation of low-income people, which undermines any vision of economic justice.

II. DIGITAL DISCRIMINATION

It is well known that algorithms can discriminate based on protected characteristics, such as race and gender.²³ Less discussed is discrimination against people experiencing poverty when powerful entities deploy automated profiling and decision-making systems.²⁴ This Part first describes how purportedly neutral computational tools such as algorithms may nevertheless import biases against legally protected groups. With this background in mind, this Part then provides four case studies showing how low-income people can also be targeted, excluded, and surveilled due to their SES.

22. *Id.*

23. See, e.g., Nicol Turner Lee, Paul Resnick & Genie Barton, *Algorithmic Bias Detection and Mitigation: Best Practices and Policies to Reduce Consumer Harms*, BROOKINGS (May 22, 2019), <https://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms> [https://perma.cc/JJG2-HZLF] (describing examples of algorithmic bias in numerous settings).

24. See Gilman, *supra* note 21, at 375–90 (describing impacts of algorithmic decision-making on low-income people and minority groups).

A. UNDERSTANDING DIGITAL DISCRIMINATION AND ALGORITHMIC BIAS

Almost every area of modern life is shaped by algorithmic decision-making. Algorithms underlie the technology used to diagnose diseases, provide GPS navigation, recommend streaming entertainment, offer on-line financial services, book travel, host remote work meetings, deliver advertising, connect people on social media, design buildings, provide on-line shopping, and more. Some definitions are helpful: in this context, an algorithm is a set of mathematical instructions that tells a computer how to complete a task.²⁵ Automated decision-making uses algorithms to simplify complex decisions by dividing a single decision into several discrete tasks performed on digital data.²⁶ Algorithms range from the very simple, such as running a decision tree, to the very complex.²⁷ At the more complex level, some algorithms use machine learning—a form of artificial intelligence (AI)—to analyze large sets of data to recognize patterns or make predictions.²⁸

Algorithmic systems are powerful; they can analyze massive data sets efficiently and consistently.²⁹ However, ample evidence shows that algorithmic systems can contain embedded biases against certain groups, potentially violating antidiscrimination law. Bias is not necessarily bad or harmful; the term “simply refers to deviation from a standard.”³⁰ In the civil rights context, bias becomes problematic when “algorithms systematically perform less well for or penalize certain subgroups.”³¹ Algorithms can appear objective compared to humans, who can be “infected by bias.”³² Yet, because humans design the algorithms, these automated systems may reflect the biases of the individuals who made them.³³

Examples abound: One prominent study revealed that a widely used healthcare algorithm, which impacted the care of millions of patients

25. See HANNAH FRY, HELLO WORLD: HOW TO BE HUMAN IN THE AGE OF THE MACHINE 7–8 (2018).

26. See *id.* at 8.

27. See *id.* at 10–11 (noting the complexity of recent machine learning developments).

28. See *id.*; Kristin N. Johnson, *Automating the Risk of Bias*, 87 GEO. WASH. L. REV. 1214, 1236–38 (2019).

29. See Johnson, *supra* note 28, at 1239; FRY, *supra* note 25, at 198–99.

30. David Danks & Alex John London, *Algorithmic Bias in Autonomous Systems*, 26 PROC. INT’L JOINT CONF. ON A.I. 4691, 4692 (2017). “Thus, we can have statistical bias in which an estimate deviates from a statistical standard (e.g., the true population value); moral bias in which a judgment deviates from a moral norm; and similarly for regulatory or legal bias, social bias, psychological bias, and others.” *Id.*

31. Alice Xiang, *Reconciling Legal and Technical Approaches to Algorithmic Bias*, 88 TENN. L. REV. 1, 10 (2021). See also Turner Lee, Resnick & Barton, *supra* note 23 (defining bias as “a term that we define broadly as it relates to outcomes which are systematically less favorable to individuals within a particular group and where there is no relevant difference between groups that justifies such harms”).

32. Laurel Eckhouse, Kristian Lum, Cynthia Conti-Cook, & Julie Ciccolini, *Layers of Bias: A Unified Approach for Understanding Problems with Risk Assessment*, 46 CRIM. JUST. & BEHAV. 185, 186 (2019).

33. See O’NEIL, *supra* note 16, at 21 (“Models are opinions embedded in mathematics.”); Solon Barocas & Andrew D. Selbst, *Big Data’s Disparate Impact*, 104 CAL. L. REV. 671, 674 (2016).

every year, was racially biased in identifying patients who needed “high-risk care management.”³⁴ The algorithm recommended more intensive levels of care to White patients—which, for the study’s purposes, counted as any patients who did not identify as a race other than White—than to similarly ill Black patients.³⁵ The study concluded that this disparity occurred because the algorithm used prior healthcare costs to predict future healthcare needs.³⁶ Yet Black Americans face numerous barriers to healthcare access, such as discrimination and underinsurance, so Black patients’ cost histories are artificially lower than their White counterparts.³⁷ Once this factor—prior healthcare costs—was eliminated from the algorithm, the racial bias disappeared.³⁸

Gender bias in algorithms is also a known problem.³⁹ For instance, Amazon tested (and then abandoned) a hiring algorithm designed to identify “top talent” for technical jobs, but it proved biased against women.⁴⁰ Programmers fed data into the algorithm culled from Amazon’s prior ten years of resumes, in which males predominated.⁴¹ The algorithm then linked the traits on those resumes to predictions about future success, thereby disfavoring resumes that contained words associated with women, such as the names of women’s colleges or women’s sports teams.⁴²

Algorithms can also produce intersectional biases, harming individuals whose identities span multiple protected categories. In a landmark study, researchers Joy Buolamwini and Timnit Gebru concluded that facial recognition technology, which is used in various commercial and governmental settings, committed errors at higher rates for women of color than for White men.⁴³ Moreover, algorithms may be biased towards more than one group. For example, many employers use video interviews in con-

34. Ziad Obermeyer, Brian Powers, Christine Vogeli & Sendhil Mullainathan, *Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations*, 366 *SCI.* 447, 447 (2019).

35. *See id.*

36. *See id.* at 449.

37. *See id.* at 450.

38. *See id.* at 453.

39. *See* Michele Estrin Gilman, *Feminism, Privacy and Law in Cyberspace*, in *OXFORD HANDBOOK OF FEMINISM AND LAW IN THE U.S.* (Deborah L. Brake, Martha Chamallas & Verna L. Williams eds., 2021).

40. Jeffrey Dastin, *Amazon Scraps Secret AI Recruiting Tool that Showed Bias Against Women*, *REUTERS* (Oct. 10, 2018, 6:04 PM), <https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secretai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G> [<https://perma.cc/Q99T-FJ9E>].

41. *Id.*

42. *Id.*

43. Joy Buolamwini & Timnit Gebru, *Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification*, 81 *PROC. MACH. LEARNING RSCH.* 77, 84 (2018). Likewise, the ACLU conducted a study of Amazon’s facial recognition tool that falsely identified twenty-eight members of Congress as criminals based on matches with a mugshot database, and representatives of color were far more likely to be falsely matched. Jacob Snow, *Amazon’s Face Recognition Falsely Matched 28 Members of Congress with Mugshots*, *ACLU* (July 26, 2018, 8:00 AM), <https://www.aclu.org/blog/privacy-technology/surveillance-technologies/amazons-face-recognition-falsely-matched-28> [<https://perma.cc/4WES-6LNF>].

junction with assessment technologies to screen job candidates.⁴⁴ The developers of these algorithms claim that they can analyze word selection, facial expressions, tone of voice, and up to 500,000 other data points to identify those candidates most likely to succeed.⁴⁵ Critics charge that the algorithms are no more than pseudoscience, with multiple potential biases.⁴⁶ In a complaint filed with the Federal Trade Commission (FTC), the Electronic Privacy Information Center alleged that the assessment system sold by a company called HireVue produced biased and unprovable results.⁴⁷ For instance, by tracking eye movement, the tool can discriminate against people with neurological differences.⁴⁸ Research suggests it will penalize certain emotional expressions made more frequently by Black candidates than White candidates.⁴⁹

This brief overview of algorithmic bias just scratches the surface. Researchers, investigative journalists, and lawyers have uncovered algorithmic biases against almost every group protected under antidiscrimination laws, including age,⁵⁰ disability,⁵¹ religion,⁵² sexual ori-

44. BOGEN & RIEKE, *supra* note 13, at 36–37.

45. Drew Harwell, *A Face-Scanning Algorithm Increasingly Decides Whether You Deserve the Job*, WASH. POST (Nov. 6, 2019), <https://www.washingtonpost.com/technology/2019/10/22/ai-hiring-face-scanning-algorithm-increasingly-decides-whether-you-deserve-job/> [<https://perma.cc/Z6NT-QU86>].

46. See Ifeoma Ajunwa, *Automated Video Interviewing as the New Phrenology*, 36 BERK. TECH. L. J. 101, 110 (2022) (“[T]here remains no scientific consensus that artificial intelligence systems are capable of accurately interpreting human emotions from facial expressions.”); Mona Sloane, Emanuel Moss & Rumman Chowdhury, *A Silicon Valley Love Triangle: Hiring Algorithms, Pseudo-Science, and the Quest for Auditability*, 3 PATTERNS 1, 3 (2022) (“Such claims have largely failed to demonstrate scientific validity, have not been replicated experimentally, do not support the additional claims made by vendors that they are useful in predicting on-the-job performance, and, most troublingly, replicate pseudo-scientific and flawed research that posits imagined links between biology and trustworthiness.”).

47. See Complaint and Request for Investigation, Injunction, and Other Relief Submitted by The Electronic Privacy Information Center (EPIC) at 1, 7, *In re HireVue, Inc.*, (F.T.C. Nov. 6, 2019), https://epic.org/wp-content/uploads/privacy/ftc/hirevue/EPIC_FTC_HireVue_Complaint.pdf [<https://perma.cc/ZN9Z-QW5N>].

48. See *id.* at 7, ¶ 43.

49. See *id.* at 8, ¶ 44.

50. E.g., Mark Díaz, Isaac Johnson, Amanda Lazar, Anne Marie Piper & Darren Gergle, *Addressing Age-Related Bias in Sentiment Analysis*, 28 PROC. CHI CONF. ON HUM. FACTORS COMPUTING SYS. 6146, 6149 (2019) (finding bias against older adults encoded in sentiment analysis algorithms). See also MARTIM BRANDÃO, *AGE AND GENDER BIAS IN PEDESTRIAN DETECTION ALGORITHMS* (2019), <https://arxiv.org/pdf/1906.10490.pdf> [<https://perma.cc/H3LA-JZ5F>] (finding that pedestrian detection algorithms are more likely to miss child pedestrians).

51. E.g., Mason Marks, *Algorithmic Disability Discrimination*, in *DISABILITY, HEALTH, LAW AND BIOETHICS* 242, 242–254 (Glenn Cohen Carmel Shachar, Anita Silvers & Michael Ashley Stein eds., 2020) (discussing disability-based discrimination by AI mining for emergent medical data).

52. E.g., Abubakar Abid, Maheen Farooqi & James Zou, *Large Language Models Associate Muslims with Violence*, 3 NATURE MACH. INTEL. 461, 461–463 (2021).

entation,⁵³ national origin,⁵⁴ pregnancy,⁵⁵ familial status,⁵⁶ and veteran status.⁵⁷

Algorithmic bias can be embedded at multiple stages of the algorithmic design process. Developers exercise human judgment at numerous points while developing an algorithm.⁵⁸ People determine and define the algorithm's goals and desired outputs; identify, collect, and clean the data that feeds the models; select and apply an algorithmic model; screen results for errors and outliers and tweak the model accordingly; set the acceptable levels of false negatives and false positives; and interpret a model's outcomes.⁵⁹ Errors and biases can be incorporated at any (or all) of these stages.

To understand how a seemingly neutral technology can result in discrimination, consider four "layers of bias." The four layers of bias, or points at which bias can manifest, are as follows: (1) the values embedded in the model; (2) the data used to train the model; (3) the ways humans use the algorithm; and (4) the foundational decision to use group characteristics to make individualized determinations.⁶⁰ At the first layer, an algorithm's designer determines how to achieve the users' desired outcomes or targets.⁶¹ Examples of desired outcomes might include a college seeking to predict which applicants will be most successful on campus; a landlord attempting to identify which prospective tenants are likely to make timely rent payments; or a lender wishing to assess the creditworthiness of potential borrowers. These entities "might want to use machine learning to find 'good' [students, tenants, or] employees to hire, but the meaning of 'good' is not self-evident. Machine learning re-

53. *E.g.*, Sophie Bishop, *Influencer Management Tools: Algorithmic Cultures, Brand Safety, and Bias*, SOC. MEDIA + SOC'Y, Jan.–March 2021, at 1, 5, 8–9.(discussing the effect of algorithmic bias against LGBTQ+ orientations in marketing).

54. *E.g.*, Ryan S. Baker & Aaron Hawn, *Algorithmic Bias in Education*, INT'L J. A.I. EDUCATION 15–16 (Nov. 18, 2021).

55. *E.g.*, FREDERIK ZUIDERVEEN BORGESIU, DISCRIMINATION, ARTIFICIAL INTELLIGENCE, AND ALGORITHMIC DECISION-MAKING 13–14 (2018) (noting an algorithm Target employs to predict pregnancy for targeted marketing); Valentina Zarya, *Employers Are Quietly Using Big Data to Track Employee Pregnancies*, FORTUNE (Feb. 17, 2016, 4:36 PM), <http://fortune.com/2016/02/17/castlight-pregnancy-data> [<https://perma.cc/FF66-8XBJ>].

56. *See, e.g.*, Fair Hous. Council v. Roommates.com, LLC, 521 F.3d 1157, 1169–70 (9th Cir. 2008) (holding that a website that matched roommates with an algorithm based on factors such as familial status was not immunized from Fair Housing Act violations by § 230 of the Communications Decency Act).

57. *E.g.*, Charles V. Bagli, *Facebook Vowed to End Discriminatory Housing Ads. Suit Says It Didn't.*, N.Y. TIMES (Mar. 27, 2018), <https://www.nytimes.com/2018/03/27/nyregion/facebook-housing-ads-discrimination-lawsuit.html> [<https://perma.cc/3XWA-DS8E>].

58. David Lehr & Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. DAVIS L. REV. 653, 717 (2017) (machine learning algorithms "are the complicated outputs of intense human labor").

59. *See id.* at 672–702.

60. This "layers of bias" framework is inspired by and adapted from Eckhouse, Lum, Conti-Cook & Ciccolini, *supra* note 32, at 187, in which the authors walk through three ways bias can infect criminal risk prediction algorithms. While the authors' approach is focused on algorithms in the criminal legal system, it applies to any "area[] where data-driven decision-making tools are now in use." *Id.*

61. Lehr & Ohm, *supra* note 58, at 672–77.

quires specific and explicit definitions, demanding that those definitions refer to something measurable.”⁶² Someone must craft these measurable definitions; a computer cannot make these value choices. Thus, for example, a programmer necessarily must decide how to calculate whether students are “good” for the algorithm’s purposes. Will students be measured by their grades, schools’ graduation rates, expected graduation date, use of campus resources, or other factors? As Solon Barocas and Andrew Selbst explain, “Through this necessarily subjective process of translation, data miners may unintentionally parse the problem in such a way that happens to systematically disadvantage protected classes.”⁶³

Notably, the people making these value judgments do not represent the impacted populations. In technical jobs and leadership positions, the tech industry is overwhelmingly male and White or Asian.⁶⁴ Only about 5% of the workforce in Silicon Valley firms consists of Black, Hispanic, and Indigenous workers.⁶⁵ At Google, only 2.5% of the workforce is Black; at Facebook and Microsoft, 4%.⁶⁶ Women hold roughly 25% of technical jobs and even fewer leadership positions.⁶⁷ These disparities stem, in part, from employers preferring to recruit and hire workers who replicate their

62. Samir Passi & Solon Barocas, *Problem Formulation and Fairness*, 2019 PROC. ACM CONF. ON FAIRNESS, ACCOUNTABILITY & TRANSPARENCY 39, 39, <https://doi.org/10.1145/3287560.3287567> [<https://perma.cc/6NUK-BPMJ>].

63. Barocas & Selbst, *supra* note 33, at 678. Eckhouse and her co-authors describe this layer as involving choices about fairness, but there are multiple ways to define fairness—value choices must be made. Eckhouse, Lim, Conti-Cook & Ciccolini, *supra* note 32, at 189–90.

64. See Sara Harrison, *Five Years of Tech Diversity Reports—and Little Progress*, WIRED (Oct. 1, 2019, 7:00 AM), <https://www.wired.com/story/five-years-tech-diversity-reports-little-progress> [<https://perma.cc/HF4F-R8A8>]; Johnson, *supra* note 28, at 1225–27 (explaining the need for diversity in leadership positions for companies that develop and adopt automated decision-making platforms); SARAH MYERS WEST, MEREDITH WHITTAKER & KATE CRAWFORD, AI NOW INST., DISCRIMINATING SYSTEMS: GENDER, RACE, AND POWER IN AI 6 (2019), <https://ainowinstitute.org/discriminatingystems.pdf> [<https://perma.cc/A4BD-68K2>] (“Currently, large scale AI systems are developed almost exclusively in a handful of technology companies and a small set of elite university laboratories, spaces that in the West tend to be extremely [W]hite, affluent, technically oriented, and male.”).

65. See Maya Beasley, *There Is a Supply of Diverse Workers in Tech, So Why Is Silicon Valley So Lacking in Diversity?*, CTR. FOR AM. PROGRESS (Mar. 29, 2017), <https://www.americanprogress.org/issues/race/reports/2017/03/29/429424/supply-diverse-workers-tech-silicon-valley-lacking-diversity> [<https://perma.cc/HB7Q-X4ZY>]. Low-income people toil for low wages at the lower rungs of the industry, including “ghost workers” and content moderators. MARY L. GRAY & SIDDHARTH SURI, GHOST WORK: HOW TO STOP SILICON VALLEY FROM BUILDING A NEW GLOBAL UNDERCLASS 2–8 (2019); SARAH T. ROBERTS, BEHIND THE SCREEN: CONTENT MODERATION IN THE SHADOWS OF SOCIAL MEDIA 33–38 (2019).

66. WEST, WHITTAKER & CRAWFORD, *supra* note 64, at 3; Ayanna Howard & Charles Isbell, *Diversity in AI: The Invisible Men and Women*, MIT SLOAN MGMT. REV. (Sept. 21, 2020), <https://sloanreview.mit.edu/article/diversity-in-ai-the-invisible-men-and-women> [<https://perma.cc/P2J7-S2VN>].

67. SASHA COSTANZA-CHOCK, DESIGN JUSTICE: COMMUNITY-LED PRACTICES TO BUILD THE WORLD WE NEED 73–74 (2020).

existing workforce.⁶⁸ There is also an “endpoint” problem⁶⁹—women, Black, and Latino employees who work in this sector leave at far higher rates than White men due to harassment, lack of mentorship, exclusion, and disrespect.⁷⁰ Catherine D’Ignazio and Lauren Klein warn of the consequences of the tech industry’s homogeneity: “When data teams are primarily composed of people from dominant groups, those perspectives come to exert outsized influence on the decisions being made—to the exclusion of other identities and perspectives.”⁷¹

At the second layer of bias, the choice of data used to implement the model can result in a disparate impact because the chosen data may reflect preexisting structural biases. Pauline Kim summarizes this dynamic: “Predictive algorithms are built by observing past patterns of behavior, and one of the enduring patterns in American economic life is the unequal distribution of opportunities along the lines of race, gender, and other personal characteristics.”⁷² The algorithms carry forward historical biases embedded in the training data. For example, police departments across the country use predictive software to identify high-crime areas and likely offenders.⁷³ Critics charge that this software merely leads police back to the same locations where high numbers of arrests were made in the past. Given that Black communities have long been over-policed, this creates a “self-reinforcing feedback loop”⁷⁴ that “perpetuate[s] historical biases in enforcement.”⁷⁵ Another example involves the Amazon

68. Maya Beasley, *There Is a Supply of Diverse Workers in Tech, So Why Is Silicon Valley So Lacking in Diversity?*, CTR. FOR AM. PROGRESS (Mar. 29, 2017), <https://www.americanprogress.org/issues/race/reports/2017/03/29/429424/supply-diverse-workers-tech-silicon-valley-lacking-diversity> [<https://perma.cc/HB7Q-X4ZY>].

69. Kimberly A. Houser, *Can AI Solve the Diversity Problem in the Tech Industry? Mitigating Noise and Bias in Employment Decision-Making*, 22 STAN. TECH. L. REV. 290, 297–303 (2019) (stating women leave the tech industry at a rate 45% higher than men); Kyla Windley & Edith Pan, *Diversity in Tech: The Endpoint Problem*, MEDIUM: THE STARTUP (Oct. 28, 2020), <https://medium.com/swlh/diversity-in-tech-the-endpoint-problem-77f3265b6aab> [<https://perma.cc/7B8L-YQ6P>].

70. COSTANZA-CHOCK, *supra* note 67, at 71 (“Tech companies reproduce intersectional oppression through their hiring, retention, and promotion practices; through internal corporate culture that tolerates misogyny, racism, and sexual harassment; and through the products they design.”).

71. CATHERINE D’IGNAZIO & LAUREN F. KLEIN, DATA FEMINISM 28 (2020). *See also* Johnson, *supra* note 28, at 1262 (stating some causes of bias “are the result of firms’ reliance on homogenous groups of developers”).

72. Pauline T. Kim, *Manipulating Opportunity*, 106 VA. L. REV. 867, 869–70 (2020).

73. *See* Andrew Guthrie Ferguson, *The “Smart” Fourth Amendment*, 102 CORNELL L. REV. 547, 570–71 (2017); *see also* Andrew D. Selbst, *Disparate Impact in Big Data Policing*, 52 GA. L. REV. 109, 129–40 (2017) (discussing both place-based and people-based predictive policing tools).

74. Caroline Haskins, *Academics Confirm Major Predictive Policing Algorithm Is Fundamentally Flawed*, VICE (Feb. 14, 2019, 11:57 AM), https://www.vice.com/en_us/article/xwbag4/academics-confirm-major-predictive-policingalgorithm-is-fundamentally-flawed [<https://perma.cc/9YQZ-2WEU>].

75. William Isaac & Kristian Lum, *Setting the Record Straight on Predictive Policing and Race*, APPEAL (Jan. 3, 2018), <https://theappeal.org/setting-the-record-straight-on-predictive-policing-and-race-fe588b457ca2> [<https://perma.cc/HQG9-WYF8>]. *See also* Kristian Lum & William Isaac, *To Predict and Serve?*, SIGNIFICANCE 14, 18 (Oct. 2016); Sandra G. Mayson, *Bias In, Bias Out*, 128 YALE L.J. 2218, 2253 (2019) (“The choice to predict arrest

hiring algorithm, discussed above.⁷⁶ Because it relied on resumes of past hires (predominantly men), it incorporated Silicon Valley's historic employment patterns. Unfortunately, simply removing data about protected classes, such as race and gender, would still not guarantee a fair result because other inherently biased proxies, such as zip code and income level, will produce substantially the same results as the characteristics they replace.⁷⁷ Bias at the second layer can also arise when the training data sets are not adequately representative, such as with facial recognition algorithms.⁷⁸ Those algorithms were developed primarily through photographs of White men and, therefore, are far less accurate in identifying women of color.⁷⁹

Bias seeps in at the third layer when people deploy it in the real world. Users may apply an algorithm outside of its intended context or misinterpret an algorithm's output.⁸⁰ For example, algorithms designed to make decisions about whether a criminal defendant should be released pending trial focus on recidivism, yet they are deployed in sentencing decisions, which should take into consideration a broader range of factors.⁸¹ One study reviewing the use of algorithmic tools to predict child abuse or neglect in the child welfare system found that some social workers failed to use the algorithm as intended.⁸² While some practitioners used the tool properly, combining the algorithm's recommendation with their judgment to make a decision, others ignored the tool entirely, exhibiting algorithm aversion.⁸³ Conversely, others put undue faith in the tool, a

has profound consequences for racial equity because in most places, for nearly all crime categories, arrest rates have been racially disparate for decades.”); Dorothy E. Roberts, *Digitizing the Carceral State*, 132 HARV. L. REV. 1695, 1720 (2019) (reviewing VIRGINIA EUBANKS, *AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR* (2018)).

76. See Dastin, *supra* note 40.

77. Eckhouse, Lum, Conti-Cook & Ciccolini, *supra* note 32, at 192–93 (“In a society structured by racism and segregation, many variables commonly included in models, from location to employment to prior police encounters, will be correlated with race.”).

78. Sara Hooker, *Moving Beyond “Algorithmic Bias Is a Data Problem,”* PATTERNS 1–2 (Apr. 9, 2022), <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8085589/pdf/main.pdf> [<https://perma.cc/UM6Y-JPGK>].

79. See Lindsey Barrett, *Ban Facial Recognition Technologies for Children—And for Everyone Else*, 26 B.U. J. SCI. & TECH. L. 223, 231, 247–48 (2020).

80. Danks & London, *supra* note 30, at 4694 (describing two forms of inappropriate uses of algorithms: transfer context bias and interpretation bias).

81. DANIELLE KEHL, PRISCILLA GUO & SAMUEL KESSLER, BERKMAN KLEIN CTR. FOR INTERNET & SOC’Y, *ALGORITHMS IN THE CRIMINAL JUSTICE SYSTEM: ASSESSING THE USE OF RISK ASSESSMENTS IN SENTENCING* 13–14 (2017), <https://dash.harvard.edu/handle/1/33746041> [<https://perma.cc/9MXQ-P7BX>].

82. Thea Snow, *From Satisficing to Artificing: The Evolution of Administrative Decision-Making in the Age of the Algorithm*, 3 DATA & POL’Y e3, 1–3 (2021), <https://www.cambridge.org/core/services/aop-cambridge-core/content/view/8962400DADAC3C740AC023A20B38E285/S2632324920000255a.pdf/from-satisficing-to-artificing-the-evolution-of-administrative-decision-making-in-the-age-of-the-algorithm.pdf> [<https://perma.cc/4YL2-AZ9K>].

83. *Id.* at 6–8, 10–12.

psychological phenomenon known as “automation bias.”⁸⁴ There are also situations in which human decision-makers use these data-centric tools to mask their “subjective judgments, burying them under a patina of objectivity and making them harder to monitor.”⁸⁵

The base layer of bias implicates concerns about the fairness of judging individuals based on their characteristics; these concerns are heightened when core civil and human rights are at stake.⁸⁶ As already noted, many algorithmic models are based on “the past behavior of other people,” and these models inevitably incorporate data regarding protected characteristics and socioeconomic variables.⁸⁷ Algorithms thus turn inequality into individualized determinations that mask the structural basis of their outputs.⁸⁸ So, even when facial recognition technology eventually works out its accuracy problems through more representative training data, the question remains: Should this technology be used at all when it deprives individuals of privacy, has a chilling effect on public protests and gatherings and is more likely to be deployed as a policing tool against minorities?⁸⁹ This is what Frank Pasquale calls a “second wave” question about algorithmic fairness, asking whether certain algorithmic systems should be deployed at all, and who gets to make that decision, rather than how to tweak and improve the algorithms.⁹⁰

In light of growing evidence of algorithmic bias, the civil rights community has coalesced, along with data privacy and consumer advocacy organizations, to demand legal and policy reforms that address the problem of digital discrimination. As a coalition of fourteen civil rights organizations stated in 2021, “[T]he United States needs new, updated, and comprehensive laws to protect our civil rights” because existing privacy laws “do not contain anti-discrimination protections or effective enforcement provisions.”⁹¹ Presidents Obama and Biden have highlighted the risks—and

84. *Id.* at 13. On automation bias more generally, see Linda J. Skitka, Kathleen L. Mosier & Mark Burdick, *Does Automation Bias Decision-Making?*, 51 INT’L J. HUM.-COMPUT. STUD. 991 (1999).

85. Angèle Christin, *Algorithms in Practice: Comparing Web Journalism and Criminal Justice*, Jul.–Dec. 2017 BIG DATA & SOC’Y 1, 10 (2017), <https://journals.sagepub.com/doi/pdf/10.1177/2053951717718855> [<https://perma.cc/2GW5-339S>].

86. See Eckhouse, Lim, Conti-Cook & Ciccolini, *supra* note 32, at 198.

87. *Id.* at 199.

88. *See id.*

89. See Barrett, *supra* note 79, at 239–251 (summarizing harms of facial recognition).

90. Frank Pasquale, *The Second Wave of Algorithmic Accountability*, L. & POL. ECON. PROJECT (Nov. 25, 2019), <https://lpeproject.org/blog/the-second-wave-of-algorithmic-accountability> [<https://perma.cc/AVE7-PN9A>].

91. C.R. PRIV. & TECH. TABLE, CIVIL RIGHTS, PRIVACY, AND TECHNOLOGY: RECOMMENDED 2021 OVERSIGHT PRIORITIES FOR THE 177TH CONGRESS, 23, 32 (2021), <https://www.civilrightstable.org/wp-content/uploads/2021/01/Civil-Rights-Privacy-and-Technology-Recommended-2021-Oversight-Priorities.pdf> [<https://perma.cc/JL9V-VGLG>]. See also Letter from The Leadership Conf. on Civ. & Hum. Rts. to Ambassador Susan Rice, Dir. Domestic Pol’y Council (Oct. 27, 2021), <https://ourfinancialsecurity.org/wp-content/uploads/2021/11/10.27.21-AI-Letter-to-Ambassador-Rice-on-Civil-Rights-and-AI.pdf> [<https://perma.cc/4CNJ-D9V6>] (“[T]he clock is already ticking on what can be accomplished during President Biden’s first term” with regard to a “public and proactive agenda on the civil rights implications of AI.”).

benefits—of AI, including civil rights violations it could cause. In 2022, the Biden White House’s Office of Science and Technology Policy released an *AI Bill of Rights*, including the principle that people “should not face discrimination by algorithms and systems should be used and designed in an equitable way.”⁹² While federal agencies have studied the benefits and risks of AI for several years⁹³ (and have even brought enforcement actions in the past),⁹⁴ the effort to curtail the use and effects of discriminatory algorithmic systems appears to have intensified in the last few years. A number of federal agencies have announced renewed commitment to enforce the laws implicated by AI and other automated systems, including civil rights protections within their regulatory authority.⁹⁵ Congress has considered but not passed legislation to enhance data privacy and algorithmic accountability, and these proposed bills typically address civil rights concerns.⁹⁶ In the face of congressional intransigence, some states have passed laws enhancing data privacy that will limit the biometric use of personal data and digital surveillance.⁹⁷ Clearly, the civil rights implications of AI are on the public agenda. However, the current framing of civil rights does not expressly encompass people who face digital discrimination based on their SES, even though automated systems

92. WHITE HOUSE OFFICE OF SCIENCE AND TECHNOLOGY POLICY, BLUEPRINT FOR AN AI BILL OF RIGHTS: MAKING AUTOMATED SYSTEMS WORK FOR THE AMERICAN PEOPLE, <https://www.whitehouse.gov/ostp/ai-bill-of-rights> [<https://perma.cc/C5US-AKE2>]. The antidiscrimination principle is linked to existing legal protections, so does not address socio-economic discrimination.

93. See, e.g., NAT’L SEC. COMM’N ON A.I., FINAL REPORT 15 (2021), <https://www.nsc.ai.gov/wp-content/uploads/2021/03/Full-Report-Digital-1.pdf> [<https://perma.cc/N7H8-MBZJ>] (presenting the Commission’s findings of a study that began in the spring of 2019); U.S. GOV’T ACCOUNTABILITY OFF., GAO-18-142SP, TECHNOLOGY ASSESSMENT: ARTIFICIAL INTELLIGENCE: EMERGING OPPORTUNITIES, CHALLENGES, AND IMPLICATIONS (2018); *National Artificial Intelligence Initiative: Overseeing and Implementing the United States National AI Strategy*, NAT’L A.I. INITIATIVE, <https://www.ai.gov> [<https://perma.cc/W6XN-PHEW>].

94. See, e.g., Charge of Discrimination, Sec’y Dep’t Hous. & Urb. Dev. v. Facebook, Inc., FHEO No. 01-18-0323-8 (March 28, 2019) (charging Facebook with housing discrimination in its ad delivery system); Lesley Fair, *\$3 Million FCRA Settlement Puts Tenant Background Screening at the Forefront*, FED. TRADE COMM’N: BUS. BLOG (Oct. 17, 2018), <https://www.ftc.gov/business-guidance/blog/2018/10/3-million-fcra-settlement-puts-tenant-background-screening-forefront> [<https://perma.cc/VN6X-BUBV>] (settling charges that tenant screening company failed to ensure accuracy of its reports).

95. See, e.g., Andrew Smith, *Using Artificial Intelligence and Algorithms*, FED. TRADE COMM’N: BUS. BLOG (Apr. 8, 2020), <https://www.ftc.gov/news-events/blogs/business-blog/2020/04/using-artificial-intelligence-algorithms> [<https://perma.cc/MJ7M-7ECV>]; Elisa Jillson, *Aiming for Truth, Fairness, and Equity in Your Company’s Use of AI*, FED. TRADE COMM’N: BUS. BLOG (Apr. 19, 2021), <https://www.ftc.gov/news-events/blogs/business-blog/2021/04/aiming-truth-fairness-equity-your-companys-use-ai> [<https://perma.cc/US8U-X3LC>]; Press Release, Equal Employment Opportunity Commission, EEOC Launches Initiative on Artificial Intelligence and Algorithmic Fairness (Oct. 28, 2021), <https://www.eeoc.gov/newsroom/eeoc-launches-initiative-artificial-intelligence-and-algorithmic-fairness> [<https://perma.cc/ES6F-R5NE>]; *Written Testimony of Director Rohit Chopra Before the House Committee on Financial Services*, CONSUMER FIN. PROT. BUREAU (Oct. 28, 2021), <https://www.consumerfinance.gov/about-us/newsroom/written-testimony-director-rohit-chopra-before-house-committee-financial-services> [<https://perma.cc/92SV-ZC75>].

96. See *infra* Part III.C.

97. *Id.*

have outsized and harmful impacts on people experiencing poverty, as the following Section clarifies.

B. DIGITAL DISCRIMINATION AGAINST PEOPLE EXPERIENCING POVERTY

People experiencing poverty have long faced stigma and discrimination in the United States.⁹⁸ The prevailing explanation for poverty in the United States is that people are poor due to behavioral choices.⁹⁹ In this “culture of poverty” perspective, the poor make deficient choices that trap them in poverty.¹⁰⁰ This theory aligns with the American myth of meritocracy, which holds that anyone can pull themselves up by their bootstraps with hard work and determination.¹⁰¹ This myth implies that failure to thrive in a capitalist economy is tied to moral failure.¹⁰² However, the reality of poverty has multiple, overlapping structural causes tied to the nature of our economy, including the increase of low-wage jobs; declining power of unions; lack of universal childcare, health care, and affordable housing; inadequate educational opportunities; limited social supports; growing income inequality; and discrimination—in sum, “a failure of the economic and political structures to provide enough decent opportunities and supports for the whole of society.”¹⁰³

Given the dominant ideology, it is unsurprising that anti-poverty discrimination in the analog world is replicated in the digital world. This Section provides four case studies that demonstrate how data-centric technologies adversely impact low-income people. It explores algorithms used in tenant screening, credit scoring, higher education, and targeted advertising. These case studies are far from comprehensive,¹⁰⁴ but they

98. See Peterman, *supra* note 7, at 1303–12. See also Mario L. Barnes & Erwin Chemerinsky, *The Disparate Treatment of Race and Class in Constitutional Jurisprudence*, 72 L. & CONTEMP. PROBS. 109, 121 (2009) (“Poverty certainly shares many of the characteristics that warrant heightened scrutiny for race. There has been a long history of discrimination against the poor, often in ways that are invisible to those with resources.”).

99. See HANDLER & HASENFELD, *supra* note 11, at 70; Jennings, *supra* note 11, at 18–19 (summarizing behavioral theories); Munger, *supra* note 11, at 3 (“More strictly than other industrialized societies, we measure the worthiness of all our citizens by the level of their commitment to the labor market . . .”).

100. Oscar Lewis first articulated this theory in social science scholarship, concluding that poor people develop their own value system, which perpetuates itself over generations and is nearly impossible to escape, even if structural conditions change. Oscar Lewis, *The Culture of Poverty*, 35 SOC’Y 7, 7 (Jan/Feb 1998). The people in this culture share a “strong feeling of marginality, of helplessness, of dependency, of not belonging Along with this feeling of powerlessness is a widespread feeling of inferiority, of personal unworthiness.” *Id.*

101. See generally STEPHEN J. MCNAMEE & ROBERT K. MILLER, JR., *THE MERITOCRACY MYTH* 1–2 (2d ed. 2009); Mark R. Rank, *Toward a New Understanding of American Poverty*, 20 WASH. U. J.L. & POL’Y 17, 25 (2006).

102. Cf. GEORGE GILDER, *WEALTH AND POVERTY* 68 (1981) (“The only dependable route from poverty is always work, family, and faith But the current poor . . . are refusing to work hard.”).

103. Mark R. Rank, *Rethinking American Poverty*, Spring 2011 CONTEXTS 16, 19 (2011).

104. For a comprehensive catalogue of algorithmic harms suffered by low-income people, see GILMAN, *supra* note 3.

illustrate how the digital economy reflects and reinforces poverty.

1. *Tenant Screening Algorithms*

Across the United States, low-income people struggle to find affordable and habitable housing. Indeed, 70% of extremely low-income renters spend more than half their income on rent and utilities, leaving little income left over to meet basic needs.¹⁰⁵ There is no county in America where a person earning minimum wage and working forty hours per week can afford a two-bedroom home.¹⁰⁶ Further, post-pandemic rental markets for low-income Americans are competitive, and rents are rising faster than wages.¹⁰⁷ Meanwhile, three out of four eligible households do not obtain any federally subsidized housing assistance.¹⁰⁸ Based on the number of low-income renter households, the market is short 3.4 million rental homes in the low-income price range.¹⁰⁹ The unaffordability crisis disproportionately impacts low-income people of color due to income inequality, discrimination in homeownership opportunities, and a large racial wealth gap.¹¹⁰ Algorithmically generated tenant screening reports pose an additional barrier for many low-income renters.

Ninety percent of landlords purchase tenant screening reports from over 2,000 companies that algorithmically score potential tenants based on various attributes, such as residential history, civil and criminal case history, credit history, and ill-defined “lifestyle” criteria like marital history and pet ownership.¹¹¹ These companies obtain this information from data brokers and public records.¹¹² Reports typically generate a tenant-

105. ANDREW AURAND, DAN EMMANUEL, DANIEL THREET, IKRA RAFI & DIANE YENTEL, NAT'L LOW INCOME HOUS. COAL., *THE GAP: A SHORTAGE OF AFFORDABLE HOMES* 2 (2021), https://reports.nlihc.org/sites/default/files/gap/Gap-Report_2021.pdf [<https://perma.cc/24FD-9BD4>].

106. ANDREW AURAND, DAN EMMANUEL, DANIEL THREET, IKRA RAFI & DIANE YENTEL, NAT'L LOW INCOME HOUS. COAL., *OUT OF REACH: THE HIGH COST OF HOUSING* 4 (2021), https://nlihc.org/sites/default/files/oor/2021/Out-of-Reach_2021.pdf [<https://perma.cc/V5GS-4VWD>].

107. See JOINT CTR. FOR HOUS. STUD., *AMERICA'S RENTAL HOUSING 2022 23–24* (2022), https://www.jchs.harvard.edu/sites/default/files/reports/files/Harvard_JCHS_Americas_Rental_Housing_2022.pdf [<https://perma.cc/XW5X-D7BJ>]; AURAND ET AL., *supra* note 105, at 3–4. Thirty-six percent of renter households earn less than \$30,000 per year; only fifteen percent of homeowner households earn under this threshold. JOINT CTR. FOR HOUS. STUD. OF HARVARD UNIV., *supra* note 107, at 13.

108. AURAND ET AL., *supra* note 105, at 3.

109. *See id.*

110. *See id.* at 7.

111. Shivangi Bhatia, *To “Otherwise Make Unavailable”: Tenant Screening Companies’ Liability Under the Fair Housing Act’s Disparate Impact Theory*, 88 *FORDHAM L. REV.* 2551, 2553, 2260 (2020); Lauren Kirchner & Matthew Goldstein, *Access Denied: Faulty Automated Background Checks Freeze Out Renters*, *MARKUP* (May 28, 2020, 5:00 PM), <https://themarkup.org/locked-out/2020/05/28/access-denied-faulty-automated-background-checks-freeze-out-renters> [<https://perma.cc/4GDM-NQV5>].

112. ARIEL NELSON., NAT'L CONSUMER L. CTR., *BROKEN RECORDS REDUX: HOW ERRORS BY CRIMINAL BACKGROUND CHECK COMPANIES CONTINUE TO HARM CONSUMERS SEEKING JOBS AND HOUSING* 10 (2019), <https://www.nclc.org/images/pdf/criminal-justice/report-broken-records-redux.pdf> [<https://perma.cc/GZ9U-CPA4>] (“It is often purchased in bulk from public sources—including law enforcement agencies, state courts, corrections

worthiness number (similar to a credit score) or provide a landlord with a thumbs-up or thumbs-down recommendation.¹¹³ Tenant screening reports have been called “tenant blacklists”¹¹⁴ or a “Scarlet E,”¹¹⁵ limiting where—and whether—people are housed.

Tenant screening reports are problematic for several reasons. To begin, they are misleading because they lack context. Reports may include eviction court filings, but they do not necessarily include whether the tenant won or raised meritorious defenses, or if the case was dismissed.¹¹⁶ The reports can also be rife with inaccuracies.¹¹⁷ A frequent error involves cross-matched data regarding people with similar names, which disproportionately impacts minorities.¹¹⁸ Countless tenants have been denied housing based on the criminal records of another person with the same or similar name.¹¹⁹

Yet even if mistakes were fixed and context provided in these reports, the adverse impacts on poor people would remain because of certain data points included in tenant screening algorithms. As mentioned above, algorithms factor in prior eviction filings, which live forever in digital reports.¹²⁰ Approximately 2.3 million low-income renters are evicted every year, largely due to nonpayment of rent,¹²¹ which reflects rising rents and stagnant wages.¹²² Sociologist Matthew Desmond claims, “Eviction is a

offices, and criminal record repositories—or obtained from public websites via web scraping technology.” (citations omitted)).

113. Kaveh Waddell, *How Tenant Screening Reports Make It Hard for People to Bounce Back from Tough Times*, CONSUMER REPS. (Mar. 11, 2021), <https://www.consumerreports.org/algorithmic-bias/tenant-screening-reports-make-it-hard-to-bounce-back-from-tough-times> [<https://perma.cc/Q67C-ABRV>].

114. Rudy Kleysteuber, *Tenant Screening Thirty Years Later: A Statutory Proposal to Protect Public Records*, 116 YALE L.J. 1344, 1381 (2007).

115. Kathryn A. Sabbeth, *Erasing the “Scarlet E” of Eviction Records*, APPEAL (Apr. 12, 2021), <https://theappeal.org/the-lab/report/erasing-the-scarlet-e-of-eviction-records> [<https://perma.cc/XA7B-ZBPN>].

116. *See id.* (“[T]enants can get marked as undesirable simply because the data collection method used by most tenant-screening bureaus includes anyone named as a defendant in an eviction case, regardless of whether any judgment is issued against them.”); Kleysteuber, *supra* note 114, at 1355.

117. Kirchner & Goldstein, *supra* note 111; Cyrus Farivar, *Tenant Screening Software Faces National Reckoning*, NBC (March 14, 2021, 6:00 AM), <https://www.nbcnews.com/tech/tech-news/tenant-screening-software-faces-national-reckoning-n1260975> [<https://perma.cc/XW4T-S2ET>].

118. Kirchner & Goldstein, *supra* note 111. Cross-matching errors particularly impact minority groups “which tend to have fewer unique last names. For example, more than 12 million Latinos nationwide share just 26 surnames, according to the census.” *Id.*

119. *See id.*

120. Sabbeth, *supra* note 115.

121. *See* David Brancaccio & Katie Long, *Millions of Americans are Evicted Every Year—and Not Just in Big Cities*, MARKETPLACE (Apr. 9, 2018), <https://www.marketplace.org/2018/04/09/eviction-desmond-princeton-housing-crisis-rent> [<https://perma.cc/22Z8-33BC>] (noting that the one million evictions impacts 2.3 million people, many of whom are children); *National Estimates: Eviction in America*, EVICTION LAB (May 11, 2018), <https://evictionlab.org/national-estimates> [<https://perma.cc/LZJ2-FLUS>] (“[W]e see almost a million evictions against tenants every single year.”).

122. *See* Pamela Foohey & Sara S. Greene, *Credit Scoring Duality*, 86 L. & CONTEMP. PROBS. (forthcoming 2022).

cause, not just a condition, of poverty.”¹²³ Eviction records are permanent data points in tenant screening reports, limiting people’s economic and geographic mobility.¹²⁴

Credit checks are also folded into tenant screening reports. This is problematic for the 11% of American adults, or 26 million people, who are “credit invisible,” meaning they have no credit history whatsoever.¹²⁵ An additional 8.3%, or 19.5 million people, have credit considered “unscorable,” meaning they lack sufficient credit histories to generate a score.¹²⁶ Credit invisible and unscorable people are concentrated in low-income neighborhoods and among Black and Latino Americans.¹²⁷ And even with credit, people living in low-income neighborhoods are more likely to have low credit scores.¹²⁸ Credit scoring is also notoriously rife with errors, particularly for people living in Black and Latino neighborhoods.¹²⁹ Accordingly, using credit scores as data points in tenant screening reports disproportionately harms low-income people.

Further, tenant screening reports include criminal background checks, yet another factor that disadvantages low-income tenants and particularly people of color. One in three Americans has a criminal record, yet many are for arrests that never resulted in a conviction.¹³⁰ Criminal records are inextricably tied to poverty—poor people are disproportionately involved with the criminal legal system.¹³¹ Poor adults are four times more likely to be incarcerated in state prisons than adults above the poverty line.¹³²

123. MATTHEW DESMOND, *EVICTED: POVERTY AND PROFIT IN THE AMERICAN CITY* 299 (2016).

124. *See id.* at 297–98.

125. KENNETH P. BREVOORT, PHILIPP GRIMM & MICHELLE KAMBARA, CONSUMER FIN. PROT. BUREAU, *DATA POINT: CREDIT INVISIBLES* 4–6 (2015), https://files.consumerfinance.gov/f/201505_cfpb_data-point-credit-invisibles.pdf [<https://perma.cc/Y35T-VQHJ>].

126. *Id.*

127. *See id.* at 6. In low-income neighborhoods, almost 45% of adults are credit invisible or credit unscorable, as compared to 9% in high-income neighborhoods. *See id.* *See also* Foohey & Greene, *supra* note 122, at 3.

128. Foohey & Greene, *supra* note 122, at 9.

129. *See id.* at 8–9; *CFPB Finds Credit Report Disputes Far More Common in Majority Black and Hispanic Neighborhoods*, CONSUMER FIN. PROT. BUREAU (Nov. 2, 2021), <https://www.consumerfinance.gov/about-us/newsroom/cfpb-finds-credit-report-disputes-far-more-common-in-majority-black-and-hispanic-neighborhoods> [<https://perma.cc/VX5V-W5HY>].

130. *See* REBECCA VALLAS, SHARON DIETRICH & BETH AVERY, *CTR. FOR AM. PROGRESS A CRIMINAL RECORD SHOULDN’T BE A LIFE SENTENCE TO POVERTY* 21 (May 2021), <https://www.americanprogress.org/article/criminal-record-shouldnt-life-sentence-poverty-2> [<https://perma.cc/VA74-XH6S>]; Matthew Friedman, *Just Facts: As Many Americans Have Criminal Records as College Diplomas*, BRENNAN CTR. FOR JUST. (Nov. 17, 2015), <https://www.brennancenter.org/our-work/analysis-opinion/just-facts-many-americans-have-criminal-records-college-diplomas> [<https://perma.cc/7XCH-2BEQ>].

131. *See* Erica J. Hashimoto, *Class Matters*, 101 J. CRIM. L. & CRIMINOLOGY 31, 55 (2011); Paul D. Butler, *Poor People Lose: Gideon and the Critique of Rights*, 122 YALE L.J. 2176, 2178 (2013). Butler points out that incarceration is also tightly linked to unemployment and low levels of education, which are additional indicators of the “correlation between poverty and incarceration.” *Id.* at 2181–82.

132. Hashimoto, *supra* note 131, at 57. In addition, individuals whose income is less than 150% of the federal poverty line are fifteen times more likely to be charged with a felony than “those above the 150% marker.” *Id.* at 61.

Moreover, thousands of people are charged with crimes directly related to poverty, such as crimes related to homelessness (e.g., loitering, public camping, and sleeping in public),¹³³ failure to pay child support, and non-payment of fines and fees imposed by the criminal legal system. Poor people are one of the most represented groups in the criminal legal system, along with drug-dependent and mentally ill defendants.¹³⁴ In turn, criminal records perpetuate poverty through their collateral consequences that formally or informally bar people from housing, jobs, public benefits, and other opportunities.¹³⁵

Criminal background checks are racially and socioeconomically discriminatory.¹³⁶ As Sarah Esther Lageson explains, using criminal records to assess a person's trustworthiness or value "legitimizes police decision-making and entrenches the criminal justice system across unrelated institutions."¹³⁷ Nevertheless, there is no evidence that criminal records accurately predict a person's ability to retain housing or comply with a lease.¹³⁸ Indeed, there is little empirical evidence regarding *any* data fed into tenant screening algorithms,¹³⁹ yet landlords heavily rely on them. An algorithmic system built on hunches rather than science continues to reflect and perpetuate poverty.

2. Financial Markets and Consumer Reporting

Due to their "quantified identities,"¹⁴⁰ poor people are targeted for subprime and predatory financial products while being excluded from mainstream financial opportunities. As with housing, this financial

133. Michael Stamm, *Between a Rock and Discriminatory Place: How Sentencing Guidelines and Mandatory Minimums Should Be Employed to Reduce Poverty Discrimination in the Criminal Justice System*, 24 GEO. J. ON POVERTY L. & POL'Y 399, 402–04 (2017).

134. Hashimoto, *supra* note 131, at 62 ("African Americans were approximately three times more likely to be prisoners than non-African Americans. While that ratio is high, the overrepresentation of poor people is even higher, with poor people being more than four times more likely to be in state prison than non-poor people.").

135. See Sarah Esther Lageson, *How Criminal Background Checks Lead to Discrimination Against Millions of Americans*, WASH. POST (July 10, 2020), <https://www.washingtonpost.com/opinions/2020/07/10/personal-data-industry-is-complicit-bad-policing-it-must-be-held-accountable> [<https://perma.cc/SC8F-JAWQ>].

136. See *id.*

137. *Id.*

138. Valerie Schneider, *Racism Knocking at the Door: The Use of Criminal Background Checks in Rental Housing*, 53 U. RICH. L. REV. 923, 933 (2019); Rebecca J. Walter, Jill Viglione & Marie Skubak Tillyer, *One Strike to Second Chances: Using Criminal Backgrounds in Admission Decisions for Assisted Housing*, 27 HOUS. POL'Y DEBATE 1, 6 (2017).

139. Walter, Viglione & Skubak Tillyer, *supra* note 138, at 7 ("Surprisingly, in the housing field, there is little research examining factors that predict a successful tenant . . . [N]othing suggests that a criminal background implies the individual will be a bad tenant."). See also Kimani Paul-Emile, *Reconsidering Criminal Background Checks: Race, Gender, and Redemption*, 25 S. CAL. INTERDISC. L.J. 395, 397 (2016) ("Studies have cast doubt on the assumption that the existence of a criminal record correctly forecasts one's work behavior, and data show that individuals with criminal records who stay clean for a few years are no more likely than anyone else to have a future arrest.").

140. Frank A. Pasquale & Danielle Keats Citron, *Promoting Innovation While Preventing Discrimination: Policy Goals for the Scored Society*, 89 WASH. L. REV. 1413, 1414 (2014).

marginalization based on sorting and segmenting consumers reflects and reinforces poverty. Digital profiling makes the economically vulnerable ripe for online targeting by high-interest lenders, including bank and fintech partnerships that are moving aggressively into the fringe banking space.¹⁴¹ Online lead generation steers low-income (predominantly Black) consumers to high-interest payday loans and other predatory products.¹⁴² The lead generation industry scrapes individuals' online interactions to generate profiles and then sells them to companies that barrage users with predatory offers.¹⁴³ One lead generator brags that it provides payday loan companies with highly segmented lists that identify "consumers who are struggling to make their bills and are looking for fast quick cash."¹⁴⁴

Payday lenders began as storefront operations disproportionately located in Black and Hispanic communities.¹⁴⁵ Now, they invest heavily in an online presence to target the same minority groups, in part because some states have outlawed payday lending.¹⁴⁶ Yet online advertisements reach consumers even in states where payday lending is unlawful. The average annual percentage rate (APR) for online payday loans is 650%.¹⁴⁷ Due to these high-interest rates, borrowers struggle to pay back loans, and "80[%] of payday loans are taken out within two weeks of repayment of a previous payday loan,"¹⁴⁸ resulting in a debt spiral and

141. See Pamela Foohey & Nathalie Martin, *Fintech's Role in Exacerbating or Reducing the Wealth Gap*, 2021 U. ILL. L. REV. 459, 482–84, 487 (2021); Cassandra Jones Havard, *Democratizing Credit: Examining the Structural Inequities of Subprime Lending*, 56 SYRACUSE L. REV. 233, 247 (2006).

142. See Alvaro Bedoya & Clare Garvie, Comments on "Follow the Lead: An FTC Workshop on Lead Generation," (Dec. 18, 2015). "[L]ead generators, an integral component of the online payday lending industry, purposefully target African American and other minority borrowers in advertising." *Id.* at 2.

143. See FED. TRADE COMM'N, "FOLLOW THE LEAD" WORKSHOP: STAFF PERSPECTIVE 4 (2016), https://www.ftc.gov/system/files/documents/reports/staff-perspective-follow-lead/staff_perspective_follow_the_lead_workshop.pdf [<https://perma.cc/5M8X-Z8KN>] (describing how the industry operates); AARON RIEKE AND LOGAN KOEPKE, UPTURN, LED ASTRAY: ONLINE LEAD GENERATION AND PAYDAY LOANS 1–6 (2015), https://www.upturn.org/static/reports/2015/led-astray/files/Upturn_-_Led_Astray_v.1.01.pdf [<https://perma.cc/WZU2-4SRE>].

144. Bedoya & Garvie, *supra* note 142, at 4 (quoting a lead generator).

145. See Robin A. Prager, *Determinants of the Locations of Payday Lenders, Pawnshops and Check-Cashing Outlets* 3 (Fed. Rsv. Bd., Working Paper No. 2009-33, 2009), <https://www.federalreserve.gov/pubs/feds/2009/200933/200933pap.pdf> [<https://perma.cc/GM54-N7L7>].

146. See Kristin Johnson, Frank Pasquale & Jennifer Chapman, *Artificial Intelligence, Machine Learning, and Bias in Finance: Toward Responsible Innovation*, 88 FORDHAM L. REV. 499, 517–18 (2019).

147. THE PEW CHARITABLE TRS., FRAUD AND ABUSE ONLINE: HARMFUL PRACTICES IN INTERNET PAYDAY LENDING 2 (2014), https://www.pewtrusts.org/-/media/assets/2014/10/payday-lending-report/fraud_and_abuse_online_harmful_practices_in_internet_payday_lending.pdf [<https://perma.cc/T8ZB-MDWE>].

148. *Payday Loan Facts and the CFPB's Impact*, THE PEW CHARITABLE TRS. (Jan. 14, 2016), <https://www.pewtrusts.org/en/research-and-analysis/fact-sheets/2016/01/payday-loan-facts-and-the-cfpbs-impact> [<https://perma.cc/68E8-LPBT>].

poverty trap.¹⁴⁹ Due to regulatory and consumer pressure, Facebook and Google imposed bans on payday lending advertisements, but predatory companies consistently evade the bans by manipulating their web pages and partnering with banks located in states with no interest rate limits.¹⁵⁰ Anyone searching online for available credit can expect to be bombarded with pop-up ads, ads on social media, emails, text messages, and other sales pitches from web-based lenders that evade state usury restrictions.¹⁵¹

Payday lending is just the tip of the iceberg. The entire consumer reporting industry sells low-income consumers' data to companies eager to target them. These companies collect and provide information to payday lenders, rent-to-own businesses, furniture stores that offer financing, high-risk consumer finance businesses, subprime home-lending businesses, and debt purchasers.¹⁵² The data broker industry sorts consumers into micro-categories for sale, such as low-income minority communities (e.g., "Urban Scramble" and "Mobile Mixers"); the elderly poor (e.g., "Rural Everlasting" and "Thrifty Elders"); and financially precarious consumers (e.g., "Underbanked Indicator" and "Pennywise Mortgagees").¹⁵³ Consumer exploitation is "made possible when a disadvantaged group is deemed risky and forced to pay a social price."¹⁵⁴

Low-income people's credit scores not only bar them from mainstream financial markets but also deprive them of opportunities that rely on creditworthiness, including housing, employment, insurance, and higher education.¹⁵⁵ "[A] fair or poor credit score can trap people in a cycle of paying more for credit and utilities, losing out on job opportunities, being denied housing and insurance, being unable to build any savings for

149. See Andrea Freeman, *Payback: A Structural Analysis of the Credit Card Problem*, 55 ARIZ. L. REV. 151, 154 (2013) ("A debt spiral occurs when a person borrows a small amount but all of her payments go towards interest and fees, never diminishing the principal. A poverty trap is when a household or individual lives below a threshold . . . where it is possible to accumulate enough assets to escape poverty through saving.").

150. Coulter Jones, Jean Eaglesham & AnnaMaria Andriotis, *How Payday Lenders Target Consumers Hurt by Coronavirus*, WALL ST. J. (June 3, 2020, 8:23 AM), https://www.wsj.com/articles/how-payday-lenders-target-consumers-hurt-by-coronavirus-11591176601?mod=article_inline [<https://perma.cc/M7U9-FMV5>]; Here & Now, *High Interest Payday Loan Lenders Target Vulnerable Communities During COVID-19*, WBUR (June 5, 2020), <https://www.wbur.org/hereandnow/2020/06/05/payday-loans-coronavirus> [<https://perma.cc/4PV8-ADP9>].

151. Jones, Eaglesham & Andriotis, *supra* note 150; Johnson, Pasquale & Chapman, *supra* note 146, at 502–03.

152. CONSUMER FIN. PROT. BUREAU *supra* note 18, at 31–33.

153. FED. TRADE COMM'N, DATA BROKERS: A CALL FOR TRANSPARENCY AND ACCOUNTABILITY 19–20 (2014), <https://www.ftc.gov/system/files/documents/reports/data-brokers-call-transparency-accountability-report-federal-trade-commission-may-2014/140527databrokerreport.pdf> [<https://perma.cc/KX2Z-D4EL>].

154. Matthew Desmond & Nathan Wilmers, *Do the Poor Pay More for Housing? Exploitation, Profit, and Risk in Rental Markets*, 124 AM. J. SOCIO. 1090, 1117 (2019).

155. See Foohey & Greene, *supra* note 122, at 7, 11. Half of U.S. employers look at applicants credit reports, "even though there is little evidence that credit history predicts workplace outcomes." Rourke L. O'Brien & Barbara Kiviati, *Disparate Impact? Race, Sex, and Credit Reports in Hiring*, 4 SOCIOUS: SOCIO. RSCH. FOR DYNAMIC WORLD 1, 1 (2018).

emergencies, and possibly facing homelessness.”¹⁵⁶ Frank Pasquale and Danielle Citron explain, “Scores can become self-fulfilling prophecies, creating the financial distress they claim merely to indicate.”¹⁵⁷ A low score can depress economic mobility, and certain groups within society have predictably lower scores. Often, “[a] good credit score is usually a proxy for wealth, and wealth is a good proxy for race and national origin.”¹⁵⁸ Poor people and minorities have lower credit scores and higher rates of credit invisibility due to legacies of discrimination and segregation.¹⁵⁹

Marion Fourcade and Kieran Healy directly link credit scoring’s “systematic measurement and exploitation of social differences” to class, which they defined as the “social distribution of life chances in markets.”¹⁶⁰ Market segmentation allows lenders to tailor their products to specific populations. Class experiences along the social continuum vary, but “markets see social differences very well, and thrive on them.”¹⁶¹ In the bottom quintile, market segmentation excludes borrowers deemed high risk from mainstream banking; at the same time, the American welfare state relies on access to credit as a substitute for a robust safety net.¹⁶² Low-income people are the biggest sources of profits for credit card companies,¹⁶³ and for those who cannot get a credit card, fringe banking proliferates. This group contains “a stubborn stratum of unscorable, unscored, and underscoring individuals—a *Lumpen-scoretariat* composed mostly of poor people.”¹⁶⁴

Despite multiple industries’ reliance on credit scores, there is little evidence that they are accurate indicators of the ability to repay loans, pay rent, or succeed in the workplace.¹⁶⁵ Rather, “[p]recarious work and housing situations, an inability to fall back on family for financial help, and barriers to building savings all show up in credit scores—and have much more to do with economic-social structures than people’s trustworthiness.”¹⁶⁶ Given the baked-in discrimination in credit scoring models

156. Foohey & Greene, *supra* note 122, at 2.

157. Citron & Pasquale, *supra* note 4, at 18.

158. Vlad A. Hertz, *Fighting Unfair Classifications in Credit Reporting: Should the United States Adopt GDPR-Inspired Rights in Regulating Consumer Credit?*, 93 N.Y.U. L. REV. 1707, 1727 (2018).

159. See Foohey & Greene, *supra* note 122, at 9–10 (“America’s history of segregation and discrimination in lending—which denied Black Americans loans to start small businesses and purchase homes, and steered minorities to high-interest and otherwise unfavorable loans—continues to show up in credit scoring.”).

160. Marion Fourcade & Kieran Healy, *Classification Situations: Life-chances in the Neoliberal Era*, 38 ACCT., ORGS. & SOC’Y. 559, 566, 569 (2013).

161. *Id.* at 562.

162. See *id.* at 565.

163. Andrea Freeman explains that the greatest source of profits for credit card companies are low-income consumers on the verge of bankruptcy. Freeman, *supra* note 149, at 153. She states that this “represents a massive redistribution of wealth from the poor to wealthier consumers and corporations.” *Id.* at 154.

164. Fourcade & Healy, *supra* note 160, at 565.

165. See Foohey & Greene, *supra* note 122, at 3.

166. *Id.* at 9.

and the problem of credit invisibility, some financial entities are developing alternate scoring models.¹⁶⁷ They promise to assist low-income people and minorities by folding in new forms of data, such as timely utility and rental payments and social media data, rather than relying on traditional data points that magnify existing disparities.¹⁶⁸ Still, there are concerns that alternative data points might “be designed to identify and target vulnerable individuals with high-cost loan products.”¹⁶⁹ Without careful design and oversight, both traditional and alternative credit rating models raise the risk that affordable credit will remain out of reach for low-income consumers.¹⁷⁰ In the interim, credit reporting will continue to be a gatekeeper, withholding fair access to life’s necessities.

3. Algorithms in Higher Education

A college degree can be a pathway out of poverty. College-educated workers have higher rates of employment and income than workers with lower levels of education.¹⁷¹ On average, college graduates earn 84% more than nongraduates.¹⁷² Poor children who do not earn a college degree are four times as likely to remain poor than those who graduate.¹⁷³ For people who grow up below the poverty line, the return on a four-year degree is 179% for lifetime earnings.¹⁷⁴ Accordingly, “[i]ncreased college degree attainment would meaningfully raise economic security for individuals near the bottom of the earnings distribution and reduce poverty rates.”¹⁷⁵ Unfortunately, children from low-income families face numerous barriers to attending college, including lower-quality high schools, lack of support for navigating the college admissions process, and tuition costs. As a result, less than 50% of children from the lowest quintile of households attend college, compared to 92% of children growing up in

167. See *id.* at 4, 11–14.

168. See Karan Kaul, *Adopting Alternative Data in Credit Scoring Would Allow Millions of Consumers to Access Credit*, URB. INST. (March 15, 2021), <https://www.urban.org/urban-wire/adopting-alternative-data-credit-scoring-would-allow-millions-consumers-access-credit> [https://perma.cc/SKV9-9AMB].

169. Mikella Hurley & Julius Adebayo, *Credit Scoring & Big Data*, 18 YALE J.L. & TECH. 148, 167 (2016); Foohey & Greene, *supra* note 122, at 20.

170. Foohey & Greene, *supra* note 122, at 22–23.

171. Brad J. Hershbein, Melissa S. Kearney & Luke W. Pardue, *College Attainment, Income Inequality, and Economic Security: A Simulation Exercise 1* (Nat’l Bureau of Econ. Rsch. Working Paper No. 26747, 2020), https://www.nber.org/system/files/working_papers/w26747/w26747.pdf [https://perma.cc/3AVF-FMV6].

172. ANTHONY P. CARNEVALE, STEPHEN J. ROSE & BAN CHEAH, GEORGETOWN UNIV. CTR. ON EDUC. & THE WORKFORCE, *THE COLLEGE PAYOFF: EDUCATION, OCCUPATIONS, LIFETIME EARNINGS 1* (2011), <https://www2.ed.gov/policy/highered/reg/hearulemaking/2011/collegepayoff.pdf> [https://perma.cc/8ETA-7G7Q].

173. Andrew P. Kelly, *Does College Really Improve Social Mobility?*, BROOKINGS (Feb. 11, 2014), <https://www.brookings.edu/blog/social-mobility-memos/2014/02/11/does-college-really-improve-social-mobility> [https://perma.cc/6HYE-ATUS].

174. Tim Bartik & Brad Hershbein, *College Does Help the Poor*, N.Y. TIMES (May 23, 2018), <https://www.nytimes.com/2018/05/23/opinion/college-does-help-the-poor.html> [https://perma.cc/7FOY-V8RR].

175. Hershbein, Kearney & Pardue, *supra* note 171 at 1.

the top quintile.¹⁷⁶ Algorithmic college admissions systems threaten to reinforce and even exacerbate these patterns.

Nonprofit colleges increasingly rely on algorithms to predict which prospective students are likely to enroll and determine the precise level of financial aid an admitted student's enrollment will bring.¹⁷⁷ In an era of declining state support for higher education, accompanied by a demographic dip in the college-age population, colleges are under pressure to remain financially stable; enrollment management algorithms promise to help colleges attain financial stability by offering to help plan and budget with greater precision.¹⁷⁸ To recruit and select students, colleges deploy algorithms that gather and aggregate data such as names purchased from testing companies, test scores, zip codes, academic interests, household income, ethnic and racial information, and student interactions with college websites and social media accounts.¹⁷⁹ Schools use this data to award students a score from 1–100, which drives the level of attention colleges pay to students in the recruiting process.¹⁸⁰ These algorithms can harm prospective students in several ways. First, they generally reduce scholarship funding that colleges offer prospective students, thus pushing students to assume larger debt loads, which raises rates of non-graduation, particularly for racial minorities.¹⁸¹ Further, the focus on yield distracts from the goal of “optimizing . . . student success, retention, or graduation.”¹⁸² Seeking to increase revenue, colleges may also favor students whose families can pay full tuition.¹⁸³

176. Sarah Reber, Chenoah Sinclair & Hannah Van Drie, *Public Colleges Are the Workhorses of Middle-Class Mobility*, BROOKINGS (July 22, 2020), <https://www.brookings.edu/blog/up-front/2020/07/22/public-colleges-are-the-workhorses-of-middle-class-mobility> [<https://perma.cc/UKW7-QXA6>].

177. Alex Engler, *Enrollment Algorithms Are Contributing to the Crises of Higher Education*, BROOKINGS (Sept. 14, 2021), <https://www.brookings.edu/research/enrollment-algorithms-are-contributing-to-the-crises-of-higher-education> [<https://perma.cc/ER8B-8KRJ>]. In 2015, 75% of colleges and universities reported using analytics for enrollment management. *Id.*

178. *See id.*

179. *See* Josh Moody, *Algorithms for College Admissions: What to Know*, U.S. NEWS & WORLD REP. (Sept. 30, 2020), <https://www.usnews.com/education/best-colleges/articles/how-admissions-algorithms-could-affect-your-college-acceptance> [<https://perma.cc/N36C-EXC7>]; Rashida Richardson & Marci Lerner Miller, *The Higher Education Industry Is Embracing Predatory and Discriminatory Student Data Practices*, SLATE (Jan. 13, 2021, 8:30 AM), <https://slate.com/technology/2021/01/higher-education-algorithms-student-data-discrimination.html> [<https://perma.cc/LH8L-U7EZ>]; Douglas MacMillan & Nick Anderson, *Student Tracking, Secret Scores: How College Admissions Offices Rank Prospects Before They Apply*, WASH. POST (Oct. 14, 2019), <https://www.washingtonpost.com/business/2019/10/14/colleges-quietly-rank-prospective-students-based-their-personal-data> [<https://perma.cc/HDF7-UTF8>].

180. *See* MacMillan & Anderson, *supra* note 179.

181. *See* Engler, *supra* note 177.

182. *Id.*

183. *See* MacMillan & Anderson, *supra* note 179; DJ Pangburn, *Schools Are Using Software to Help Pick Who Gets in. What Could Go Wrong?*, FAST CO. (May 17, 2019), <https://www.fastcompany.com/90342596/schools-are-quietly-turning-to-ai-to-help-pick-who-gets-in-what-could-go-wrong> [<https://perma.cc/DZT7-CDL7>].

To the degree algorithms are making predictions based on historical data, they may embed existing biases in college admissions against low-income and minority students.¹⁸⁴ The algorithms may “learn” that white and wealthy students are correlated with higher graduation rates or other metrics of “success.” How different populations engage with college websites may also create biases. For example, students with vision impairments or other disabilities may struggle to access college web pages and thus look less interested in a school that tracks demonstrated interest.¹⁸⁵ By contrast, affluent students may benefit from having the resources to visit campus and receive college counseling advice to click on college websites and emails regularly.¹⁸⁶ As with most algorithmic systems, these college admission algorithms are not transparent, and it is hard to know exactly how they gauge student yield rates or student success. Thus, “the complexity of the algorithmic process, the many potential entry points for bias, and the separation between vendor-developed algorithms and college employees all contribute to the potential for discriminatory outcomes.”¹⁸⁷

The for-profit wing of the higher education industry poses a different set of disadvantages for low-income students who assume crippling debt with few job prospects and low graduation rates.¹⁸⁸ Whereas algorithms in the nonprofit higher education sector favor the wealthy, those in the for-profit sector seek to “find inequality and feast on it.”¹⁸⁹ A United States Senate committee investigation found that colleges were targeting the most vulnerable populations; for instance, one chain told its recruiters to focus on students who were in the categories of “Welfare Mom w/ Kids,” “Pregnant Ladies,” “Recent Incarceration,” and “Drug Rehabili-

184. See Rebecca Koenig, *As Colleges Move Away from the SAT, Will Admissions Algorithms Step In?*, ED SURGE (July 10, 2020), <https://www.edsurge.com/news/2020-07-10-as-colleges-move-away-from-the-sat-will-admissions-algorithms-step-in> [https://perma.cc/Y7K5-VPK7].

185. See Engler, *supra* note 177.

186. See Richardson & Miller, *supra* note 179.

187. Engler, *supra* note 177. Other algorithmic systems of concern in the college setting are those used to identify which current students are high-risk and those used for exam proctoring—both have the potential to harm marginalized students. See Shea Swauger, *The Next Normal: Algorithms Will Take Over College, From Admissions to Advising*, WASH. POST (Nov. 12, 2021, 9:07 AM), https://www.washingtonpost.com/outlook/next-normal-algorithms-college/2021/11/12/366fe8dc-4264-11ec-a3aa-0255edc02eb7_story.html [https://perma.cc/9NMG-WYZT].

188. See Dundon, *supra* note 15, at 376–77; Genevieve Bonadies, Joshua Rovenger, Eileen Connor, Brenda Shum, & Toby Merrill, *For-Profit Schools’ Predatory Practices and Students of Color: A Mission to Enroll Rather than Educate*, HARV. L. REV. BLOG (July 30, 2018), <https://blog.harvardlawreview.org/for-profit-schools-predatory-practices-and-students-of-color-a-mission-to-enroll-rather-than-educate> [https://perma.cc/5LLX-FV6Q]; Luis Armona, Rajashri Chakrabati & Michael F. Lovenheim, *Student Debt and Default: The Role of For-Profit Colleges* 32–33 (Fed. Rsv. Bank of N.Y., Working Paper No. 811, 2021), https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr811.pdf?la=EN [https://perma.cc/U9QD-XWCP].

189. O’NEIL, *supra* note 16, at 70. Almost one million students were enrolled in for-profit colleges in 2018. Armona, Chakrabati & Lovenheim, *supra* note 188, at 1.

tation.”¹⁹⁰ Likewise, a lawsuit against the Corinthian College alleged that the school was targeting students who were “isolated,” had “low self esteem,” lacked “people in their lives who care about them,” and were “stuck” and “unable to see and plan well for the future.”¹⁹¹ For-profit colleges rely heavily on algorithms to identify these vulnerable people.

Algorithmic tools include targeted advertising on platforms such as Google and Facebook, as well as lead generation.¹⁹² Consumers who search online for terms related to education, welfare, or employment are tagged by web browser cookies that track consumers’ online activities, thereby allowing for-profit colleges to communicate with consumers across the internet with targeted ads.¹⁹³ Consumers are shown fake ads promising jobs or public benefits to harvest the consumers’ cell phone numbers.¹⁹⁴ In addition, when consumers fill out online forms posted by lead generators, their information is combined with other personal data to generate a score assessing their desirability as targets.¹⁹⁵ A Government Accountability Office investigation found that, within five minutes of entering the name and phone number of a potential “student” into a single lead-generation site, the student received a recruiting call, followed by over 180 additional calls within a single month.¹⁹⁶

This targeting is effective and has consequences that compound poverty. One study found that 76% of students who pay their own way at for-profit colleges were poor or near poor.¹⁹⁷ Only 26% of the students who enrolled in for-profit colleges in 2014 graduated within six years, as compared to over 60% at public and private nonprofit schools.¹⁹⁸ Even for those students who graduate, for-profit degrees “modestly increase the likelihood of employment, but appear to do little to raise earnings.”¹⁹⁹

190. See S. COMM. ON HEALTH, EDUC., LAB. & PENSIONS, 112TH CONG., FOR PROFIT HIGHER EDUCATION: THE FAILURE TO SAFEGUARD THE FEDERAL INVESTMENT & ENSURE STUDENT SUCCESS 766 (Comm. Print 2012).

191. O’NEIL, *supra* note 16, at 71.

192. See Sam Gilman, *Proliferating Predation: Reverse Redlining, the Digital Proliferation of Inferior Social Welfare Products, and How to Stop It*, 56 HARV. C.R.—C.L. L. REV. 169, 196–200 (2021) [hereinafter *Proliferating Predation*] (“Online lead generators are third-party data brokers that collect contact data for prospective students . . . or market themselves as college comparison tools to unsuspecting consumers.”). See also ALYCE MYATT, U.S. PUB. INT. RSCH. GRP. & CTR. FOR DIGIT. DEMOCRACY, PRIVATE FOR-PROFIT COLLEGES AND ONLINE LEAD GENERATION: PRIVATE UNIVERSITIES USE DIGITAL MARKETING TO TARGET PROSPECTS, INCLUDING VETERANS VIA THE INTERNET 1 (2015), https://www.democraticmedia.org/sites/default/files/field/public-files/2015/forprofitcollegeleadgenreport_may2015_uspirgef_cdd_0.pdf [<https://perma.cc/3BPU-HD55>].

193. See MYATT, *supra* note 192, at 2.

194. See *id.* at 1–2.

195. See *id.*

196. U.S. GOV’T ACCOUNTABILITY OFF., GAO-10-948T, FOR-PROFIT COLLEGES: UNDERCOVER TESTING FINDS COLLEGES ENCOURAGED FRAUD AND ENGAGED IN DECEPTIVE AND QUESTIONABLE MARKETING PRACTICES 15 (2010).

197. *Proliferating Predation*, *supra* note 192, at 196.

198. Nat’l Ctr. for Educ. Stats., *Fast Facts: Graduation Rates*, U.S. DEP’T OF EDUC., <https://nces.ed.gov/fastfacts/display.asp?id=40> [<https://perma.cc/ARU7-9GBG>].

199. Stephanie Riegg Cellini & Nicholas Turner, *Gainfully Employed? Assessing the Employment and Earnings of For-Profit College Students Using Administrative Data* 23–25 (Nat’l Bureau of Econ. Rsch., Working Paper No. 22287, 2018), <https://www.nber.org/sys->

Thirty-two percent of the students who enroll in four-year for-profit programs and 40% of those who enroll in two-year for-profit programs default on their loans within five years of entering repayment,²⁰⁰ and there is no statute of limitations on collecting federal student debt. In 2017, the Attorney General of California investigated one chain of for-profit schools for a range of abuses from enrollment to graduation.²⁰¹ The university was charged with lying to students about job prospects, employing aggressive admissions counselors forced to meet rigid enrollment targets, saddling students with massive debt, and using unlawful debt collection practices.²⁰² With such high levels of default on non-dischargeable debt, students who enroll in for-profit colleges often end up with ruined credit scores and economic instability.²⁰³ Algorithmic systems turbocharge the recruiting practices, ultimately leading to debt and financial distress for many of these students.²⁰⁴

4. Advertising and Opportunity

The data scraping dynamics discussed thus far are part of “surveillance capitalism,” which “claims human experience as free raw material for translation into behavioral data” so companies can predict and even shape human choices.²⁰⁵ In coining the term, Shoshana Zuboff traces how big-tech companies learned to transform the digital exhaust emitted by users into profits.²⁰⁶ While targeting people with ads for sneakers or headphones might not seem like a threat to human rights, some advertising ecosystems manipulate opportunity, as Pauline Kim puts it.²⁰⁷ That is, these advertisements can “operate as key intermediaries in the markets for employment, housing, and financial services . . . to segment the audience and determine precisely what information will be delivered to which

tem/files/working_papers/w22287/w22287.pdf [https://perma.cc/U8CA-4FQJ]; David J. Deming, Claudia Goldin & Lawrence F. Katz, *The For-Profit Postsecondary School Sector: Nimble Critters or Agile Predators?*, 26 J. ECON. PERSPS. 139, 143 (2012), <https://www.aeaweb.org/articles?id=10.1257/jep.26.1.139> [https://perma.cc/JZ7M-RH5S].

200. Kadija Yilla & David Wessel, *Five Facts About Student Loans*, BROOKINGS (Nov. 12, 2019), <https://www.brookings.edu/blog/up-front/2019/11/12/five-facts-about-student-loans> [https://perma.cc/EFL3-2VGM]; Zina Kumok & Brianna McGurran, *What Is the Statute of Limitations on a Student Loan?*, FORBES (May 13, 2021, 1:58 PM), <https://www.forbes.com/advisor/student-loans/student-loan-statute-of-limitations> [https://perma.cc/WD2J-QDKA].

201. See Danielle Douglas-Gabriel, *California Attorney General Sues For-Profit Bridgepoint Education*, WASH. POST (Nov. 29, 2017, 5:02 PM), <https://www.washingtonpost.com/news/grade-point/wp/2017/11/29/california-attorney-general-sues-for-profit-bridgepoint-education> [https://perma.cc/EE37-H8XA].

202. See *id.*

203. See *Proliferating Predation*, *supra* note 192, at 203.

204. See *id.* at 228.

205. SHOSHANA ZUBOFF, *THE AGE OF SURVEILLANCE CAPITALISM: THE FIGHT FOR A HUMAN FUTURE AT THE NEW FRONTIER OF POWER* 8 (2019).

206. See *id.* State and corporate surveillance pre-date the digital age, but new technologies add vastly increased scope, speed, and scale. See Seeta Peña Gangadharan, *Digital Inclusion and Data Profiling*, 17 FIRST MONDAY (2012), <https://journals.uic.edu/ojs/index.php/fm/article/download/3821/3199> [https://perma.cc/5DZJ-HSLU].

207. Kim, *supra* note 72.

users.”²⁰⁸ Online platforms limit exposure to “opportunities in ways that reproduce or reinforce historical forms of discrimination.”²⁰⁹ Facebook, in particular, has come under scrutiny. Over 98% of its profits are derived from advertising, and it controls 22% percent of the market for digital ads in the United States.²¹⁰

Starting in 2016, investigative journalists at ProPublica uncovered that Facebook allowed advertisers to target housing ads at specific, highly segmented groups of Facebook’s users based on race, gender, age, and ethnic affinity.²¹¹ Thereafter, various fair housing, civil rights, and labor organizations sued Facebook, alleging the platform permitted advertisers to target housing, employment, and credit ads on the basis of race, sex, age, and other protected characteristics.²¹² According to the allegations, “Facebook’s advertisement system excluded people with a certain ‘ethnic affinity’ from seeing housing ads and prevented women from viewing job postings that employers wanted targeted for men, such as Uber drivers, truck drivers, and roofers.”²¹³ Facebook offered these targeted ads by “classif[ying] people into more than 50,000 categories such as ‘English as a second language,’ ‘disabled parking permit,’ or ‘Telemundo.’”²¹⁴

Initially, Facebook disclaimed responsibility, asserting that the advertisers were responsible for any discrimination as Facebook was merely a neutral platform.²¹⁵ However, the cases ultimately settled in 2019.²¹⁶

208. *Id.* at 869.

209. *Id.*

210. Rishi Iyengar, *Here’s How Big Facebook’s Ad Business Really Is*, CNN (July 1, 2020), <https://www.cnn.com/2020/06/30/tech/facebook-ad-business-boycott/index.html> [<https://perma.cc/6HXE-PFCU>]; Kurt Wagner, *Digital Advertising in the US is Finally Bigger than Print and Television*, VOX (Feb. 20, 2019, 9:02 AM), <https://www.vox.com/2019/2/20/18232433/digital-advertising-facebook-google-growth-tv-print-emarketer-2019> [<https://perma.cc/LE5L-RMFP>].

211. Julia Angwin & Terry Parris Jr., *Facebook Lets Advertisers Exclude Users by Race*, PROPUBLICA (Oct. 26, 2016, 1:00 PM), <https://www.propublica.org/article/facebook-lets-advertisers-exclude-users-by-race> [<https://perma.cc/5V2W-8UB3>]. Facebook permitted housing advertisers to exclude specific people on the basis of “Ethnic Affinity,” based on “pages and posts [users] have liked or engaged with on Facebook.” *Id.*; see also Julia Angwin, Ariana Tobin & Madeleine Varner, *Facebook (Still) Letting Housing Advertisers Exclude Users by Race*, PROPUBLICA (Nov. 21, 2017, 1:23 PM), <https://www.propublica.org/article/facebook-advertising-discrimination-housing-race-sex-national-origin> [<https://perma.cc/QN33-ELGD>] (explaining that Facebook allowed rental housing ads to exclude certain categories, including “African Americans, mothers of high school kids, people interested in wheelchair ramps, Jews, expats from Argentina and Spanish speakers”); Julia Angwin, Madeleine Varner & Ariana Tobin, *Facebook Enabled Advertiser to Reach ‘Jew Haters’*, PROPUBLICA (Sept. 14, 2017, 4:00 PM), <https://www.propublica.org/article/facebook-enabled-advertisers-to-reach-jew-haters> [<https://perma.cc/ZK2V-JRF5>].

212. *Facebook Agrees to Sweeping Reforms to Curb Discriminatory Ad Targeting Practices*, ACLU (Mar. 19, 2019), <https://www.aclu.org/press-releases/facebook-agrees-sweeping-reforms-curb-discriminatory-ad-targeting-practices> [<https://perma.cc/D5V7-27YM>].

213. See *Five Privacy Principles*, *supra* note 21, at 380–81 (internal citations omitted).

214. *Id.* at 381; see also Angwin & Parris, *supra* note 211.

215. See Kim, *supra* note 72, at 884.

216. See Settlement Agreement and Release at 3, Nat’l Fair Hous. All. v. Facebook, Inc., No. 1:18-cv-02689-JGK (S.D.N.Y. Mar. 19, 2019). The Department of Housing and Urban Development brought charges against Facebook for discrimination in violation of the Fair Housing Act, and that case continues. Charge of Discrimination, *supra* note 94, at 3.

Under the terms of the settlement, Facebook agreed to prohibit advertisers from targeting people based on a number of categories, including age, gender, zip code, and race.²¹⁷ Nevertheless, numerous studies have found that advertising discrimination on Facebook persists post-settlement.²¹⁸ For instance, one study found that Facebook was showing ads for secretarial and supermarket jobs primarily to women.²¹⁹ Another study found that more men were shown ads for credit, while more women were shown ads for debt relief.²²⁰ One cause of this ongoing bias may be the algorithm's use of proxy characteristics that correlate with protected classes.²²¹ In addition, the content of ads appears to play a role in determining who sees them, even when advertisers do not select the viewers themselves.²²² Further, some of Facebook's internal ad-placement systems match ads with users based on users' Facebook activity and demographic information pulled from their personal pages.²²³ In light of ongoing pressure to counter ad bias, Facebook placed an additional limitation on advertisers in 2021, keeping them from targeting people based on their interests as inferred from their interactions with Facebook on specific topics.²²⁴

As Facebook faces ongoing pressure to change its advertising practices further, the settlement (and its ongoing enforcement) nevertheless excludes poverty discrimination. The settlement does not forbid discrimination based on SES; instead, the settlement tracks only recognized

217. Settlement Agreement and Release *supra* note 216, at 20.

218. See Kim, *supra* note 72, at 887–92 (reviewing studies); Ava Kofman & Ariana Tobin, *Facebook Ads Can Still Discriminate Against Women and Older Workers, Despite a Civil Rights Settlement*, PROPUBLICA (Dec. 13, 2019), <https://www.propublica.org/article/facebook-ads-can-still-discriminate-against-women-and-older-workers-despite-a-civil-rights-settlement> [<https://perma.cc/SCH6-HKMB>]; Jeremy B. Merrill, *Does Facebook Still Sell Discriminatory Ads?*, MARKUP (Aug. 25, 2020, 8:00 AM), <https://themarkup.org/ask-the-markup/2020/08/25/does-facebook-still-sell-discriminatory-ads> [<https://perma.cc/8GP4-4R9X>].

219. Muhammad Ali, Piotr Sapiezynski, Miranda Bogen, Aleksandra Korolova, Alan Mislove & Aaron Rieke, *Discrimination Through Optimization: How Facebook's Ad Delivery Can Lead to Biased Outcomes*, 3 PROC. ACM ON HUM.-COMPUT. INTERACTION 1, 21, 30 (2019), <https://doi.org/10.1145/3359301> [<https://perma.cc/9DTB-FMCF>].

220. SARA KINGSLEY, CLARA WANG, ALEXANDRA MIKHALENKO, PROTEETI SINHA & CHINMAY KULKARNI, *AUDITING DIGITAL PLATFORMS FOR DISCRIMINATION IN ECONOMIC OPPORTUNITY ADVERTISING* 21 (2020), <https://arxiv.org/pdf/2008.09656.pdf> [<https://perma.cc/57BR-938K>].

221. See Jinyan Zang, *Solving the Problem of Racially Discriminatory Advertising on Facebook*, BROOKINGS (Oct. 19, 2021), <https://www.brookings.edu/research/solving-the-problem-of-racially-discriminatory-advertising-on-facebook> [<https://perma.cc/9FRG-Q7S2>].

222. See Ali et al., *supra* note 219. “Where a particular ad appears is influenced by the advertiser (who specifies its target audience), other advertisers (who are competing for advertising space), users themselves (who choose whether or not to click on particular ads), and the platform that coordinates these preferences.” Kim, *supra* note 72, at 886.

223. See Merrill, *supra* note 218.

224. See Shannon Bond, *Facebook Scraps Ad Targeting Based on Politics, Race and Other ‘Sensitive’ Topics*, NAT'L PUB. RADIO (Nov. 9, 2021, 5:06 PM), <https://www.npr.org/2021/11/09/1054021911/facebook-scraps-ad-targeting-politics-race-sensitive-topics> [<https://perma.cc/VF59-H9XL>].

categories protected under civil rights laws.²²⁵ Thus, advertisers may intentionally and legally discriminate against poor people, even in employment, housing, and credit. They can target poor people for predatory products and exclude them from mainstream opportunities. Moreover, various advertisements that feed off economic vulnerability are outside the scope of the settlement, such as for-profit colleges or predatory financial services.²²⁶ These gaps in the ongoing struggle between the civil rights community and internet platforms such as Facebook will continue to exacerbate economic inequality.

III. ANTIDISCRIMINATION LAW, DIGITAL RIGHTS, AND POVERTY

This Part explains how and why SES is not protected in existing civil rights law and how this loophole is perpetuated in digital-discrimination proposals at the federal and state levels.

A. THE POVERTY LOOPHOLE IN CIVIL RIGHTS LAW

The Supreme Court has held that poverty is not a suspect class under the Constitution for Equal Protection purposes.²²⁷ As a result, laws that discriminate against the poor are subject to more lenient review, “which requires only that the State’s system be shown to bear some rational relationship to legitimate state purposes.”²²⁸ Further, the Court has ruled that the Constitution does not guarantee core socioeconomic rights, such as housing or welfare.²²⁹ These doctrines impact digital discrimination wrought by the government. This “deconstitutionalization” of poverty law²³⁰ is significant given that the private sector sells and shares data troves via interconnected networks and that governments purchase algorithmic decision-making tools from private vendors.²³¹ Consider the

225. See Settlement Agreement and Release, *supra* note 216, at 20.

226. *Proliferating Predation*, *supra* note 192, at 184.

227. *Harris v. McRae*, 448 U.S. 297, 323 (1980) (“[T]his Court has held repeatedly that poverty, standing alone is not a suspect classification.”).

228. *San Antonio Indep. Sch. Dist. v. Rodriguez*, 411 U.S. 1, 40 (1973).

229. For an overview of the Court’s jurisprudence with regard to poverty, see Michele E. Gilman, *A Court for the One Percent: How the Supreme Court Contributes to Economic Inequality*, 2014 UTAH L. REV. 389, 401–10 (2014).

230. Julie Nice, *No Scrutiny Whatsoever: Deconstitutionalization of Poverty Law, Dual Rules of Law, & Dialogic Default*, 35 FORDHAM URB. L.J. 629 (2008).

231. On government reliance on private vendors, see DAVID FREEMAN ENGSTROM, DANIEL E. HO, CATHERINE M. SHARKEY & MARIANO-FLORENTINO CUÉLLAR, GOVERNMENT BY ALGORITHM: ARTIFICIAL INTELLIGENCE IN FEDERAL ADMINISTRATIVE AGENCIES 88 (Feb. 2020), <https://www-cdn.law.stanford.edu/wp-content/uploads/2020/02/ACUS-AI-Report.pdf> [<https://perma.cc/S3DD-WDXB>] (finding that one-third of federal AI technologies come from private commercial sources); Dierdre K. Mulligan & Kenneth A. Bamberger, *Procurement as Policy: Administrative Process for Machine Learning*, 34 BERKELEY TECH. L.J. 773, 778 (2019) (“At every level of government, officials purchase, or contract for use of, technology systems that employ machine learning”); Robert Brauneis & Ellen P. Goodman, *Algorithmic Transparency for the Smart City*, 20 YALE J.L. & TECH. 103, 107 (2018) (explaining that local governments lack expertise to develop data analytics and rely on “privately developed algorithmic processes”). On private vendors’

case studies above. Public housing authorities sometimes use tenant-screening algorithms.²³² Government agencies rely on credit reports in collecting child support and considering eligibility for public assistance, government licenses, and employment.²³³ The Constitution covers public colleges, so their algorithmic systems must comply with the Equal Protection Clause.²³⁴ Yet no viable Equal Protection arguments govern digital discrimination against the poor in these realms.

For the most part, existing civil rights laws similarly fail to prohibit discrimination against the poor. At the federal level, individuals are protected against discrimination based on “race, color, religion, or national origin” in public accommodations (i.e., spaces serving the public, such as restaurants and hotels) and in programs receiving federal funding.²³⁵ These characteristics are also covered by employment discrimination law, along with sex, sexual orientation,²³⁶ age,²³⁷ pregnancy,²³⁸ and veteran status.²³⁹ The Fair Housing Act prohibits discrimination on the basis of race, color, national origin, religion, sex, familial status, or disability.²⁴⁰ The disabled are protected against discrimination in all of these contexts.²⁴¹ In addition, people cannot be discriminated against based on their genetic information with regard to health insurance or employment.²⁴² State and city antidiscrimination laws are similar in the characteristics they protect, though they can sometimes be more expansive. For

reliance on public data, see WOLFIE CHRISTL, *CRACKED LABS, CORPORATE SURVEILLANCE IN EVERYDAY LIFE: HOW COMPANIES COLLECT, COMBINE, ANALYZE, TRADE AND USE PERSONAL DATA ON BILLIONS 9–10* (2017), <https://crackedlabs.org/en/corporate-surveillance/#3> [<https://perma.cc/HPY3-XHDK>]; Steven Melendez & Alex Pasternack, *Here are the Data Brokers Quietly Buying and Selling Your Personal Information*, FAST CO. (Mar. 2, 2019), <https://www.fastcompany.com/90310803/here-are-the-data-brokers-quietly-buying-and-selling-your-personal-information> [<https://perma.cc/E7Q8-PA4K>] (“By buying or licensing data or scraping public records, third-party data companies can assemble thousands of attributes each for billions of people.”); JUSTIN SHERMAN, *DATA BROKERS AND SENSITIVE DATA ON U.S. INDIVIDUALS: THREATS TO AMERICAN CIVIL RIGHTS, NATIONAL SECURITY, AND DEMOCRACY 8* (2021), <https://sites.sanford.duke.edu/techpolicy/wp-content/uploads/sites/17/2021/08/Data-Brokers-and-Sensitive-Data-on-US-Individuals-Sherman-2021.pdf>. [<https://perma.cc/K8V3-ATGP>] (describing data brokers scraping public records).

232. Lauren Kirchner, *How We Investigated the Tenant Screening Industry*, MARKUP (May 28, 2020), <https://themarkup.org/show-your-work/2020/05/28/how-we-investigated-the-tenant-screening-industry> [<https://perma.cc/7MQ6-F3SF>].

233. NAT’L CONSUMER L. CTR., *FAIR CREDIT REPORTING*, 317–328 (10th ed. 2022).

234. See U.S. CONST. amend. XIV, § 1; *Fisher v. Univ. of Tex.* 570 U.S. 297, 307–11 (2013) (applying the Equal Protections Clause to admissions schemes of a public university).

235. 42 U.S.C.A. § 2000a.

236. See *Bostock v. Clayton Cnty.*, 140 S. Ct. 1731, 1754 (2020).

237. See 29 U.S.C. § 623.

238. See 42 U.S.C. § 2000e(k) (prohibiting discrimination on the basis of certain conditions biologically tied to sex, including “pregnancy, childbirth, or related medical conditions”).

239. See 38 U.S.C. § 4311; 3 U.S.C. § 416(a)(1) (“It shall be unlawful for an employing office to discriminate, within the meaning of [38 U.S.C. § 4311] . . .”).

240. 42 U.S.C. § 3604.

241. See *id.* §§ 3604, 12112, 12132.

242. *Id.* § 2000ff-1; *Genetic Information Discrimination*, U.S. EQUAL EMP. OPPORTUNITY COMM’N, <https://www.eeoc.gov/genetic-information-discrimination> [<https://perma.cc/>

instance, in employment discrimination, some states protect against discrimination based on marital status, breastfeeding, medical marijuana use, or status as a victim of domestic violence.²⁴³

There are a few statutes that protect against discrimination based on factors related to economic status. For instance, the Equal Credit Opportunity Act prohibits creditors from discriminating against credit applicants not only based on race, color, religion, national origin, sex, marital status, or age but also based on an applicant's receiving income from a public assistance program (meaning that lenders must treat income from public assistance the same as other income sources).²⁴⁴ Some states and localities go beyond the Fair Housing Act's protected grounds by forbidding source-of-income discrimination in housing, meaning landlords cannot refuse to rent to a tenant because they pay their rent with a federally subsidized housing assistance voucher or other forms of governmental assistance.²⁴⁵ Several states banned credit reporting for certain employment decisions,²⁴⁶ and studies show these bans effectively increase employment rates among job applicants with poor credit.²⁴⁷ Several states and cities prohibit the use of criminal background records in the initial stages of hiring, college admissions, or both; these laws are often called ban-the-box laws, and they are designed to expand opportunities.²⁴⁸ These laws and constitutional protections may be narrow in scope and scattered in coverage, but they suggest a level of political support for economic-justice initiatives.²⁴⁹ This momentum should be harnessed and expanded to prevent digital discrimination based on poverty.

B. DIGITAL DISCRIMINATION AND CIVIL RIGHTS

Commentators and advocates have concluded that combatting digital discrimination requires new laws. Simply put, our existing analog-era laws

BTW3-VMWB] ("Under Title II of GINA, it is illegal to discriminate against employees or applicants because of genetic information.").

243. See *State Employment-Related Discrimination Statutes*, NAT'L CONF. STATE LEG. (July 2015), <https://www.ncsl.org/documents/employ/Discrimination-Chart-2015.pdf> [<https://perma.cc/689L-PL4B>].

244. See 15 U.S.C. § 1691.

245. See Robert G. Schwemm, *State and Local Laws Banning Source-of-Income Discrimination*, 28 J. AFFORDABLE HOUS. & CMTY. DEV. L. 373, 375–386 (2019).

246. See Foohey & Greene, *supra* note 122, at 10.

247. See AMY TRAUB & SEAN McELWEE, DEMOS, *BAD CREDIT SHOULDN'T BLOCK EMPLOYMENT: HOW TO MAKE STATE BANS ON EMPLOYMENT CREDIT CHECKS MORE EFFECTIVE* 7–8 (2016), <https://www.demos.org/research/bad-credit-shouldnt-block-employment-how-make-state-bans-employment-credit-checks-more> [<https://perma.cc/2S2G-4UPX>]; Robert Clifford & Daniel Shoag, "No More Credit Score": *Employer Credit Check Bans and Signal Substitution*, (Fed. Rsrv. Bank of Bos., Working Paper No. 16-10, 2016), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2836374 [<https://perma.cc/GH2Y-2GAL>].

248. See BETH AVERY & HAN LU, NAT'L EMP. L. PROJECT, *BAN THE BOX: U.S. CITIES, COUNTIES, AND STATES ADOPT FAIR-CHANCE POLICIES TO ADVANCE EMPLOYMENT OPPORTUNITIES FOR PEOPLE WITH PAST CONVICTIONS* 4 (2021), <https://s27147.pcdn.co/wp-content/uploads/Ban-the-Box-Fair-Chance-State-and-Local-Guide-Oct-2021.pdf> [<https://perma.cc/6MFW-XVAL>].

249. See Peterman, *supra* note 7, at 1357–58.

are ill-fit for protecting against the harms of automated systems. As one group of commentators explains, “algorithms present challenges in interpretation under current antidiscrimination laws, which were written to address discrimination by human decision-makers.”²⁵⁰ Whereas traditional civil rights laws aimed to address biases harbored by employers, landlords, and other decision-makers, “in the 21st century, decisions can be made by machines or software—without a human in the loop.”²⁵¹

In their groundbreaking article *Big Data’s Disparate Impact*, Andrew Selbst and Solon Barocas explained the difficulties of prevailing on a disparate impact claim for discrimination in automated decision-making.²⁵² Title VII disparate impact claims have a three-part burden-shifting framework: First, a plaintiff must establish that an employer’s facially neutral policy or practice has a disparate impact on a protected class.²⁵³ Second, to rebut this prima facie case, the employer must establish that a legitimate business need justifies the challenged policy or practice.²⁵⁴ Third, the burden shifts back to the plaintiff to show that the employer’s legitimate business need can reasonably be achieved through alternate means with less discriminatory results.²⁵⁵ With respect to algorithms, a plaintiff’s burden is especially difficult because courts have approved hiring criteria that are job-relevant, and computer models have access to massive amounts of data that are highly predictive of future performance.²⁵⁶ Moreover, data collection and mining incorporate unconscious biases baked into current structural disparities, making it difficult for a plaintiff to identify alternative employment practices that achieve the same goals and are less discriminatory, as Title VII requires.²⁵⁷

Other scholars have suggested creative interpretations of existing Title VII law to bring digital discrimination into the statute’s coverage,²⁵⁸

250. CAMERON F. KERRY, JOHN B. MORRIS, JR., CAITLIN T. CHIN & NICOL E. TURNER LEE, BROOKINGS, BRIDGING THE GAPS: A PATH FORWARD TO FEDERAL PRIVACY LEGISLATION 9 (2020), https://www.brookings.edu/wp-content/uploads/2020/06/Bridging-the-gaps_a-path-forward-to-federal-privacy-legislation.pdf [<https://perma.cc/NMK3-JJL3>]; see also Erin Simpson & Adam Conner, *How to Regulate Tech: A Technology Policy Framework for Online Services*, CTR. FOR AM. PROGRESS (Nov. 16, 2021), <https://www.americanprogress.org/article/how-to-regulate-tech-a-technology-policy-framework-for-online-services> [<https://perma.cc/R8W2-ZFPE>] (“The evolution of online services has outpaced the application and interpretation of civil rights laws to digital properties and transactions.”).

251. KERRY, MORRIS, CHIN & LEE, *supra* note 250, at 39.

252. Barocas & Selbst, *supra* note 33. But see Michael Selmi, *Algorithms, Discrimination and the Law*, 82 OHIO ST. L.J. 611, 618 (2021) (arguing that existing law is adequate to counter algorithmic discrimination).

253. See *Ricci v. DeStefano*, 557 U.S. 557, 578 (2009); 42 U.S.C. § 2000e-2(k)(1)(A).

254. See *Ricci*, 557 U.S. at 578; 42 U.S.C. § 2000e-2(k)(1)(A).

255. See *Ricci*, 557 U.S. at 578; 42 U.S.C. § 2000e-2(k)(1)(A).

256. See Barocas & Selbst, *supra* note 33, at 707–12.

257. See *id.*

258. See Stephanie Bornstein, *Antidiscriminatory Algorithms*, 70 ALA. L. REV. 519, 525–26 (2018) (arguing that the anti-stereotyping theory under Title VII can be used to combat algorithmic discrimination); Pauline T. Kim, *Data-Driven Discrimination at Work*, 58 WM. & MARY L. REV. 857, 890–91 (2017) (developing a theory of “classification bias” under Title VII).

but courts have yet to interpret the law in such a manner. Accordingly, these interpretations cannot provide relief for plaintiffs or guidance for businesses to structure their algorithmic systems. Relatedly, there is a split among the federal courts of appeals as to whether the ban on disability discrimination in public accommodations applies to online platforms.²⁵⁹ There is similar uncertainty regarding the public-accommodations protections under Title II of the Civil Rights Act of 1964.²⁶⁰ At the state level, “the public accommodations laws of California and New York apply to online entities, covering both Silicon Valley and Wall Street,” yet the scope of digital coverage remains unresolved in many other states.²⁶¹ With respect to the Fair Housing Act, courts are split on whether the Act reaches data-processing entities that provide screening information to landlords, such as credit bureaus and tenant-screening companies.²⁶² Yet another potential barrier to obtaining civil rights relief is Section 230, which courts have interpreted as immunizing platforms for discriminatory content posted by other entities.²⁶³ Facebook successfully raised this defense to defeat a class action lawsuit alleging ad discrimination violating the Fair Housing Act.²⁶⁴

The executive branch’s interpretation and application of these laws to algorithmic systems can fluctuate depending on political priorities. In 2019, the Trump Administration proposed a safe harbor under Fair Housing Act regulations for housing providers that rely on algorithms to make decisions.²⁶⁵ The proposed rule also changed the burden-shifting framework for disparate impact claims under the Act in ways that favor defendants.²⁶⁶ Over 45,000 comments were received in opposition to the

259. See Katy Brennan, *The Internet as a Place of Public Accommodation: Are Business Websites Required to be ADA Compliant?*, COLUM. UNDERGRADUATE L. REV. (Jan. 24, 2020), <https://www.culawreview.org/journal/internet-ada-compliance> [<https://perma.cc/Z9DH-DF4C>]; Mason Marks, *Websites Need to Become ‘Places of Public Accommodation’ Under the Americans with Disabilities Act*, HILL (June 8, 2020, 6:30 PM), <https://thehill.com/opinion/technology/501680-websites-need-to-become-places-of-public-accommodation> [<https://perma.cc/PJ2S-7JVC>].

260. See generally Nancy Leong & Aaron Belzer, *The New Public Accommodations: Race Discrimination in the Platform Economy*, 105 GEO. L.J. 1271, 1275 (2017).

261. DAVID BRODY & SEAN BICKFORD, LAWS.’ COMM. FOR C.R. UNDER L., DISCRIMINATORY DENIAL OF SERVICE: APPLYING STATE PUBLIC ACCOMMODATIONS LAWS TO ONLINE COMMERCE 2 (Jan. 2020), <https://lawyerscommittee.org/wp-content/uploads/2019/12/Online-Public-Accommodations-Report.pdf> [<https://perma.cc/KD8R-8T7U>]. “The public accommodations laws of five states currently apply to online businesses: California, Colorado, New Mexico, New York, and Oregon.” *Id.* at 3. However, six states either have no “general-purpose public accommodations law at all or have a law that is so narrow as to be effectively meaningless.” *Id.*

262. See Bhatia, *supra* note 111.

263. See Bertram Lee, *Where the Rubber Meets the Road: Section 230 and Civil Rights*, PUBLIC KNOWLEDGE (Aug. 12, 2020), <https://publicknowledge.org/where-the-rubber-meets-the-road-section-230-and-civil-rights> [<https://perma.cc/9SEJ-8YEQ>].

264. See *Vargas v. Facebook, Inc.*, No. 19-cv-05081-WHO, 2021 WL 3709083, at *4–5 (N.D. Cal. Aug. 20, 2021), *argued*, No. 21-16499 (9th Cir. July 28, 2022).

265. See HUD’s Implementation of the Fair Housing Act’s Disparate Impact Standard, 85 Fed. Reg. 60,288, 60,288, 60,316 (Sept. 24, 2020) (to be codified at 24 C.F.R. pt. 100).

266. See *id.* at 60,288; 24 C.F.R. § 100.500 (2021).

rule during the notice and comment period.²⁶⁷ While the final rule did not include an explicit safe harbor for algorithms, it adopted a burden-shifting regime that makes it nearly impossible for plaintiffs to challenge algorithms that are used for tenant-screening reports (as discussed above) as well as algorithms that make decisions on home financing, marketing, sales, and zoning.²⁶⁸ In brief, the final rule requires a plaintiff to make a detailed showing about the “internal workings of the challenged algorithm—information that will generally be proprietary, and thus unavailable to plaintiffs who have not yet had access to discovery.”²⁶⁹

In October 2021, a court enjoined the rule from taking effect, stating that it “run[s] the risk of effectively neutering disparate impact liability under the Fair Housing Act” and “appear[s] inadequately justified.”²⁷⁰ President Biden issued an executive order directing the Department of Housing and Urban Development (HUD) to “examine the effects” of the rule and take any steps to ensure that the Act’s purpose is fulfilled, “including . . . preventing practices with an unjustified discriminatory effect.”²⁷¹ In 2021, HUD announced a proposal to reinstate the Obama-era standard set forth in its 2013 Rule.²⁷² This controversy reveals the instability of agency interpretations of existing laws written for an analog world that do not textually address issues of algorithmic accountability. These ambiguities generate opportunities for political flip-flops depending on administrations’ priorities.

C. LEGISLATIVE PROPOSALS TO BRING DIGITAL DISCRIMINATION INTO CIVIL RIGHTS LAW

Given the civil rights implications of data-centric technologies and the shortcomings of existing laws, numerous legislative proposals have been advanced to combat algorithmic bias and to regulate the personal data market. However, as with the antidiscrimination laws on the books, they generally do not cover socioeconomic discrimination. Rather, these proposals generally extend new protections to the existing categories of pro-

267. See Lauren Sarkesian & Spandana Singh, *HUD’s New Rule Paves the Way for Rampant Algorithmic Discrimination in Housing Decisions*, NEW AMERICA: OUR TECH. INST. (Oct. 1, 2020), <https://www.newamerica.org/oti/blog/huds-new-rule-paves-the-way-for-rampant-algorithmic-discrimination-in-housing-decisions> [https://perma.cc/5UE4-E9UC].

268. See John Villasenor & Virginia Foggo, *Algorithms and Housing Discrimination: Rethinking HUD’s New Disparate Impact Rule*, BROOKINGS (Mar. 5, 2021) [hereinafter *Rethinking HUD*], <https://www.brookings.edu/blog/techtank/2021/03/05/algorithms-and-housing-discrimination-rethinking-huds-new-disparate-impact-rule> [https://perma.cc/BR2R-CAK7]. For extended analysis of the rule see Virginia Foggo & John Villasenor, *Algorithms, Housing Discrimination, and the New Disparate Impact Rule*, 22 COLUM. SCI. & TECH. L. REV. 1–62 (2021).

269. *Rethinking HUD*, *supra* note 268.

270. *Mass. Fair Hous. Ctr. v. U.S. Dep’t of Hous. & Urb. Dev.*, 496 F. Supp. 3d 600, 611 (D. Mass. 2020).

271. Memorandum on Redressing Our Nation’s and the Federal Government’s History of Discriminatory Housing Practices and Policies, 86 Fed. Reg. 7487 (Jan. 26, 2021).

272. Dept. of Hous. & Urb. Dev., Reinstatement of HUD’s Discriminatory Effects Standard, 86 Fed. Reg. 33590, (June 25, 2021).

tected traits. Still, it is important to survey this landscape to understand where including protections based on SES might make a positive difference for low-income people. Proposals fall into three broad categories: digital-discrimination laws, data-privacy laws, and algorithmic-accountability laws. To be sure, there are overlaps among these categories, and many bills take more than one approach.

First, there are proposals to extend traditional civil rights protections by clarifying that online platforms constitute public accommodations.²⁷³ The District of Columbia is the first jurisdiction to pass such a law, amending its public-accommodations statute to expressly state that it applies regardless of whether the entity is physically located in the District, thus making it illegal for an online platform to discriminate based on protected traits, including the source of income.²⁷⁴ At the federal level, there are similar proposals, such as a bill Senator Markey (D-MA) introduced, called the Algorithmic Justice and Online Platform Transparency Act.²⁷⁵ The Act would, among other things, explicitly extend public accommodations law to “any commercial entity that offers goods or services through the internet to the general public.”²⁷⁶ There have also been congressional proposals to expressly extend Americans with Disabilities Act protections to the internet.²⁷⁷ None of these proposals have yet passed into law.

The second type of legislative reform impacting digital discrimination involves data-privacy laws. Most data-privacy bills proposed at the federal level—as well as existing laws in Europe and certain U.S. states—include certain civil rights protections because privacy and civil rights are intertwined: “[I]f discrimination results from the collection and use of personal information, it becomes an information privacy issue.”²⁷⁸ Generally, data-privacy laws govern how entities can obtain, use, share, and store personal data while granting consumers greater rights to control their personal data, such as rights to understand how their data is used, delete their data, and move their data from one service to another. How-

273. See BRODY & BICKFORD, *supra* note 261.

274. Bella Evangelista and Tony Hunter Panic Defense Prohibition and Hate Crimes Response Amendment Act of 2020, 68 D.C. Reg. 764 (Jan. 15, 2021); “Place of Public Accommodation” Under the D.C. Human Rights Act, D.C. OFF. OF HUM. RTS. (Dec. 16, 2021), <https://ohr.dc.gov/sites/default/files/dc/sites/ohr/publication/attachments/Place%20of%20Public%20Accommodation%20-%20Factsheet%20and%20Guidance%20on%20New%20Definition%20-%20121621.pdf> [<https://perma.cc/P7YR-KXEM>]. In a handful of other states, this extension of public accommodations law was achieved via judicial rulings. See BRODY & BICKFORD, *supra* note 261, at 3.

275. Algorithmic Justice and Online Platform Transparency Act of 2021, S. 1896, 117th Cong.

276. *Id.* § 3(11)(B) (2021).

277. See, e.g., Online Accessibility Act, H.R. 1100, 117th Cong. (2021).

278. KERRY, MORRIS, CHIN & LEE, *supra* note 250, at 8. See also Simpson & Conner, *supra* note 250 (“[P]rivacy rights are also civil rights . . . wherein mined data feed into algorithms that are used to profile individuals, make decisions, target ads and content, and ultimately lead to discrimination.”); Alvaro M. Bedoya, *Privacy as Civil Right*, 50 N.M. L. REV. 301, 306 (2020) (“Surveillance threatens vulnerable people fighting for equality. Privacy is what protects them and makes it possible.”).

ever, in the United States, there is no comprehensive data-privacy law.²⁷⁹ Rather, “American privacy laws are fragmented and sectoral, meaning they cover specific industries, such as health care providers or financial services companies, or specific forms of data, such as children’s online activity.”²⁸⁰ As a result, the market for personal data remains largely unimpeded, as personal data is gathered, used, and shared without people’s knowledge or consent.²⁸¹ In recent years there has been a “techlash,” spurring bipartisan support in Congress for the passage of a comprehensive data-privacy law,²⁸² but the two parties remain deadlocked on certain core issues, such as preemption (whether any federal law would preempt the states) and private rights of action (whether consumers should have the ability to sue for violations).²⁸³

By contrast, the European Union (EU) is protected by the General Data Protection Regulation (GDPR).²⁸⁴ The GDPR is influential in shaping American data-privacy proposals, and it has real-world impact on Americans, as many tech companies with international business models comply with the GDPR even when they are outside the jurisdiction of the EU.²⁸⁵ Overall, the GDPR places multiple obligations on the entities that gather, hold, and use personal data (called “controllers”) while also granting consumers (called “data subjects”) rights to enhance their control over personal information.²⁸⁶ Whereas in the United States, data collection is freely allowed unless a specific law prohibits it, the EU restricts data controllers to collect data only on a legally granted basis.²⁸⁷ The GDPR further contains certain provisions that promote antidiscrimination. For example, it limits processing “special categories” of data to specified circumstances, such as when “the data subject has given explicit.”²⁸⁸

279. See *Five Privacy Principles*, *supra* note 21, at 400.

280. *Id.* at 402.

281. See Daniel J. Solove, *Introduction: Privacy Self-Management and the Consent Dilemma*, 126 HARV. L. REV. 1879, 1880 (2013).

282. See *Five Privacy Principles*, *supra* note 21, at 371.

283. See Tatiana Rice, *Addressing the Intersection of Civil Rights and Privacy: Federal Legislative Efforts*, FUTURE OF PRIV. F. (Jan. 24, 2022), <https://fpf.org/blog/addressing-the-intersection-of-civil-rights-and-privacy-federal-legislative-efforts> [<https://perma.cc/G7GB-TF2W>].

284. Regulation 2016/679, of the European Parliament and of the Council of 27 April 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, 2016 O.J. (L 119) 1, 32–33 [hereinafter GDPR].

285. See *Five Privacy Principles*, *supra* note 21, at 373; RACHEL F. FEFER & KRISTIN ARCHICK, CONG. RSCH. SERV., IF10896, EU DATA PROTECTION RULES AND U.S. IMPLICATIONS 1–2 (2020) (“Many U.S. firms have made changes to comply with the GDPR, such as revising and clarifying user terms of agreement and asking for explicit consent.”); Margaret Harding McGill & Kim Hart, *How the U.S. Got Boxed in on Privacy*, AXIOS (June 9, 2021), <https://www.axios.com/online-privacy-boxed-in-congress-gdpr-82fd5462-3ad7-481a-b48e-70774ac2bd2d.html> [<https://perma.cc/T7JF-HY3Q>] (“Businesses have already spent big to comply with [the GDPR].”).

286. See generally GDPR, *supra* note 284, art. 4(1), (7).

287. See Lindsey Barrett, *Confiding in Con Men: U.S. Privacy Law, the GDPR, and Information Fiduciaries*, 42 SEATTLE U. L. REV. 1057, 1083 (2019).

288. GDPR, *supra* note 284, art. 9(1), (2)(a), at 38 (“special categories” including “racial or ethnic origin, political opinions, religious or philosophical beliefs, or trade union

It also gives people the right not to be subject to automated decisions—including profiling—which significantly impacts on peoples’ daily lives.²⁸⁹ Any recognized exceptions to this rule cannot involve processing the special categories of personal data.²⁹⁰ “It is therefore apparent that [the GDPR] aims at preventing algorithmic discrimination, as it prevents important algorithmic decisions from being based on data which reveals an individual’s belonging to a protected ground under anti-discrimination law”²⁹¹ The special categories, however, do not include SES (although some European human rights laws protect people based on their SES).²⁹²

The United States’ major congressional proposals to regulate personal data are influenced by the GDPR. In 2022, a proposed federal privacy law called the American Data Privacy and Protection Act (ADPPA)²⁹³ gained bipartisan support and advanced in the legislative process farther than any of its many predecessors, clearing the House Committee on Energy and Commerce by a vote of 53–2.²⁹⁴ Its chances of passage by the full Congress are mixed,²⁹⁵ but even if it fails to move forward in 2022, it is the result of intense bipartisan negotiations and will thus be a likely template for any future bills. In general, the ADPPA requires covered entities to minimize the amount of data they collect, provides consumers with rights to control the collection and use of their data, and bans targeted advertising to children and to any persons who opt out.²⁹⁶ Most importantly for this discussion, the ADPPA’s civil rights protections prohibit the use of personal data in a manner that discriminates on the basis of “race, color, religion, national origin, sex, or disability.”²⁹⁷ It also mandates algorithmic impact assessments before covered entities deploy al-

membership,” genetic data, biometric data, health data, and data concerning a person’s sex life or sexual orientation).

289. *Id.* art. 22(1).

290. *Id.* art. 22.

291. Davide Baldini, *Article 22 GDPR and Prohibition of Discrimination. An Outdated Provision?*, CYBERLAWS (Aug. 20, 2019), <https://www.cyberlaws.it/en/2019/article-22-gdpr-and-prohibition-of-discrimination-an-outdated-provision> [<https://perma.cc/W5NU-R6W6>].

292. *See generally* TAMAS KADAR, EQUAL. & RTS. ALL., AN ANALYSIS OF THE INTRODUCTION OF SOCIO-ECONOMIC STATUS AS A DISCRIMINATION GROUND 8–10 (2016), <http://17october.ie/wp-content/uploads/2019/08/Analysis-of-socio-economic-status-as-discrimination-final.pdf> [<https://perma.cc/K4ZB-TSCJ>]; Sarah Ganty, *Poverty as Misrecognition: What Role for Antidiscrimination Law in Europe?*, 21 HUM. RTS. L. REV. 962 (2021).

293. American Data Privacy and Protection Act, H.R. 8152, 117th Cong. (2022).

294. *See* Rebecca Klar, *House Committee Advances Landmark Federal Data Privacy Bill*, HILL (June 20, 2022), <https://thehill.com/policy/technology/3567822-house-panel-advances-landmark-federal-data-privacy-bill> [<https://perma.cc/V3KU-GXLY>].

295. *See* Cristiano Lima, *Top Senate Democrat Casts Doubt on Prospect of Major Data Privacy Bill*, WASH. POST (June 22, 2022, 2:15 PM), <https://www.washingtonpost.com/technology/2022/06/22/privacy-bill-maria-cantwell-congress> [<https://perma.cc/S24E-5MJR>] (discussing objections from Democratic senators concerned about the bill’s preemption provisions).

296. H.R. 8152, §§ 101, 201–10. As for the two longstanding sticking points between the political parties, the ADPPA compromises by preempting most conflicting state laws (favored by Republicans), as well as permitting private rights of action to enforce its provisions (favored by Democrats). *Id.* §§ 204(b), 403(a).

297. *Id.* § 207(a).

gorithmic systems with the potential to harm individuals through disparate impact or by limiting their access to housing, education, employment, health care, insurance or credit.²⁹⁸ The ADPAA does not expressly include considerations of socio-economic status, although its recognition of the gatekeeping impact of algorithms upon marginalized populations could possibly be interpreted to encompass socio-economic distinctions. And, if the ADPPA is not enacted in 2022, future iterations of the bill could include socio-economic status discrimination among the express harms that covered entities must assess and limit.

In the face of congressional inaction, four states have passed their own comprehensive data-privacy laws—California,²⁹⁹ Colorado,³⁰⁰ Virginia,³⁰¹ and Utah³⁰²—and more states are likely to follow.³⁰³ The California law is the most impactful due to the state’s size and influence as the home of Silicon Valley. The California Consumer Privacy Act (CCPA) creates three core rights for consumers: the right (1) to know what personal information companies collect and share about them; (2) to have personal information deleted upon request; and (3) to opt-out of the sale of personal information.³⁰⁴ However, the CCPA does not address data in connection with protected characteristics. Beginning in 2023, the California Privacy Rights Act (CPRA) will supersede the CCPA.³⁰⁵ The CPRA builds upon the existing rights under the CCPA, but goes further to protect “sensitive personal information,” such as “racial or ethnic origin, religious or philosophical beliefs, or union membership, the contents of a consumer’s mail, email and text messages,” genetic data, bio-

298. *See id.* § 207(c).

299. CAL. CIV. CODE § 1798.100 (2020).

300. Colorado Privacy Act, COLO. REV. STAT. ANN. § 6-1-1301 (2022) (effective July 1, 2023). The Act states, “A controller shall not process a consumer’s sensitive data without first obtaining the consumer’s consent” and requires controllers to document assessments of the processing of sensitive data. *Id.* §§ 6-1-1308(7), 6-1-1309(1). Sensitive data includes “racial or ethnic origin, religious beliefs, a mental or physical health condition or diagnosis, sex life or sexual orientation, or citizenship or citizenship status; genetic or biometric data;” and personal data of a child younger than 13. *Id.* § 6-1-1301(24).

301. Consumer Data Protection Act, VA. CODE ANN. § 59.1-578 (2021) (effective Jan. 1, 2023). Virginia similarly prohibits controllers from processing a consumer’s sensitive data without the consumer’s consent and requires controllers to document a data protection assessment of processing sensitive data. *Id.* § 59.1-578(A)(5). Sensitive data includes personal data that reveals “racial or ethnic origin, religious beliefs, mental or physical health diagnosis, sexual orientation, or citizenship or immigration status,” genetic or biometric data, and personal data of child under 13 years old. *Id.* § 59.1-575.

302. Utah Consumer Privacy Act, S.B. 200, § 13-61-102(1). Similar to the other state laws, Utah’s definition of and protections for sensitive data do not include socio-economic status. *See id.* at § 13-61-101(32).

303. *See* Taylor Kay Lively, *US State Privacy Legislation Tracker*, IAPP, (Aug. 11, 2022), <https://iapp.org/resources/article/us-state-privacy-legislation-tracker> [<https://perma.cc/J9V6-5CM4>].

304. CAL. CIV. CODE § 1798.100 (2020).

305. The CPRA was passed by ballot initiative and will be codified under § 1798.100 of the California Education Code. On the differences between the two laws, see *CCPA vs CPRA: What’s the Difference?*, BLOOMBERG (July 13, 2021), <https://pro.bloomberglaw.com/brief/the-far-reaching-implications-of-the-california-consumer-privacy-act-ccpa> [<https://perma.cc/YX3B-Z3KE>].

metric data, and data collected and analyzed concerning a consumer's health, sex life, or sexual orientation.³⁰⁶ The Attorney General of California has the authority to expand these categories through rulemaking and could perhaps expand them to include socio-economic status. Under the CPRA, consumers have the right to know when their sensitive personal information is gathered, along with opt-out rights to limit the use and disclosure of sensitive personal information.³⁰⁷

The third type of legislative reform focuses on enhancing algorithmic accountability by regulating automated decision-making systems. These proposals often overlap with or are included in data-privacy proposals. In general, these proposals require companies and government agencies using algorithmic systems that impact consumers to identify and understand the risks of unfairness, discrimination, and bias.³⁰⁸ The primary suggested tools for making these determinations are algorithmic impact assessments (AIAs) and audits.³⁰⁹ While they can vary widely in their structure and goals, AIAs generally involve an analysis of the proposed or existing societal impacts of an algorithmic system.³¹⁰ Modeled after impact assessments in the environmental field, they aim to bring social values into technical systems and “create and provide documentation of the decisions made during development and their rationales, which in turn can lead to better accountability for those decisions and useful information for future policy interventions.”³¹¹ Audits typically refer to a “targeted, non-comprehensive approach focused on assessing algorithmic systems for bias,” either in-house or by an outside party or government agency.³¹² These accountability mechanisms are important; they impose duties on the entities that benefit from data processing rather than placing the entire onus on impacted individuals to enforce their rights, which is the model of the current notice and consent regime.

The Algorithmic Accountability Act of 2022, introduced by Senator Ron Wyden (D-OR) and Representative Yvette Clark (D-NY), is the

306. California Privacy Rights Act, § 1798.140(ae) (2020).

307. *Id.* §§ 3(A)(1), 1798.135(a)(1).

308. See generally DILLON REISMAN, JASON SCHULTZ, KATE CRAWFORD & MEREDITH WHITTAKER, AI NOW INST., ALGORITHMIC IMPACT ASSESSMENTS: A PRACTICAL FRAMEWORK FOR PUBLIC AGENCY ACCOUNTABILITY (2018), <https://ainowinstitute.org/aiareport2018.pdf> [<https://perma.cc/CHW2-G2J2>]; EMANUEL MOSS, ELIZABETH ANNE WATKINS, RANJIT SINGH, MADELEINE CLARE ELISH & JACOB METCALF, DATA & SOC'Y, ASSEMBLING ACCOUNTABILITY: ALGORITHMIC IMPACT ASSESSMENT FOR THE PUBLIC INTEREST (2021), <https://datasociety.net/library/assembling-accountability-algorithmic-impact-assessment-for-the-public-interest> [<https://perma.cc/Z9XZ-5J8J>].

309. See ADA LOVELACE INST., EXAMINING THE BLACK BOX: TOOLS FOR ASSESSING ALGORITHMIC SYSTEMS 15–16 (2020), <https://www.adalovelaceinstitute.org/report/examining-the-black-box-tools-for-assessing-algorithmic-systems> [<https://perma.cc/U9NX-UTZ8>].

310. Andrew D. Selbst, *An Institutional View of Algorithmic Impact Assessments*, 35 HARV. J.L. & TECH 117, 127 (2021) (“An Algorithmic Impact Assessment is a process in which the developer of an algorithmic system aims to anticipate, test, and investigate potential harms of the system before implementation; document those findings; and then either publicize them or report them to a regulator.”).

311. *Id.* at 122.

312. See ADA LOVELACE INST., *supra* note 309, at 3.

rare bill that would mandate assessments of automated decision-making systems for people based on their SES.³¹³ The Act would also direct the FTC to issue regulations requiring large businesses to conduct impact assessments for automated-decisions systems that make critical decisions affecting consumers in education, employment, financial services, and housing.³¹⁴ Entities would have to eliminate or mitigate the negative impacts of these systems on consumers' lives. The Bill mandates "an evaluation of any differential performance associated with consumers' race, color, sex, gender, age, disability, religion, family status, *socioeconomic status*, or veteran status."³¹⁵ In addition to the rare nod to socio-economic status as a protected characteristic, the Bill also requires covered entities to "meaningfully consult" with relevant internal and external stakeholders and document those consultations.³¹⁶ The impact assessments would be submitted annually to the FTC,³¹⁷ and the FTC and State Attorneys General would be charged with the law's enforcement.³¹⁸

At the state and local level, algorithmic accountability laws have been proposed to regulate public and private algorithmic systems.³¹⁹ As with federal proposals, they generally rely upon mechanisms such as requiring algorithmic impact assessments or audits.³²⁰ Creating task forces to review algorithmic systems and make recommendations is also a popular proposal for governmental systems. In 2017, New York City passed a law creating an Automated Decision Systems Task Force to make recommendations about the city's use of algorithms.³²¹ Unfortunately, the result was disappointing to many, as the task force could not get the city to identify the forms of automated decision systems it used. Consequently, the task force was only able to make broad recommendations.³²² For the most part, attempts to regulate government algorithms have failed due to

313. See Press Release, Senator Ron Wyden, Wyden, Booker and Clarke Introduce Algorithmic Accountability Act of 2022 to Require New Transparency And Accountability For Automated Decision Systems (Feb. 3, 2022), <https://www.wyden.senate.gov/news/press-releases/wyden-booker-and-clarke-introduce-algorithmic-accountability-act-of-2022-to-require-new-transparency-and-accountability-for-automated-decision-systems> [https://perma.cc/3HXB-PDSZ].

314. See S. 3572, 117th Cong. (2022); H.R. 6580, 117th Cong. (2022).

315. S. 3572 § 4(a)(4)(E) (emphasis added).

316. *Id.* § 3(b)(1)(G).

317. See *id.* § 3(b)(1)(D).

318. See *id.* § 3(b)(1).

319. See Khari Johnson, *The Movement to Hold AI Accountable Gains More Steam*, WIRED (Dec. 2, 2021, 7:00 AM), <https://www.wired.com/story/movement-hold-ai-accountable-gains-steam> [https://perma.cc/VT5E-UHYV]; D.J. Pangburn, *Washington Could Be The First State to Rein In Automated Decision-Making*, FAST Co. (Feb. 8, 2019), <https://www.fastcompany.com/90302465/washington-introduces-landmark-algorithmic-accountability-laws> [https://perma.cc/2RYX-NM26].

320. See *id.*

321. N.Y.C., N.Y. Loc. L. 2018/49 (Jan. 11, 2018).

322. AUTOMATED DECISION SYS. TASK FORCE, NEW YORK CITY: REPORT 283 (2019), <https://www1.nyc.gov/assets/adstaskforce/downloads/pdf/ADS-Report-11192019.pdf> [https://perma.cc/2DGE-FNNN]. For the shortcomings of the report, see Rebecca Heilweil, *New York City Couldn't Pry Open its Own Black Box Algorithms. So Now What?*, VOX (Dec. 18, 2019, 8:20 AM), <https://www.vox.com/recode/2019/12/18/21026229/nyc-ai-algorithms-shadow-report> [https://perma.cc/QR2J-DCJ4].

a combination of tech-industry lobbying and legislators' lack of understanding about how algorithms are deployed and impact constituents.³²³ Lawmakers have had somewhat greater success at the state and local level in enacting laws that govern private companies' use of algorithms.³²⁴ For example, New York City passed a bill requiring private companies that use hiring algorithms to conduct bias audits prior to deployment, and Illinois passed a law requiring private employers to give job candidates notice that they are being evaluated by an algorithmic system and report demographic data about job candidates to a state agency for a biased assessment.³²⁵ Yet, as with most of the laws discussed in this Section, these laws tend to cover the traditional categories of protected classes while excluding poverty.

IV. EXPANDING DIGITAL CIVIL RIGHTS TO INCLUDE POVERTY AND DIGITAL DISCRIMINATION

Without a doubt, digital profiling and automated decision-making adversely impact poor people based on their economic status. Yet existing and proposed laws designed to counter digital discrimination generally do not extend to SES. Rather, they follow a long American civil rights tradition of excluding poverty discrimination from civil rights laws. There are several reasons to take advantage of emerging lawmaking around data privacy and algorithmic accountability to include the poor as a protected class. This Part sets out the case for banning digital discrimination based on low SES and considers the likely counterarguments against this proposed expansion of civil rights.

A. A PROPOSAL FOR ENHANCING DIGITAL RIGHTS ON THE BASIS OF SES

In *Socioeconomic Status Discrimination*, Danieli Evans Peterman sets out a robust case for including people experiencing poverty in traditional civil rights statutes.³²⁶ As she explains, low-SES people experience routine discrimination.³²⁷ She provides examples:

Employers screen applicants by residential address and weed out people who live in notoriously poor neighborhoods. Municipalities enact zoning rules for the purpose of excluding low income residents. Schools place wealthier students in more advanced classes with more experienced teachers. States require voters to show identification documents that poor people have more difficulty obtaining.³²⁸

323. See Todd Feathers, *Why It's So Hard to Regulate Algorithms*, MARKUP (Jan. 4, 2022, 8:00 AM), <https://themarkup.org/news/2022/01/04/why-its-so-hard-to-regulate-algorithms> [<https://perma.cc/N7RF-PQJE>].

324. See *id.*

325. See *id.*

326. See Peterman, *supra* note 7, *passim*.

327. *Id.* at 1286.

328. *Id.*

Technology can make each form of poverty discrimination even easier but far less transparent. Employers use screening services to weed low-income people out of job applicant pools.³²⁹ Credit-scoring algorithms lead banks to deny low-income people loans, thereby entrenching zoning disparities.³³⁰ Public-school-placement algorithms favor technologically sophisticated and wealthy parents.³³¹ Algorithms can be used to gerrymander districts in ways that dilute the votes of poor people and people of color.³³² In short, many existing forms of discrimination against the poor can be amplified in the online universe.

Peterman argues that the moral values underlying existing discrimination laws apply equally to poverty.³³³ Discrimination law is animated by “a moral and political commitment to the ideals of social mobility and self-determination,” and as a result, civil rights laws “protect traits that are subject to pervasive and illegitimate social bias.”³³⁴ Poor people are subject to entrenched, long-standing social bias, similar to the biases faced by protected groups,³³⁵ and that bias is embedded in and magnified by technology. As with race or sex, there can be an immutable aspect to poverty. There is extreme stickiness at both ends of the income scale—the status of an individual’s parents is highly determinative of that individual’s economic status as an adult.³³⁶ Furthermore, being born into poverty negatively impacts cognitive and emotional development and is linked to a range of negative outcomes that can cascade over a lifetime.³³⁷ When people fall into poverty from higher rungs on the economic ladder, it is usually due to factors outside their control, such as a global pandemic, natural disaster, divorce, or job loss,³³⁸ making it an involuntary condition. Further, it can be hard to climb out of poverty

329. See BOGEN & RIEKE, *supra* note 13, at 14–26.

330. Karen Hao, *The Coming War on the Hidden Algorithms That Trap People in Poverty*, MIT TECH. REV. (Dec. 4, 2020), <https://www.technologyreview.com/2020/12/04/1013068/algorithms-create-a-poverty-trap-lawyers-fight-back> [<https://perma.cc/QXK9-ECX2>].

331. See Matt Kasman & Jon Valant, *The Opportunities and Risks of K-12 Student Placement Algorithms*, BROOKINGS (Feb. 28, 2019), <https://www.brookings.edu/research/the-opportunities-and-risks-of-k-12-student-placement-algorithms> [<https://perma.cc/QT6T-H5T8>].

332. Daniel Oberhaus, *Algorithms Supercharged Gerrymandering. We Should Use Them to Fix It*, VICE (Oct. 3, 2017, 2:11 PM), <https://www.vice.com/en/article/7xkmg/gerrymandering-algorithms> [<https://perma.cc/R3CD-V3HE>]. Algorithms could also be used as a tool to flight gerrymandering. *See id.*

333. Peterman, *supra* note 7, at 1327–32.

334. *Id.* at 1326.

335. *See id.* at 1327–29.

336. See MICHAEL GREENSTONE, ADAM LOONEY, JEREMY PATASHNIK & MUXIN YU, THE HAMILTON PROJECT, THIRTEEN ECONOMIC FACTS ABOUT SOCIAL MOBILITY AND THE ROLE OF EDUCATION 6 (June 2013), https://www.brookings.edu/wp-content/uploads/2016/06/thp_13econfacts_final.pdf [<https://perma.cc/8G5B-AYDS>].

337. See Hirokazu Yoshikawa, J. Lawrence Aber & William R. Beardslee, *The Effects of Poverty on the Mental, Emotional, and Behavioral Health of Children and Youth: Implications for Prevention*, 67 AM. PSYCH. 272, 273–74 (2012).

338. See David A. Super, *Acute Poverty: The Fatal Flaw in U.S. Anti-Poverty Law*, 10 U.C. IRVINE L. REV. 1273, 1280 (2020) (describing how people fall into acute, or episodic, poverty).

given that low wages and high housing costs push people to assume debt, often at predatory rates, creating a vicious cycle.³³⁹ In these ways, poverty shares aspects of involuntariness similar to race and sex. As John A. Powell says, the “‘discrete and insular minorit[ies]’ today are the poor or extreme poor.”³⁴⁰ In addition, because poverty discrimination and racial discrimination are interrelated, fighting SES discrimination can have positive racial justice outcomes.³⁴¹ Oftentimes, discrimination against the poor is based on racial stereotypes, such as the “welfare queen,” which is shorthand for a poor woman of color who lives an extravagant lifestyle on the government dole by cheating taxpayers.³⁴² While “the welfare queen . . . is a myth,”³⁴³ the entanglement of race, gender, and class underlying this stereotype makes it “difficult if not impossible to disentangle bias against the poor from racial bias.”³⁴⁴ In America, Black, Latino, Indigenous, and other people of color are frequently excluded from accessing the same income, wealth, and social mobility as White Americans do.³⁴⁵ Despite living in a country of vast wealth, minorities disproportionately live in material hardship as a result of historical and ongoing oppression.³⁴⁶ Black Americans have a poverty rate nearly twice that of the national rate.³⁴⁷ As a result, policies that discriminate against the poor fall most harshly on minorities.³⁴⁸ Consider that, in each of the case studies above, the automated decision-making systems have both a disparate SES impact and a disparate racial impact, among other identity-based impacts.

In some situations, policymakers disclaim racial motives for discriminatory policies, claiming they are motivated solely by anti-poor bias, which

339. See, e.g., *High Housing Cost Burdens in the United States*, HABITAT FOR HUMAN., <https://www.habitat.org/stories/high-housing-cost-burdens-united-states> [<https://perma.cc/HG3R-VC3Q>].

340. John A. Powell, *Constitutionalism and the Extreme Poor: Neo-Dred Scott and the Contemporary “Discrete and Insular Minorities,”* 60 *DRAKE L. REV.* 1069, 1076 (2012).

341. See Peterman, *supra* note 7, at 1334.

342. Michele E. Gilman, *The Return of the Welfare Queen*, 22 *AM. U. J. GENDER SOC. POL’Y & L.* 247, 257–60 (2014) (“She challenges gender norms by failing to conform to patriarchal notions of a proper family; she ignites racist stereotypes about minorities; and her failure to succeed in a capitalist society makes her a subject of derision.”).

343. *Id.* at 263–66.

344. Peterman, *supra* note 7, at 1334.

345. See John Creamer, *Inequalities Persist Despite Decline in Poverty For All Major Race and Hispanic Origin Groups*, U.S. CENSUS BUREAU (Sept. 20, 2020), <https://www.census.gov/library/stories/2020/09/poverty-rates-for-blacks-and-hispanics-reached-historic-lows-in-2019.html> [<https://perma.cc/KX9M-E2HZ>]; Danyelle Solomon, Connor Maxwell & Abril Castro, *Systemic Inequality: Displacement, Exclusion, and Segregation*, *CTR. FOR AM. PROGRESS* (Aug. 7, 2019), <https://www.americanprogress.org/article/systemic-inequality-displacement-exclusion-segregation> [<https://perma.cc/M27J-PPCR>].

346. Creamer, *supra* note 345.

347. *Poverty Rate by Race/Ethnicity*, KAISER FAM. FOUND., <https://www.kff.org/other/state-indicator/poverty-rate-by-race-ethnicity-cps/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D> [<https://perma.cc/W5WN-9AKD>]. Based on information from the Census Bureau, 19.4% of Black Americans were living in poverty in 2021, compared to 11.7% of total Americans. *Id.*

348. See Peterman, *supra* note 7, at 1335.

is socially acceptable—and legal.³⁴⁹ Discrimination is often intersectional, meaning structural systems of oppression can impact people across their multiple identities. The intersection of multiple forms of oppression generates a specific life experience, and as a result, efforts to enhance equality must account for these multiple dimensions.³⁵⁰ By protecting SES, the “class, not race” defense would no longer be acceptable, and the law would more fully recognize how discrimination operates. Peterman explains, “Because SES-based discrimination is so intertwined with racial bias, addressing SES discrimination is part of a comprehensive strategy for addressing racial discrimination.”³⁵¹ Given the links between gender and poverty, we could expect benefits in the fight for gender equity as well.³⁵² Not only would protecting against SES discrimination “promote the acceptance of a more sophisticated approach to intersectionality,” it would also reach people facing discrimination where the “traditional” grounds for discrimination do not protect them—that is, when they face discrimination solely due to their social class.³⁵³ Notably, there is new research showing that legal prohibitions on discrimination can make people more sympathetic to protected classes.³⁵⁴ Conversely, as Emily Burke and Roseanna Sommers write, “when discrimination is tolerated by law, it can hurt members of the target group [T]he refusal to outlaw discrimination sends a denigrating signal about the status of the victim’s group and plays a causal role in lowering public regard for them.”³⁵⁵ Thus, the absence of poverty as a protected characteristic may be feeding existing stereotypes and stigmas about poor people, thereby furthering punitive policies in a cyclical manner.

Protecting against SES discrimination could unite a “cross-racial coalition” with the potential to advance shared economic interests.³⁵⁶ Race has long been a wedge to split low-income Blacks and Whites, preventing them from organizing to advance their shared economic interests.³⁵⁷ By contrast, “[g]iving litigants the option of framing disparate-impact claims in terms of SES would draw attention to the ways that lower-SES people of all races share common experiences of exclusion and marginaliza-

349. *See id.*

350. *See* S. Charusheela, *Intersectionality*, in *HANDBOOK OF RESEARCH ON GENDER AND ECONOMIC LIFE* 32, 32–43 (Deborah M. Figart & Tonia L. Warnecke eds., 2013).

351. Peterman, note 7, at 1335.

352. *See generally* Michele Gilman, *En-Gendering Economic Inequality*, 32 *COLUM. J. GENDER & L.* 1 (2016).

353. KADAR, *supra* note 292, at 19–20. *See also* Sandra Fredman, *Positive Duties and Socio-Economic Disadvantage: Bringing Disadvantage onto the Equality Agenda*, 2010 *EUR. HUM. RTS. L. REV.* 290, 291 (2010) (“Paying attention to socio-economic disadvantage can only assist and strengthen the effectiveness of status-based anti-discrimination laws.”).

354. *See* Sara Emily Burke & Roseanna Sommers, *Reducing Prejudice Through Law: Evidence from Experimental Psychology*, 89 *U. CHI. L. REV.* 1369 (2022).

355. *Id.* at 1410–11.

356. Peterman, *supra* note 7, at 1336.

357. *See id.* 1306 (“[R]ace was used as a wedge to impede a cross-racial, class-based political coalition from gaining power. Jim Crow laws enforcing racial segregation prevented lower-SES whites and nonwhites from developing social and political ties.”).

tion.”³⁵⁸ Across the country, progressive activists with economic and racial justice commitments are taking heed of the power balances embedded in technological systems and their outputs.³⁵⁹ There is a surge of labor activism by workers whose lives are controlled by algorithmic systems, such as Amazon warehouse workers and Instacart delivery drivers resisting the ways that automation ruthlessly pushes them to dangerous levels of productivity.³⁶⁰ “Tech workers, too, are forming unions and coalitions that unite those building technologies of social control—or, refusing to build them—with the communities harmed by them.”³⁶¹ Employees at big-tech companies have walked off the job (or threatened to do so) to resist the development and use of facial recognition technology, software for Immigration and Customs Enforcement, and tech tools to optimize drone strikes.³⁶² Progressive movements see the linkage between race, class, sex, disability, and other identities, but the law has fallen behind. Expanding our core civil rights law to include SES would strengthen movements for worker justice, civil liberties, tenants’ rights, anti-surveillance, tech accountability, and many other movements linked to data justice.

Recognizing SES status within discrimination law could also have a legal benefit. The Supreme Court is increasingly wary of race-based classifications, even when designed to benefit minorities and other historically disenfranchised groups.³⁶³ By contrast, because poverty is not a suspect characteristic, any affirmative steps to assist low-SES people or alleviate a disparate impact on them would survive any Equal Protection gauntlet. Recognizing SES status may help litigants avoid “the identity trap,” or courts’ refusal to recognize that a person’s racial identity, and not another source of vulnerability, brought about unfair treatment.³⁶⁴ Hila Keren explains that in “reverse redlining” cases (i.e., cases in which minorities are targeted for predatory loans), courts distinguish between harms attributable to race and harms occurring for nonracial reasons.³⁶⁵ In so doing, they deny relief to Black borrowers for exploitative lending practices because

358. *Id.* at 1336.

359. See Hannah Bloch-Wehba, *Algorithmic Governance from the Bottom Up*, *BYU L. REV.* (forthcoming 2023), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4054640.

360. See Nantina Vgontzas & Meredith Whittaker, *These Machines Won’t Kill Fascism: Toward a Militant Progressive Vision for Tech*, *NATION* (Jan. 29, 2021), <https://www.thenation.com/article/society/tech-labor-progressive> [<https://perma.cc/J9YX-VGQD>].

361. *Id.*

362. Alexia Fernández Campbell, *How Tech Employees Are Pushing Silicon Valley to Put Ethics Before Profit*, *Vox* (Oct. 18, 2018, 4:30 PM), <https://www.vox.com/technology/2018/10/18/17989482/google-amazon-employee-ethics-contracts> [<https://perma.cc/GN8Z-UBMJ>]; Matt Laviertes, *Silicon Valley Firms Are Facing a Rise in Anger from a New Source: Their Own Employees*, *CNBC* (Jul. 8, 2018, 11:58 AM), <https://www.cnn.com/2018/07/05/tech-ceos-are-losing-unilateral-power-rapidly-in-a-new-unexpected-way.html> [<https://perma.cc/5T6X-JPAY>].

363. See, e.g., *Gratz v. Bollinger*, 539 U.S. 244, 270 (2003).

364. Hila Keren, *Law and Economic Exploitation in an Anti-Classification Age*, 42 *FLA. ST. U. L. REV.* 313, 329–30 (2015).

365. *Id.* at 315.

they see race as only one factor in their vulnerability as consumers.³⁶⁶ By contrast, legally recognizing economic vulnerability could provide a way out of this colorblindness trap and allow for a more intersectional consideration of why certain populations are targeted.

Recognizing poverty within digital discrimination law is all the more urgent given that the sheer scale of digital discrimination possible via automated decision-making systems dwarfs human decisions. Ifeoma Ajunwa explains with regard to automated employment systems:

To be sure, human managers hold biases that are reflected in unfavorable employment decisions for protected classes, but the impact of one biased human manager is constrained in comparison to the potential adverse reach of algorithms that could be used to exclude millions of job applicants from viewing a job advertisement or to sort thousands of resumes.³⁶⁷

It is particularly urgent to ferret out and eliminate societal bias against the poor in automated systems, as people become increasingly ensnared in multiple and overlapping algorithmic systems, usually without their knowledge.

In addition, the permanency of digital data risks trapping people in poverty in ways that hinder economic mobility. Though poverty is largely involuntary, for many people it is transient. “More than half of all bouts of poverty last four months or less.”³⁶⁸ However, digital encoding of hardship may limit people’s ability to escape acute periods of poverty. The pandemic has brought this into stark relief. During the pandemic, as people lost work, millions struggled to pay rent and mortgage expenses and to cover utilities, food, health care, and other material costs.³⁶⁹ As they fell behind on these payments, they faced evictions, foreclosures, utility shut-offs, and collection actions.³⁷⁰ Each financial hardship is a data point embedded in individuals’ digital profiles, creating a barrier to future financial stability as lenders, employers, landlords, and other entities penalize individuals based on their digital footprints.³⁷¹ At the same time, digital profiling that identifies financially struggling people makes them targets for predatory marketers.³⁷² Prohibiting SES discrimination could alleviate the digital profiling of economic distress.

Finally, by ignoring class within law, we risk magnifying gaping holes in data collection and research about poor people and their experiences. In

366. *See id.* at 322. Notably, digital profiling helped to fuel redlining in the aftermath of the 2008 recession. *See id.*

367. Ifeoma Ajunwa, *The Paradox of Automation as Anti-Bias Intervention*, 41 CARDOZO L. REV. 1671, 1679–80 (2020).

368. Super, *supra* note 338, at 1291.

369. *See* MICHELE GILMAN & MARY MADDEN, DATA & SOC’Y, DIGITAL BARRIERS TO ECONOMIC JUSTICE IN THE WAKE OF COVID-19 29–32 (2021), <https://datasociety.net/library/digital-barriers-to-economic-justice-in-the-wake-of-covid-19> [<https://perma.cc/F6U6-EAS6>].

370. *See id.*

371. *See id.* at 27.

372. *See id.* at 34.

the context of criminal justice, Erica Hashimoto points out that legislators spend billions of dollars and develop policies and laws without understanding why the poor are overrepresented in the criminal legal system.³⁷³ “[C]riminal defendants are disproportionately poor,”³⁷⁴ yet without knowledge of the underlying causes of this disparity, it is impossible to develop effective solutions.³⁷⁵ Further, the lack of data threatens the evenhanded administration of the law.³⁷⁶ Without data on “who is being prosecuted, convicted and punished, and for what,” there is no assurance that “laws are being enforced uniformly.”³⁷⁷ Similarly, as more jurisdictions mandate impact assessments and audits for algorithms, excluding class as a protected category will deepen the disparity between digital harms and solutions. Exclusion from data sets and routine data flows—the phenomenon of living in the “surveillance gap”—can be just as harmful to people as over-surveillance.³⁷⁸ People who are credit invisible, work in an underground economy without proof of pay and hours, and are homeless are pushed to the margins of public spaces and subject to predation while they remain disconnected from sources of social support that could provide economic stability.³⁷⁹ Poor people tend to live on the extremes of the privacy spectrum, having too much or too little privacy—and excluding SES status from civil rights protections entrenches this dynamic.

B. CONSIDERING COUNTERARGUMENTS

This Section responds to likely arguments against the incorporation of SES into digital discrimination law: (1) the nebulous nature of poverty or socioeconomic disadvantage; (2) the risk that regulating tech will harm innovation; and (3) the inefficacy of rights to counter inequality.

First, there is a definitional challenge—what is poverty? “Poverty is not simply a lack of goods or income; it’s a multivariate condition that is marked by a lack of membership, citizenship, and human concern.”³⁸⁰ Sociologists Matthew Desmond and Bruce Western explain that poverty is “better understood as something akin to correlated adversity that cuts

373. Hashimoto, *supra* note 131, at 32.

374. *Id.* at 55.

375. *Id.* at 32, 62 (“In order to develop the most successful and cost-effective solutions for the crime problems we face, we need to target criminal justice programs towards the people most likely to be defendants.”).

376. *See id.* at 32–33.

377. *Id.* at 33.

378. *See* Michele Gilman & Rebecca Green, *The Surveillance Gap: The Harms of Extreme Privacy and Data Marginalization*, 42 N.Y.U. REV. L. & SOC. CHANGE 253, 255 (2018).

379. *See id.* at 257, 280–81.

380. powell, *supra* note 340, at 1076. *See also* Shreya Atrey, *The Intersectional Case of Poverty in Discrimination Law*, 18 HUM. RTS. L. REV. 411, 416 (2018) (“While some consider poverty to be solely income related, such as the World Bank’s [\$1.25] a day definition, human rights lawyers, development specialists, and leading economists among others have preferred more rounded definitions of poverty which acknowledge its complex intersectional character.”).

across multiple dimensions (material, social, bodily, psychological) and institutions (schools, neighborhoods, prisons).”³⁸¹ The fine-grained classifications of algorithmic systems capture all of these dimensions of poverty (though usually to the detriment of marginalized people). Yet laws are less capable of capturing this level of nuance.

Still, America’s anti-poverty policies use economic-based definitions of poverty that draw discrete lines for measuring and delivering assistance. Every year, the Census measures the official poverty rate and sets the new poverty threshold.³⁸² Government agencies rely on similar poverty guidelines to determine eligibility for governmental assistance.³⁸³ These measures are necessarily imperfect,³⁸⁴ but they provide a uniform metric for observing hardship over time. Moreover, “because financial resources are highly correlated with other components of class, protecting people who lack financial resources (or who are perceived as lacking them) will protect, by and large, people who lack education, have low-status occupations, or who were raised by poor parents.”³⁸⁵

Thus, antidiscrimination laws can adopt existing measures of poverty to identify people most likely to suffer from digital discrimination. It would be highly ironic to let definitional challenges stymie legal protections against digital discrimination, given the fine-grained assessments and social sorting that algorithmic systems churn out about individuals. Further, the lack of a categorical boundary should not be a barrier to banning SES discrimination. Along these lines, categories currently recognized under antidiscrimination law, such as race and gender, can also be fluid.³⁸⁶ Many people identify as biracial or multiracial. Some people reject the gender binary. Still, antidiscrimination law can accommodate claims of unequal treatment arising along these spectrums.³⁸⁷

Second, any call to add a protected class to antidiscrimination law will inevitably raise concerns that additional regulations will stifle innovation in the tech sector.³⁸⁸ For years, the tech industry convinced lawmakers

381. Matthew Desmond & Bruce Western, *Poverty in America: New Directions and Debates*, 44 ANN. REV. SOCIO. 305, 308 (2018).

382. *Guidance for Poverty Data Users: How the Census Bureau Measures Poverty*, U.S. CENSUS BUREAU (Nov. 22, 2021), <https://www.census.gov/topics/income-poverty/poverty/guidance/poverty-measures.html> [<https://perma.cc/V79E-AFAF>].

383. See Annual Update of the HHS Poverty Guidelines, 87 Fed. Reg. 3315 (Jan. 21, 2022).

384. On controversies regarding poverty measurement, see Areeba Haider & Justin Schweitzer, *The Poverty Line Matters, But It Isn’t Capturing Everyone It Should*, CTR. FOR AM. PROGRESS (Mar. 5, 2020), <https://www.americanprogress.org/article/poverty-line-matters-isnt-capturing-everyone> [<https://perma.cc/78CP-JKG7>].

385. Peterman, *supra* note 7, at 1341.

386. See *id.* at 1343.

387. *E.g.*, *Bostock v. Clayton Cnty.*, 140 S.Ct. 1731, 1737 (2020) (extending traditional antidiscrimination laws to cover discrimination based on sexual orientation and gender identity).

388. See Jonathan B. Wiener, *The Regulation of Technology, and the Technology of Regulation*, 26 TECH. SOC’Y 483, 483 (2004) (“Technology and regulation are often posed as adversaries. Technology symbolizes markets, enterprise, and growth, while regulation represents government, bureaucracy, and limits to growth.”).

that “what they were doing was digital magic and that regulatory oversight could break that wizardry.”³⁸⁹ They had the power and influence to make this argument since internet related businesses constitute 10% of the United States’ gross domestic product.³⁹⁰ However, in recent years, the magic spell has been broken. The industry faces a public “techlash” in the face of a drumbeat of data breaches, widespread incidents of online harassment, social media misinformation campaigns, and targeted advertising that consumers increasingly find creepy and annoying. Americans realize that their online and offline behavior is being tracked and sold as part of a massive, networked system of data for-profit and surveillance. Indeed, a majority of Americans now believe that big tech should face more regulation, with 68% reporting that “these firms have too much power and influence in the economy.”³⁹¹ The tide has also turned within the industry. With the rise of varying state statutes and more on the horizon, the tech industry now supports some version of uniform federal regulation.³⁹²

Of course, there are a variety of forms of regulation, of which antidiscrimination law is only one.³⁹³ Will banning socioeconomic discrimination harm innovation? To be sure, this may be the wrong question. If discrimination is morally wrong, then economic impacts are not determinative.³⁹⁴ However, regulation may not require a trade-off. There is ample evidence that antidiscrimination laws can support innovation and the economy.³⁹⁵ For example, several scholars studied the economic impacts of state laws barring workplace discrimination based on sexual orientation and gender identity.³⁹⁶ One study found that firms in states with these laws had 8%

389. Tom Wheeler, *The Tragedy of Tech Companies: Getting the Regulation They Want*, BROOKINGS (Mar. 26, 2019), <https://www.brookings.edu/blog/techtank/2019/03/26/the-tragedy-of-tech-companies-getting-the-regulation-they-want> [<https://perma.cc/K99L-X3JK>].

390. Simpson & Conner, *supra* note 250.

391. Emily A. Vogels, *56% of Americans Support More Regulation of Major Technology Companies*, PEW RSCH. CTR. (July 20, 2021), <https://www.pewresearch.org/fact-tank/2021/07/20/56-of-americans-support-more-regulation-of-major-technology-companies> [<https://perma.cc/2AT6-95UK>].

392. See Monica Nickelsburg, *Tech Experts Agree It’s Time to Regulate Artificial Intelligence—If Only It Were That Simple*, GEEKWIRE (Dec. 12, 2019, 4:00 PM), <https://www.geekwire.com/2019/tech-experts-agree-time-regulate-artificial-intelligence-simple> [<https://perma.cc/VN3G-N3UU>].

393. See Gary E. Marchant, *Governance of Emerging Technologies as a Wicked Problem*, 73 VAND. L. REV. 1861, 1865 (2020) (“Rather than traditional regulation . . . emerging technologies will require a ‘governance’ approach that expands the categories of responsible parties beyond government to include the private sector, nongovernmental organizations, and think tanks and also expands the relevant oversight mechanism beyond enforceable government regulations.”).

394. See Avi Goldfarb & Catherine Tucker, *Privacy and Innovation*, 12 INNOVATION POL’Y & ECON. 65 (describing tradeoffs between economic concerns and privacy values).

395. See *id.*

396. M.V. LEE BADGETT, ANDREW PAR & ANDREW FLORES, THE WILLIAMS INST., *LINKS BETWEEN ECONOMIC DEVELOPMENT AND NEW MEASURES OF LGBT INCLUSION* 3–5 (2018), <https://williamsinstitute.law.ucla.edu/wp-content/uploads/Global-Economy-and-LGBT-Inclusion-Mar-2018.pdf> [<https://perma.cc/NXC3-FJR9>].

higher patents than those without such laws.³⁹⁷ The authors concluded that “discrimination in the labor market imposes significant costs on the economy by decreasing corporate innovativeness.”³⁹⁸ Another study found that the quality of entrepreneurial ventures in states that adopted these civil rights protections was higher.³⁹⁹ There is also significant research demonstrating the economic costs of racism on society.⁴⁰⁰ According to one study, if racial gaps for Black Americans had been closed twenty years ago in terms of wages, education, housing, and investment, the U.S. economy would have had \$16 trillion more dollars.⁴⁰¹ And closing these gaps today would add \$5 trillion to the U.S. GDP over the next five years.⁴⁰² Banning SES discrimination is one tool to help close these gaps in the digital space.⁴⁰³

The third and most potent counterargument is that antidiscrimination law, with its focus on individual rights, fails to unmask or reform structural systems of subordination and can even perpetuate injustice.⁴⁰⁴ In this view, the value of antidiscrimination law is limited to removing formal barriers to equal participation rather than addressing “the underlying institutional frameworks, or remedy[ing] centuries of disinvestment in communities.”⁴⁰⁵ Another limitation stems from a reliance on courts to implement the nondiscrimination norm, as they are not suited “to the multidimensional work of implementing social and economic inclusion.”⁴⁰⁶ Anna Lauren Hoffmann situates this rights critique directly in

397. Huasheng Gao & Wei Zhang, Does Workplace Discrimination Impede Innovation? 3 (June 2015) (unpublished manuscript), http://cicfconf.org/sites/default/files/paper_70.pdf [<https://perma.cc/5C4C-6JJA>].

398. *Id.* at 5.

399. See Raffaele Conti, Olenka Kacperczyk & Giovanni Valentini, *Institutional Protection of Minority Employees and Entrepreneurship: Evidence from the LGBT Employment Non-Discrimination Acts*, 43 STRATEGIC MGMT. J. 758, 786 (2021).

400. Lisa D. Cook, *Racism Impoverishes the Whole Economy*, N.Y. TIMES (Nov. 18, 2020), <https://www.nytimes.com/2020/11/18/business/racism-impoverishes-the-whole-economy.html> [<https://perma.cc/E6Y9-PGLT>] (summarizing research and providing links to key studies).

401. DANA M. PETERSON & CATHERINE L. MANN, CITI GLOB. PERSPS. & SOLS., CLOSING THE RACIAL INEQUALITY GAPS: THE ECONOMIC COST OF BLACK INEQUALITY IN THE U.S. 7 (2020), https://ir.citi.com/NvIUkIHPilz14Hwd3oxqZBLMn1_XPqo5FrxsZD0x6hhil84ZxaxEuJUWmak51UHvYk75VKeHCMI%3D [<https://perma.cc/F3L3-N5RH>].

402. *Id.* at 8.

403. See Frank A. Pasquale & Danielle Keats Citron, *Promoting Innovation While Preventing Discrimination: Policy Goals for the Scored Society*, 89 WASH. U. L. REV. 1413, 1421 (2014) (“Without mandating privacy-respecting innovation, new technology can be abused in order to hide (and ultimately promote) discrimination, rather than to promote truly productive innovation.”).

404. The rights critique has its roots in Mark Tushnet, *An Essay on Rights*, 62 TEX. L. REV. 1363, 1384 (1984). See also Paul D. Butler, *Poor People Lose: Gideon and the Critique of Rights*, 122 YALE L.J. 2176, 2178 (2013) (The rights critique “posits that ‘nothing whatever follows from a court’s adoption of some legal rule’ and that ‘winning a legal victory can actually impede further progressive change.’”).

405. Olatunde C.A. Johnson, *Equality Law Pluralism*, 117 COLUM. L. REV. 1973, 1976 (2017) (summarizing arguments of the critique).

406. *Id.* at 1977.

the realm of AI and big data.⁴⁰⁷ She warns that the search for the “bad actor” in analog discrimination cases will transform into the search for the “bad algorithm” in the context of technology.⁴⁰⁸ In either setting, the focus on individualized blame “reduc[es] a system’s shortcomings to the biases of its imperfect human designers.”⁴⁰⁹ Further, by focusing on disadvantage, “we fail to question the normative conditions that produce—and promote the qualities or interests of—advantaged subjects.”⁴¹⁰ In sum, Hoffmann asks whether an individualized digital rights regime can ever be an effective counterweight to the power imbalances reflected in, and reified by, technology.⁴¹¹

In response to the rights critique, other scholars have stood up for rights, particularly in the context of race. Patricia Williams acknowledges the limits of rights but argues, “[I]t remains that rights rhetoric has been and continues to be an effective form of discourse for [B]lacks” and a source for “politically effective action.”⁴¹² Similarly, Kimberlé Crenshaw explains that, by failing to consider racism, critical legal scholars fail to see how “the expression of rights . . . was a central organizing feature of the civil rights movement” and “constituted a serious ideological challenge to white supremacy.”⁴¹³ More recently, Olatunde Johnson described how rights-based advocacy has led to important litigation victories “with the courts emerging as a bulwark against potential government excesses.”⁴¹⁴ There is also considerable evidence that antidiscrimination laws shape compliance efforts by businesses and government entities and can lead to decreased incidents of discrimination.⁴¹⁵ With regard to poor people, in particular, Julie Nice states that “without rights as leverage, poor people have great difficulty making political gains, and without political leverage, poor people have great difficulty obtaining protection of rights.”⁴¹⁶ These perspectives resonate with practicing legal services advocates (including this author) who need legal tools grounded in rights to assist clients *now* and cannot wait for an alternate ideology to become a reality if it ever does. Moreover, working within the legal system certainly does not prevent advocates from standing in solidarity with

407. Anna Lauren Hoffmann, *Where Fairness Fails: Data, Algorithms, and the Limits of Antidiscrimination Discourse*, 22 INFO. COMM. & SOC’Y 900 (2019).

408. *Id.* at 903–05.

409. *Id.* at 904.

410. *Id.* at 907.

411. *See id.* at 909–10.

412. Patricia J. Williams, *Alchemical Notes: Reconstructing Ideals from Deconstructed Rights*, 22 HARV. C.R.-C.L.L. REV. 401, 410, 412 (1987).

413. Kimberlé Williams Crenshaw, *Race, Reform, and Retrenchment: Transformation and Legitimation in Antidiscrimination Law*, 101 HARV. L. REV. 1331, 1364–65 (1988).

414. Johnson, *supra* note 405, at 1983, 1990.

415. *Id.* at 1982 (“Researchers have shown that Title VII litigation can spur change not just by those subject to the litigation, but that it can have broader effects on increasing the hiring of women and minorities.”).

416. Julie Nice, *Wither the Canaries: On the Exclusion of Poor People from Equal Constitutional Protections*, 60 DRAKE L. REV. 1023, 1031 (2012) (discussing the importance of constitutional rights for poor people).

and providing technical support to grassroots and community-based movements for structural interventions and justice outside the courtroom.

Indeed, a multi-faceted approach is essential. Adding SES as a protected trait in digital discrimination law does not solve all harms of data-centric technologies for marginalized people. Algorithmic bias is not the only cause of oppression.⁴¹⁷ Poor people are often ensnared in systems of exploitation and domination where the more privileged are entirely absent; indeed, their privilege removes them from these settings. And yet, discrimination law assumes and requires a more privileged, rights-bearing comparator.⁴¹⁸ As I have written previously,

[t]he ability to obtain a low-skill job with a living wage, predictable hours, health care benefits, and affordable childcare is not solely a matter of purging discriminatory employers from the workplace. There is an entire sector of our economy that exploits workers regardless of their race, ethnicity, or gender. Likewise, there is not enough affordable housing in the United States, and thus getting rid of discriminatory lenders and landlords can reduce segregation, but it will not solve the structural problem of supply and demand. Public benefit systems serve only poor people, so a welfare movement that asks to be treated the same as the rich is meaningless to the social service bureaucracy.⁴¹⁹

Simply put, equality doctrine alone cannot lead to equity because it is about treating people the same. By contrast, equity is about giving people what they need to flourish. It requires accounting for “power differentials and distributing (or redistributing) resources accordingly.”⁴²⁰ Because discrimination law is not about fulfilling substantive guarantees to life’s necessities, it cannot eliminate all forms of digital exploitation. It is one piece in a larger, multi-pronged struggle to shift the power imbalances embedded in data-centric technologies away from the powerful entities that control data towards the people whose data fuels these systems. Significantly, civil rights laws can help open the “black box” of algorithmic systems, which are opaque and inaccessible, and in turn, potentially lead to equity-focused reforms. At the end of the day, equity requires more than law; it centers on substantive demands for empowering tech tools, grassroots resistance to subordinating technologies, a commitment to ethical norms and design justice, and ongoing exploration of technical solutions for oppressive systems.

417. See Johnson, *supra* note 405, at 1986 (discussing commentators who “have observed that discrimination is at most a partial explanation for inequality”); COSTANZA-CHOCK, *supra* note 67, at 27 (“We need to discuss the difference between algorithmic colorblindness and algorithmic justice.”); D’IGNAZIO & KLEIN, *supra* note 71, at 63 (“[O]ppression is the problem, not bias.”).

418. See Suzanne B. Goldberg, *Discrimination by Comparison*, 120 YALE L.J. 728, 731, 750 (2011).

419. *Five Privacy Principles*, *supra* note 21, at 411.

420. D’IGNAZIO & KLEIN, *supra* note 71, at 62.

V. CONCLUSION

People experiencing poverty suffer digital discrimination based on their socioeconomic status. Algorithmic decision-making systems act as gatekeepers to the basic necessities of modern life, such as housing, jobs, healthcare, and education. In the United States, these systems lack transparency, and there are few mechanisms to hold the entities that deploy them accountable for their harm. Credit scoring algorithms embed financial hardship and thus reinforce poverty. Tenant screening algorithms weigh characteristics with no proven connection to renter reliability. Algorithms used in higher education favor the wealthy and prey on the poor. Digital advertising systems can feed or deny opportunities to people based on their status as financially vulnerable.

These examples are just the tip of the iceberg of algorithmic harms facing low-income people. Yet American law provides scant recourse to remedy these harms because poverty is not a protected characteristic under the Constitution or in antidiscrimination statutes. We are at the cusp of a wave of lawmaking to enhance data privacy and algorithmic accountability to rein in algorithmic bias against marginalized people. We should seize this moment and include socioeconomic status as a protected characteristic, similar to the protections afforded to people on the basis of their race, gender, disability, and other recognized categories. This would enhance economic opportunity for millions of Americans, advance the fight for racial justice, and generate the data to improve anti-poverty policymaking. It also can enhance technological innovation while furthering structural reforms for economic justice. Technology should be a tool to empower people rather than oppress them. Expanding civil rights to ban digital discrimination based on poverty is one step in the right direction.