Maryland Law Review

Volume 81 | Issue 3 Article 2

Defining and Demystifying Automated Decision Systems

Rashida Richardson

DEFINING AND DEMYSTIFYING AUTOMATED DECISION SYSTEMS

RASHIDA RICHARDSON*

Government agencies are increasingly using automated decision systems to aid or supplant human decision-making and policy enforcement in various sensitive social domains. They determine who will have their food subsidies terminated, how many health care benefits a person is entitled to, and who is likely to be a victim of a crime. Yet, existing legislative and regulatory definitions fail to adequately describe or clarify how these technologies are used in practice and their impact on society. This failure to adequately describe and define "automated decision systems" leads to such systems evading scrutiny that policymakers are increasingly recognizing is warranted and potentially impedes avenues for legal redress. Such oversights can have concrete consequences for individuals and communities, such as increased law enforcement harassment, deportation, denial of housing or employment opportunities, and death.

This Article is the first in law review literature to provide two clear and measured definitions of "automated decision systems" for legislative and regulatory purposes and to suggest how these definitions should be applied. The definitions and analytical framework offered in this Article clarify automated decision systems as prominent modes of governance and social control that warrant greater public scrutiny and immediate regulation. The definitions foreground the social implications of these technologies in addition to capturing the multifarious functions these technologies perform as they relate to rights, liberties, public safety, access, and opportunities. To demonstrate the significance and practicality of these definitions I analyze and apply them to two modern use cases: teacher evaluation systems and gang databases. I then explore how policymakers should determine exemptions and evaluate two technologies routinely used in government: email filters and accounting software. This law review provides a much-needed intervention in global public policy discourse and interdisciplinary scholarship regarding the regulation of emergent, data-driven technologies.

* Rashida Richardson is a Visiting Scholar at Rutgers Law School and incoming Assistant Professor of Law and Political Science at Northeastern University. The author appreciates the helpful feedback on early drafts of this Article from Roel Dobbe, Ellen Goodman, Ben Green, Kathryn Kovacs, Varoon Mathur, Kimberly Mutcherson, Jacob Russell, Carl Slater, Jr., Rick Swedloff, Michael Thomas, Jr., and Meredith Whittaker. A special thanks to Theodora Dryer who helped with an earlier draft of this project.

INTRODUCTION

Over the last two decades the increased accessibility of vast amounts of data and advancements in computational techniques and resources have fueled what some call a "technological renaissance" where industry and governments alike seek to use "big data" for a variety of tasks and interests.[1] Yet, recurring public relations failures of these technologies not working as marketed,[2] producing stereotypical or biased outcomes,[3] and leading to unintended and sometimes fatal consequences[4] have forced governments to

1. *Accomplishments and Innovations*, ALLEGHENY CNTY., https://www.alleghenycounty.us/Human-Services/News-Events/Accomplishments-and-Innovations.aspx (last visited Nov. 12, 2021) (describing Allegheny County's adoption of several data-driven technology projects to address social issues).

2. *See generally* JOE FLOOD, THE FIRES: HOW A COMPUTER FORMULA BURNED DOWN NEW YORK CITY—AND DETERMINED THE FUTURE OF AMERICAN CITIES (2010) (detailing the New York City Fire Department's use of an algorithmic system that made recommendations for fire departments to close without increasing response time to fires that ultimately failed and resulted in mass fires that killed and displaced thousands of people).

3. CATRIONA WILKEY ET AL., C4 INNOVATIONS, COORDINATED ENTRY SYSTEMS: RACIAL EQUITY ANALYSIS OF ASSESSMENT DATA 8 (2019) (finding a housing prioritization algorithmic system used in Washington State produced racially biased outcomes); Ziad Obermeyer et al., *Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations*, 366 SCIENCE 447 (2019) (finding evidence of racial bias in a widely used health care algorithm).

4. RASHIDA RICHARDSON ET AL., LITIGATING ALGORITHMS 2019 US REPORT: NEW CHALLENGES TO GOVERNMENT USE OF ALGORITHMIC DECISION SYSTEMS 19–23 (2019). *See*

consider policy interventions to address the variety of challenges presented by the recent explosion in technological adoption. There is growing recognition that the common practice of deploying technologies without concomitant legal mechanisms to detect and mitigate attendant risks and harms can no longer suffice. Yet, policymakers' attempts at developing laws and regulations are often stymied by the difficulty of defining these technologies.[5]

Artificial intelligence ("AI") and automated decision systems ("ADS") have become the most prominent categorical terms used to refer to the suite of "big data" technologies and applications for legal and regulatory purposes. Though "algorithm" is the term commonly used in public discourse to refer to a variety of technologies and applications, this usage is a misnomer because algorithms are computer-implementable methods that are inherent in most technologies and applications, only some of which fit within the AI or ADS categorical label. For example, an algorithm that is not AI or ADS is the solving of a Rubik's Cube.[6]

Some policymakers evade the difficulty of defining these terms by focusing on particularly concerning functions[7] or systems,[8] categories of

---

generally VIRGINIA EUBANKS, AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR (2017).

5. *See, e.g.*, RASHIDA RICHARDSON, JASON M. SCHULTZ & VINCENT M. SOUTHERLAND, CONFRONTING BLACK BOXES: A SHADOW REPORT OF THE NEW YORK CITY AUTOMATED DECISION SYSTEM TASK FORCE (2019) (describing a New York City government task force's failed effort to develop an ADS definition for legislation and regulations); CTR. FOR DATA ETHICS & INNOVATION, REVIEW INTO BIAS IN ALGORITHMIC DECISION-MAKING 67 (2020) (acknowledging that the lack of standards or clear definitions of algorithmic systems makes it difficult to account for the scale of adoption); NEW ZEALAND GOV'T, ALGORITHM CHARTER FOR AOTEAROA NEW ZEALAND (2020) (noting the range of advanced techniques and tools that are referred to as algorithms but failing to provide a definition in its consultation with New Zealand government agencies).

6. Rubik's, *You Can Do the Rubik's Cube: Solution Guide*, https://www.rubiks.com/media/guides/RBL_solve_guide_CUBE_US_5.375x8.375in_AW_27Feb2020_VISUAL.pdf (describing the Rubik's Cube as an algorithm); *see also* Sheila Jasanoff, *Virtual, Visible, and Actionable: Data Assemblages and the Sightlines of Justice*, BIG DATA & SOC'Y, July–Dec. 2017, at 1, 6 ("Though conceptualized in mathematical terms, an algorithm does the same kind of work that a human eye might do in principle, combing and raking through masses of information to discern patterned activities and transactions that would not arouse notice unless sorted and aggregated.").

7. The European General Data Protection Regulation's primary provisions for compliance and enforcement focus on the act of and actors performing processing of personal data. *See* Regulation 2016/679 2016 O.J. (L 119) 1 (EU) [hereinafter General Data Protection Regulation]. Article 22 regulates automated processing of personal data, Article 30 requires companies to produce records of data processing activities to aid compliance monitoring, and Article 32 sets out technical and organizational standards for protecting, storing and processing personal data covered by the regulation. *Id.* art. 22, 30, 32.

8. U.S. DEP'T OF DEF., DIRECTIVE 3000.09, AUTONOMY IN WEAPONS SYSTEMS (Nov. 21, 2012) (establishing U.S. policy on autonomous weapons systems).

risks,[9] or specific effects and outcomes.[10] Other policymakers have relied on technical and mathematical terms or descriptions to define or explain the meaning of AI and ADS in order to avoid inclusion of seemingly mundane or routinely used technologies.[11] While the functionality of such systems are typically communicated in mathematical or technical terms, technical language is informed by and meant for discipline-specific contexts because it enables those who use the language to "say more in a more comprehensible, thorough, and exact way, using less time and fewer words than . . . ordinary English."[12] Thus, when technical language is heedlessly used in statutory or regulatory text, its misapplication can lead to misinterpretations that can frustrate the law's purpose.[13] It can also pose challenges for legal compliance, enforcement, and judicial interpretations due to sector or discipline-related semantic ambiguities.[14]

---

9. *Proposal for a Regulation of the European Parliament and of the Council Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act) and Amending Certain Union Legislative Acts*, COM (2021) 206 final (Apr. 21, 2021) [hereinafter *Proposal*] (proposing a risk-based regulation for the development and use of AI systems); 2022 N.Y.C. Local Law No. 35, N.Y.C. Admin. Code § 3-119.5 (regulating the use of AI in hiring, compensation, and other human resource-related decisions).

10. General Data Protection Regulation, *supra* note 7, at 46 ("The data subject shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her."); 740 ILL. COMP. STAT. 14/15 (2008) (regulating the collection and storage of biometric information).

11. Automated Decision Systems Accountability Act, A.B. 2269, 2019–2020 Reg. Sess. (Cal. 2020) ("'Automated decision system' . . . means a computational process, including one derived from machine learning, statistics, or other data processing or artificial intelligence techniques, that makes a decision or facilitates human decision making, that impacts persons."); Int. No. 1696-A, Law No. 2018/049 (N.Y.C. Council, enacted Jan. 11, 2018) ("The term 'automated decision system' means computerized implementations of algorithms, including those derived from machine learning or other data processing or artificial intelligence techniques, which are used to make or assist in making decisions."); OECD, *Recommendation of the Council on Artificial Intelligence*, OECD/LEGAL/0449, at 7 (2021) ("An AI system is a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments."); SING. DIGIT., MODEL ARTIFICIAL INTELLIGENCE GOVERNANCE FRAMEWORK 18 (2d ed. 2020) ("AI technologies rely on AI algorithms to generate models. The most appropriate model(s) is/are selected and deployed in a production system.").

12. Mary Jane Morrison, *Excursions into the Nature of Legal Language*, 37 CLEV. ST. L. REV. 271, 306 (1989) (describing the development and utility of mathematical and technical language for discipline-specific contexts).

13. Jeanne Frazier Price, *Wagging, Not Barking: Statutory Definitions*, 60 CLEV. ST. L. REV. 999, 1032–33 (2013) (describing the various challenges and consequences that stem from poorly constructed statutory definitions).

14. STEPHEN C. REA, INST. FOR MONEY, TECH. & FIN. INCLUSION, A SURVEY OF FAIR AND RESPONSIBLE MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE: IMPLICATIONS OF CONSUMER FINANCIAL SERVICES 20–25 (2020) (describing semantic gaps with respect to how AI fairness is used in different disciplines and contexts); *see also* Tressie McMillan Cottom, *Where Platform Capitalism and Racial Capitalism Meet: The Sociology of Race and Racism in the Digital Society*, 6 SOCIO. RACE & ETHNICITY 441, 443 (2020) (arguing that reliance on needlessly complex

AI and ADS are socio-technical systems that depend on and must be responsive to the contextual settings in which they function.[15] Yet, the failure to incorporate such reflexivity in legal definitions reinforces the mythology of mathematics and algorithm-based technologies by shrouding these technologies with a veneer of legitimacy because their primary functions are expressed in mathematical or technical terms.[16] For example, in the criminal justice context, whether the constitutional standard of probable cause is met can hinge on the accuracy and reliability of a technology used to determine issues of fact (e.g., the use of facial recognition to determine the identity of a suspect in a crime scene image).[17] Accuracy and reliability are typically represented through mathematical terminology such as "true positive" or "false positive," but these metrics alone lack the context needed to interpret their true implications under situational circumstances and can mislead decisionmakers into assuming that accuracy is a simple binary rather than a spectrum.[18]

---

technical jargon is an obfuscation strategy used by individual and institutional actors to inhibit access to information that could reveal inherent biases in technology).

15. *See* GEOFFREY C. BOWKER & SUSAN LEIGH STAR, SORTING THINGS OUT: CLASSIFICATION AND ITS CONSEQUENCES 24 (1999) ("Algorithms for codification do not resolve the moral questions involved, although they may obscure them."); Scott Decker & Kimberly Kempf-Leonard, *Constructing Gangs: The Social Definition of Youth Activities*, 5 CRIM. JUST. POL'Y REV. 271, 286 (1991) ("Since the definition of problems—both their nature and magnitude—drives policy, a clear definition of 'the problem' is needed before goals can be set, responses formulated, policies implemented and outcomes evaluated. A number of policies are dependent upon such a definition.").

16. Matteo Pasquinelli & Vladan Joler, *The Nooscope Manifested: AI as Instrument of Knowledge Extractivism*, 36 AI & SOC'Y 1263, 1270 (2020) ("Given the degree of myth-making and social bias around its mathematical constructs, AI has indeed inaugurated the age of *statistical science fiction*."); OSCAR H. GANDY, JR., COMING TO TERMS WITH CHANCE: ENGAGING RATIONAL DISCRIMINATION AND CUMULATIVE DISADVANTAGE 7 (2016) (arguing that mathematical formulas and scientific approaches to social problems have achieved a "special, nearly mystical social status" of being accepted without significant inquiry).

17. *See* Michael L. Rich, *Machine Learning, Automated Suspicion Algorithms, and the Fourth Amendment*, 164 U. PA. L. REV. 871, 886–92 (2016).

18. *See, e.g.*, Pete Fussey, Bethan Davies & Martin Innes, *'Assisted' Facial Recognition and the Reinvention of Suspicion and Discretion in Digital Policing*, 61 BRIT. J. CRIMINOLOGY 325, 332–41 (2021) (noting groups of factors that must be evaluated to understand how facial recognition functions in practice); Karen Hao & Jonathan Stray, *Can You Make AI Fairer than a Judge? Play Our Courtroom Algorithm Game*, MIT TECH. REV. (Oct. 17, 2019), https://www.technologyreview.com/2019/10/17/75285/ai-fairer-than-judge-criminal-risk-assessment-algorithm/ (simulating how to understand accuracy and fairness concerns regarding predictive algorithms in judicial decision-making); Aakash Bindal, *Measuring Just Accuracy Is Not Enough in Machine Learning, A Better Technique Is Required..*, MEDIUM (Mar. 24, 2019), https://medium.com/techspace-usict/measuring-just-accuracy-is-not-enough-in-machine-learning-a-better-technique-is-required-e7199ac36856 (describing how only measuring accuracy of a machine learning model may not fully capture or communicate the efficacy and reliability of the model).

Despite their integral role to our understanding of and the success of legislation and regulations,[19] legal definitions remain under-examined by legal and social science scholarship, and legislative drafting manuals pay scant attention to this part of the drafting process, with few manuals offering tactical or substantive guidance. A review of state legislative drafting manuals revealed that most manuals only provide generic advice on drafting or the purpose of definitions, and some were completely silent on definitions.[20] This lack of attention and guidance is significant because the scope, application, and meaning of statutory definitions are a frequent source of federal litigation.[21] When definitions are absent or poorly constructed, statutes and regulations are susceptible to normal evolutions in word meaning and varying interpretations, which can ultimately lead to invalidation.[22]

Nonetheless, legal definitions remain important instruments of governance.[23] By giving meaning to terms as applied to factual circumstances, legal definitions can resolve ambiguity and communicate meaning to various audiences that interact with and relate to statutes and regulations differently (e.g., lawyers, judges, civil servants, corporations, the public).[24] Definitions create constraints for both legal and normative inquiries, designating the relevant contexts or circumstances for applying statutes and regulations and establishing limits of legal liability and coercive outcomes.[25] It is through this authoritative and inherently political function

---

19. AUDREY AMREIN-BEARDSLEY, RETHINKING VALUE-ADDED MODELS IN EDUCATION: CRITICAL PERSPECTIVES ON TESTS AND ASSESSMENT-BASED ACCOUNTABILITY 6 (2014) ("By definition, a public policy is in itself a tool used by governments to define a course of action that will ultimately lead to a high-level, supreme, and desirable end.").

20. Delaware's legislative drafting manual was an exception because it provided substantive and tactical advice on definition drafting in more than one section of the manual. LEGIS. COUNCIL'S DIV. OF RSCH., DELAWARE LEGISLATIVE DRAFTING MANUAL (2019); *see also* Grace E. Hart, *State Legislative Drafting Manuals and Statutory Interpretation*, 126 YALE L.J. 438 (2016) (surveying state legislative drafting manuals to highlight common features and omissions and how these manuals affect statutory interpretation).

21. *See* Price, *supra* note 13, at 1001–02.

22. *Id.* at 1009.

23. Here and throughout this Article, I use the term governance to "suggest that these policies are not selected according to narrow instrumental criteria such as efficiency and cost-effectiveness, but rather according to complex political [and social] goals and considerations . . . ." Katherine Beckett & Bruce Western, *Governing Social Marginality: Welfare, Incarceration, and the Transformation of State Policy*, 3 PUNISHMENT & SOC'Y 43, 55 n.1 (2016).

24. Price, *supra* note 13, at 1031; Yaniv Roznai, *'A Bird Is Known by Its Feathers'—On the Importance and Complexities of Definitions in Legislation*, 2 THEORY & PRAC. LEGIS. 145 (2014).

25. Margaret Burnham, *Was Ahmaud Arbery Lynched and Why Does It Matter?*, CIV. RTS. & RESTORATIVE JUST. (May 9, 2020), https://crrj.org/2020/05/was-ahmaud-arbery-lynched-and-why-does-it-matter/ (highlighting Civil Rights advocates' intentions to create a broad legal definition of lynching so murders in collusion with state actors and police killings were not perfunctorily excluded by apathetic prosecutors).

that legal definitions help provide legal certainty and uniformity because they limit the scope of areas where a law seeks to regulate, where a law's normative provisions have effect, and where interpreters can venture.[26]

Creating legal definitions pertaining to technology is particularly vexed because of the co-constitutive nature of technology and society—they enable and influence as much as they limit and catechize one another.[27] Throughout history, various kinds of technologies have become embedded in the conditions of modern politics and society, often without regard to their attendant consequences.[28] Policymakers and consumers alike narrowly focus on the stated or professed uses and outcomes of a technology, which diverts attention from tacit functions, such as managing power and social dynamics or facilitating exclusionary practices that privilege some over others.[29]

Such parochial conceptions of technology can also influence two problematic tendencies, particularly amongst policymakers. First, policymakers tend to focus on "the retreating horizon of systems still-to-be-created at the risk of passing over autonomous systems already in place."[30] Second, policymakers tend to undervalue or misconstrue demonstrable risks and harms by assuming that flaws are a necessary social cost for innovation, which normalizes problems rather than regulating them.[31]

26. Price, *supra* note 13, at 1019–26; Roznai, *supra* note 24, at 145–46.

27. *See generally* STATES OF KNOWLEDGE: THE CO-PRODUCTION OF SCIENCE AND SOCIAL ORDER (Sheila Jasanoff ed., 2004). *See also* Sandra G. Harding, *Objectivity and Diversity*, *in* ENCYC. OF DIVERSITY IN EDUC. 1625–30 (James A. Banks ed., 2012), https://sk.sagepub.com/reference/diversityineducation/n522.xml.

28. ROBERT A. CARO, THE POWER BROKER: ROBERT MOSES AND THE FALL OF NEW YORK 318 (1975) (alleging Robert Moses designed the Southern State Parkway with low bridges to exclude Black residents that would rely on chartered buses to access Long Island, New York); Jeffrey Dastin, *Amazon Scraps Secret AI Recruiting Tool That Showed Bias Against Women*, REUTERS (Oct. 10, 2018, 7:04 PM), https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G (describing an AI hiring software that downgraded women's resumes); Ben Hutchinson et al., *Unintended Machine Learning Biases as Social Barriers for Persons with Disabilities*, 125 SIGACCESS (SIG Access, New York, NY), Oct. 2019, http://sigaccess.org/newsletter/2019-10/hutchinson.html.

29. ROBERT A. CARO, THE POWER BROKER: ROBERT MOSES AND THE FALL OF NEW YORK 318 (1975) (alleging Robert Moses designed the Southern State Parkway with low bridges to exclude Black residents that would rely on chartered buses to access Long Island, New York); Jeffrey Dastin, *Amazon Scraps Secret AI Recruiting Tool That Showed Bias Against Women*, REUTERS (Oct. 10, 2018, 7:04 PM), https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G (describing an AI hiring software that downgraded women's resumes); Hutchinson et al., *supra* note 28.

30. P.M. Krafft et al., *Defining AI in Policy Versus Practice*, PROC. 2020 AAA/CM CONF. ON AI, ETHICS, & SOC'Y (AIES) 6 (2020), https://arxiv.org/pdf/1912.11095.pdf.

31. *See, e.g.*, Shea Swauger, *Our Bodies Encoded: Algorithmic Test Proctoring in Higher Education*, HYBRID PEDAGOGY (Apr. 2, 2020), https://hybridpedagogy.org/our-bodies-encoded-

AI and ADS are similar to laws in that they both can construct social reality by reflecting and preserving power relations and social conditions.[32] Therefore, legal definitions of AI and ADS that demonstrate awareness of the social and political dimensions of the policymaking process and of the technology itself can serve as an important public policy intervention. "[D]efinition inevitably—sometimes subtly, sometimes radically—changes meaning even as it tries to accurately reflect it."[33] So, modernizing the meanings of AI and ADS for legislation and regulation can "fundamentally change[] the exercise of power and the experience of citizenship."[34]

In this Article, I focus on defining automated decision systems used by government agencies and actors, but the definitions can also apply to private uses and actors. This particular domain is both an active area of public policy development and an area ripe for intervention in light of how modern governance operates. In 2018, the Canadian federal government issued a directive on ADS and implemented an Algorithmic Impact Assessment ("AIA") questionnaire through the Treasury Board of Canada Secretariat, the federal government body that reviews and approves spending by the Government of Canada, including procurement of technologies.[35] This AIA was designed to help government agencies "assess and mitigate the impacts associated with deploying an automated decision system."[36] In the United States, ADS have been the focus of governmental task forces or commissions seeking to evaluate current uses and identify necessary legislative or

algorithmic-test-proctoring-in-higher-education/ (describing the various risks and harms associated with algorithmic test proctoring that remain unregulated and unscrutinized by policymakers and educational officials); United States v. Curry, 965 F.3d 313, 348 (4th Cir. 2020) (Wilkinson, J., dissenting) ("I do not for a moment contend that hot spot policing is free of problems . . . . But by stripping departments of effective public safety programs . . . courts risk inducing police officers to simply abandon inner cities as part of their mission.").

32. Roznai, *supra* note 24, at 164. *See generally* SAFIYA UMOJA NOBLE, ALGORITHMS OF OPPRESSION: HOW SEARCH ENGINES REINFORCE RACISM (2018).

33. Price, *supra* note 13, at 1017.

34. LANGDON WINNER, THE WHALE AND THE REACTOR: A SEARCH FOR LIMITS IN AN AGE OF HIGH TECHNOLOGY 20 (1986); *see also* STUART RUSSELL, HUMAN COMPATIBLE: ARTIFICIAL INTELLIGENCE AND THE PROBLEM OF CONTROL 105 (2019) (describing how human behavior can be subtly changed by modifying the information environment, which can be enabled through the use of AI and ADS).

35. Directive on Automated Decision Making, R.S.C. 1985, c F-11 (Can.).

36. *Algorithmic Impact Assessment*, GOV'T. OF CAN. (Mar. 22, 2021), https://open.canada.ca/aia-eia-js/?; *see also* Michael Karlin & Noel Corriveau, *The Government of Canada's Algorithmic Impact Assessment: Take Two*, MEDIUM: SUPERGOVERNANCE (Aug. 7, 2018), https://medium.com/@supergovernance/the-government-of-canadas-algorithmic-impact-assessment-take-two-8a22a87acf6f.

regulatory reforms,[37] litigation challenging biased and harmful outcomes produced by the use of ADS,[38] and proposed legislation or regulations seeking to provide transparency and accountability regarding current and future ADS use.[39] In Europe, most relevant laws focus on the outcomes of automated processing or high-risk AI rather than ADS specifically,[40] but there have been legal challenges to government use of specific ADS and government commissioned research on ADS policy frameworks.[41] Currently, no countries in the Global South have laws or regulations focused on ADS, but there is a growing body of research and public scrutiny regarding government use of some ADS.[42]

Government use of ADS is also a ripe area for intervention not only because it implicates particular legal interests and concerns, but also because unfettered and unexamined use of ADS can distort perceptions of government operations, thus making deferred reform or regulation difficult and deficient. For example, in 2014, Boston Public Schools attempted to address decades of de facto racial and socioeconomic segregation in public schools by implementing a "home-based assignment" ADS.[43] This ADS was geographically driven and attempted to improve school choice options closer to the student's home address. However, a 2018 evaluation of this ADS project revealed that it failed to achieve most of its goals and the ADS

37. N.Y.C. AUTOMATED DECISION SYS. TASK FORCE, NEW YORK CITY AUTOMATED DECISION SYSTEMS TASK FORCE REPORT 3 (2019); VT. A.I. TASK FORCE, FINAL REPORT 4 (2020) (focusing on public and private use of AI in Vermont but also evaluating ADS generally).

38. RICHARDSON ET AL., *supra* note 4, at 3; AI NOW INST., CTR. ON RACE, INEQ. & L. & ELEC. FRONTIER FOUND., LITIGATING ALGORITHMS: CHALLENGING GOVERNMENT USE OF ALGORITHMIC DECISION SYSTEMS 3 (2018) [hereinafter LITIGATING ALGORITHMS].

39. *See, e.g.*, Algorithmic Accountability Act, H.R. 2231, 116th Cong. (2019); H.B. 1655, 66th Leg., Reg. Sess. (Wash. 2019); Int. No. 1806-A, Law No. 2022/035 (N.Y.C. Council, enacted Jan. 15, 2022); Automated Decision Systems Accountability Act, A.B. 2269, 2019–2020 Reg. Sess. (Cal. 2020).

40. *See* General Data Protection Regulation, *supra* note 7, art. 22; *Proposal*, *supra* note 9, at 21.

41. *See, e.g.*, Rechtbank Den Haag [Court of the Hague] 5 februari 2020, Case No. C-09-550982-HA ZA 18-388, m.nt (NJCM/the Netherlands) (Neth.) (finding that Dutch public authorities use of public benefits fraud detection ADS to be an unlawful violation of the right to privacy); ANSGAR KOENE ET. AL, EUR. PARLIAMENTARY RSCH. SERV., A GOVERNANCE FRAMEWORK FOR ALGORITHMIC ACCOUNTABILITY AND TRANSPARENCY 1 (2019).

42. *See* Vidushi Marda & Shivangi Narayan, *Data in New Delhi's Predictive Policing System*, FAT* '20: PROC. 2020 CONF. ON FAIRNESS, ACCOUNTABILITY, & TRANSPARENCY (2020), https://doi.org/10.1145/3351095.3372865; Subhashish Panigrahi, *#MarginalizedAadhaar: Is India's Aadhaar Enabling More Exclusion in Social Welfare for Marginalized Communities?*, GLOBALVOICES (Feb. 17, 2020, 10:14 GMT), https://globalvoices.org/2020/02/17/marginalizedaadhaar-is-indias-aadhaar-enabling-more-exclusion-in-social-welfare-for-marginalized-communities/.

43. BOS. AREA RSCH. INITIATIVE, AN EVALUATION OF EQUITY IN THE BOSTON PUBLIC SCHOOLS' HOME-BASED ASSIGNMENT POLICY 1 (2018).

actually intensified segregation across the city's public schools.[44] Luckily, in this case, Boston Public Schools commissioned an evaluation of this ADS project that revealed it was a failure, but most current government ADS projects lack meaningful transparency and retrospective evaluations.[45] This means that ADS can be implemented and fail without public awareness or scrutiny, and government officials can leverage this information asymmetry to advance narratives of progress as structural conditions worsen or to avoid necessary reforms.

Decades of research suggests that statistical models, like those commonly employed in ADS, outperform human experts on prognostic and optimization tasks.[46] These findings, along with ADS marketing claims of increased efficiency, cost-savings, and even bias reduction, make their integration into modern governance seem like a logical progression.[47] Modern government decision-making is significantly diffused yet structured, where decisions are delegated and distributed across multiple actors within a hierarchical organizational structure, so ADS should ideally "improve consistency, decrease bias, and lower costs."[48] Yet, this logic is not normatively grounded because it ignores the role of pre-existing social inequities, how discretion and power dynamics operate within this evolved governance structure, and it assumes that technologically mediated decision-making is neutral. Such oversights can conceal inherent tradeoffs associated with ADS use or belie government decision-making and policy implementation,[49] both of which are pertinent to evaluating the value and

44. *Id.* at 68.

45. Maria De-Arteaga et al., *A Case for Humans-in-the-Loop: Decisions in the Presence of Erroneous Algorithmic Scores*, CHI '20: PROC. OF THE 2020 CHI CONF. ON HUM. FACTORS IN COMPUTING SYS. 1–2 (Apr. 21, 2020), E**rror! Hyperlink reference not valid.**https://dl.acm.org/doi/abs/10.1145/3313831.3376638 (noting that technical issues with ADS are common but organizations are rarely transparent about their occurrence); Letter from Ron Wyden, U.S. Senator, et al., to the Honorable Merrick Garland, Att'y Gen., U.S. Dep't of Just. (Apr. 15, 2021) (asking that Department of Justice-funded predictive policing projects be retrospectively reviewed).

46. PAUL E. MEEHL, CLINICAL VERSUS STATISTICAL PREDICTION: A THEORETICAL ANALYSIS AND A REVIEW OF THE EVIDENCE 91–92 (1954); Stefanía Ægisdóttir et al., *The Meta-Analysis of Clinical Judgment Project: Fifty-Six Years of Accumulated Research on Clinical Versus Statistical Prediction*, 34 COUNSELING PSYCH. 341 (2006); Robyn M. Dawes et al., *Clinical Versus Actuarial Judgment*, 243 SCIENCE 1668, 1671 (1989).

47. FRANK PASQUALE, THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION 8 (2015); David Scharfenberg, *Computers Can Solve Your Problem. You May Not Like the Answer.*, BOS. GLOBE (Sept. 21, 2018), https://apps.bostonglobe.com/ideas/graphics/2018/09/equity-machine; FLOOD, *supra* note 2, at 68.

48. Katherine J. Strandburg, *Rulemaking and Inscrutable Automated Decision Tools*, 119 COLUM. L. REV. 1851, 1855–58 (2019) (describing modern government decision-making systems and the incorporation of ADS).

49. EDWARD TENNER, THE EFFICIENCY PARADOX: WHAT BIG DATA CAN'T DO, at xv (2018).

performance of ADS in the government context. Neglecting these concerns also eschews questions related to capitalism, imperialism, and other subjugating phenomena that are aligned with market interests. Thus, creating a normatively grounded and reflexive definition of ADS is the necessary premise for any meaningful legislative or regulatory reform.

In this Article, I offer two nested definitions of ADS—one comprehensive and one narrow—developed through a series of workshops with a group of interdisciplinary scholars and practitioners[50] that can be used in legislation and proposed regulations:

Comprehensive ADS Definition: *"Automated Decision System" is any tool, software, system, process, function, program, method, model, and/or formula designed with or using computation to automate, analyze, aid, augment, and/or replace government decisions, judgments, and/or policy implementation. Automated decision systems impact opportunities, access, liberties, safety, rights, needs, behavior, residence, and/or status by predicting, scoring, analyzing, classifying, demarcating, recommending, allocating, listing, ranking, tracking, mapping, optimizing, imputing, inferring, labeling, identifying, clustering, excluding, simulating, modeling, assessing, merging, processing, aggregating, and/or calculating.*

Narrow ADS Definition: *"Automated Decision Systems" are any systems, software, or processes that use computation to aid or replace government decisions, judgments, and/or policy implementation that impact opportunities, access, liberties, rights, and/or safety. Automated Decision Systems can involve predicting, classifying, optimizing, identifying, and/or recommending.*

Two definitions are warranted because the current ADS policy landscape is oriented around two distinct goals that require different assumptions, approaches, and definitional constraints. One policy goal assumes uncertainty or incompleteness regarding the complexities of the problem and seeks to better understand ADS as currently and prospectively implemented to then inform subsequent reform. This policy goal requires a descriptive definition that aims to expand ordinary meanings or usage of terms by depicting attributes of what is defined, and not to rigidly establish boundaries of the definition.[51] The comprehensive definition meets this goal

50. Workshop participants included: Amba Kak, Ben Green, Erin McElroy, Genevieve Fried, Inioluwa Deborah Raji, Meredith Whittaker, Roel Dobbe, Theodora Dryer, and Varoon Mathur. Together this group covered a range of disciplinary and relevant work experiences, which allowed us to explore various aspects of ADS design, procurement, uses, and outcomes (material and inconsequential). The group's expertise and experience includes, but is not limited to, private sector technology development, public sector technology policy, machine learning, civil and human rights law, and history of technology and computing.

51. Price, *supra* note 13, at 1010–13 (2013).

because it is an intentionally inclusive definition designed for legislation and regulations that are investigatory or diagnostic in purpose. The comprehensive definition can be used in legislation that seeks to create a task force, commission, other quasi-government bodies, or government-commissioned studies that seek to understand ADS use and its implications. The comprehensive definition can also be used in legislation or regulations mandating the enumeration of ADS in use. These types of legislative or regulatory approaches are typically created to inform more prescriptive interventions, which is where the second policy goal and definition take effect.

The second policy goal makes some assumptions regarding the nature of the problem and conditions relevant to governance, and it seeks to assign obligations, invest rights, mitigate risks, and create greater accountability and responsibility regarding the development and use of ADS. This policy goal requires a prescriptive definition that consists of a set of conditions, where compliance with each is necessary to fall within the scope of the definition and therefore the reach of relevant laws.[52] The narrow definition is honed for legislation and regulations that are restrictive in purpose or onerous in practice. This narrow definition can be used in legislation that seeks to ban or limit uses of ADS (generally or in specific sectors) or regulations and laws that mandate stringent requirements for ADS use, such as disclosure or audit requirements.

Prevailing statutory and regulatory ADS definitions fall short in meeting these policy goals because they are neither precise nor clarifying, which leads to two significant problems for ADS legislation or regulations to be successful.[53] First, prevailing definitions infer cultural baselines of expectations and presume knowledge, or at least a shared level of comprehension, amongst various audiences that must interpret the definitions and relevant laws. For instance, definitions that merely adopt mathematical or technical terms like "linear regression" or "neural networks"[54] assume that the public, judges, lawyers, and government actors charged with enforcing,

52. *Id.*

53. *See supra* note 11.

54. *E.g.*, 2022 N.Y.C. Local Law No. 35, N.Y.C. Admin. Code § 3-119.5 ("The term 'automated employment decision tool' means any system whose function is governed by statistical theory, or systems whose parameters are defined by such systems, including inferential methodologies, linear regression, neural networks, decision trees, random forests, and other learning algorithms . . . ."); Directive on Automated Decision Making, *supra* note 35 ("Automated Decision System [i]ncludes any technology that either assists or replaces the judgement of human decision-makers. These systems draw from fields like statistics, linguistics, and computer science, and use techniques such as rules-based systems, regression, predictive analytics, machine learning, deep learning, and neural nets.").

conforming to, and interpreting relevant laws or regulations know what these terms mean or can reasonably ascertain the correct meaning consistently.

Second, prevailing definitions present a time-bound conceptual framing of ADS that is limited to current capabilities and stripped of social, political, and economic forces and contexts. Some definitions suggest that ADS are technologies that merely aid human decision-makers using a range of techniques,[55] but such characterizations often fail to anticipate that current techniques and technical capabilities can and will evolve.[56] The omissions in these definitions also downplay the fact that many of the technical actions or functions performed by ADS are inherently normative or value-laden,[57] and they tend to efface the nature of decisions made using ADS and thus the significance of their impact.[58]

A major task of this Article is to change the meaning of ADS, and therefore the impact of relevant statutes and regulations, by accurately reflecting what ADS are actually doing and their impact in a sector-agnostic manner. This Article proceeds in four parts. Part I further situates the comprehensive and narrow definitions of ADS. It describes the key components of each definition and their relevance for ADS regulation. This Part clarifies why my definitional project creates a new modality of regulation that does not presume knowledge or expertise amongst the various stakeholders and audiences within or affected by the broader ADS policy and regulatory landscape.

Part II explores two examples of ADS currently used by government agencies in the United States: teacher evaluation systems and gang databases. Each use case details the social and political history that engendered the development of these particular ADS and how these technologies are practically implemented. I apply each ADS case study to the narrow definition to demonstrate how these ADS could otherwise evade scrutiny in the absence of the definitions and how the clarity offered through the

55. *See, e.g.*, Directive on Automated Decision Making, *supra* note 35.

56. Yann LeCun, *Deep Learning Hardware: Past, Present, and Future*, 2019 IEEE INT'L SOLID-STATE CIR. CONF. 16 (2019), https://ieeexplore.ieee.org/abstract/document/8662396.

57. *See* Anthony Danna & Oscar H. Gandy, Jr., *All That Glitters Is Not Gold: Digging Beneath the Surface of Data Mining*, 40 J. BUS. ETHICS 373, 378 (2002) (arguing that data mining techniques enable risk and value-based categorization); BOWKER & STAR, *supra* note 15, at 6 ("For any individual, group or situation, classifications and standards give advantage or they give suffering.").

58. *Compare* GANDY, JR., *supra* note 16, at 30 ("Less well known are the ways in which the classification of a person as high risk actually results in their being placed at risk, including the risk of physical harm."), *with* Ben Green & Yiling Chen, *Algorithmic Risk Assessments Can Alter Human Decision-Making Processes in High-Stakes Government Contexts*, PROC. ACM ON HUM.-COMPUT. INTERACTION, Oct. 2021, at 13 (finding risk assessment use alters an actor's decision-making process to focus more on risk. In the bail context this means risk became a stronger determinant in decisions).

definitions is valuable within each sectoral context. This Part is intended to clarify the political and social dimensions of ADS within their sectoral contexts as well as demonstrate how the definitions bring new meaning and urgency to ADS that are often misconstrued as neutral or passive.

Part III evaluates potential exemptions to the ADS definitions. This Part examines three technologies commonly used by government agencies and demonstrates how policymakers should holistically analyze exemptions for ADS legislation and regulations.

The Conclusion fastens analytical threads developed in the preceding Parts to reveal how the definitions and analysis bring new understandings to the problems of ADS. While some ADS appear to be new or novel, the problems and concerns they present are not, and this Article provides policymakers, advocates, and the public with a new framework and insights for addressing them.

I. TWO DEFINITIONS OF AUTOMATED DECISION SYSTEMS

Conventionally, the American legal system has dealt with emergent technologies and their attendant policy concerns under distinct issue spaces that are governed by separate regulatory bodies, legal frameworks, and processes—e.g., privacy, intellectual property, antitrust, consumer protection, security, and telecommunications. Yet, this institutional and jurisdictional configuration becomes less ideal and practically challenging when a technology's design, use, and impact is trans-substantive and implicates more than one of these distinct issue spaces. Government use of ADS occupies this problem space, which is why policymakers are seeking alternative or novel approaches to regulation.

Globally, governments seeking to regulate ADS are interested in using categorical, conceptual, and technology-neutral definitions because they can help clarify the suitability of existing legal rules, broaden the reach of laws beyond present-day sectoral or institutional configurations, and potentially withstand the pace of innovation.[59] Such definitions can also enable greater

---

59. *See, e.g.*, *Consultation on the OPC's Proposals for Ensuring Appropriate Regulation of Artificial Intelligence,* OFF. OF THE PRIV. COMM'R OF CAN. (Jan. 28, 2020), https://www.priv.gc.ca/en/about-the-opc/what-we-do/consultations/completed-consultations/consultation-ai/pos_ai_202001/ (describing interest in privacy laws remaining technologically neutral and soliciting feedback on suitability of current regulatory frameworks); *Commission White Paper on Artificial Intelligence – A European Approach to Excellence and Trust*, COM (2020) 65 final, at 16 (Feb. 19, 2020) ("In any new legal instrument, the definition of AI will need to be sufficiently flexible to accommodate technical progress while being precise enough to provide the necessary legal certainty.").

global cooperation amongst governments with different legal frameworks.[60] Yet, legal scholarship offers little to no aid or clarity in achieving this objective. Legal scholarship on government use of ADS often focuses on specific technologies or sectoral uses,[61] and scholarship that employs categorical terms like ADS tends to avoid definitions, instead providing detailed descriptions or illustrative examples as conceptual guidance that cannot be adopted or used in legislative or regulatory drafting.[62]

Though the challenge of crafting legislative and regulatory definitions for controversial and rapidly evolving technologies is not new, history also offers little guidance on how to do this in a way that meets policymakers' objectives regarding ADS regulation. For instance, in the late 1990s, following the announcement that Scottish scientists successfully cloned a sheep, governmental bodies around the world began to debate the ethics of cloning and the need for regulation that would not stymie genetic research.[63] This led to a patchwork of policies with inconsistent definitions of cloning, globally and throughout the United States.[64] Cloning definitions in legislative proposals in the United States used highly technical language that focused on restricting or permitting specific procedures available at the time.[65] Other countries, like Canada, adopted more expansive and conceptual definitions that could encompass more speculative cloning technologies that may arise in the future.[66] Some argue that the lack of a comprehensive national policy on cloning, including consistent definitions, put the United States behind many other countries, and the lack of global consensus has left

---

60. JOSHUA P. MELTZER ET AL., BROOKINGS INST., THE IMPORTANCE AND OPPORTUNITIES OF TRANSATLANTIC COOPERATION ON AI (2020) (emphasizing the importance of global cooperation on AI regulation that allows governments to maintain legal rules and values).

61. *See, e.g.*, Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 8–10 (2014); Sean Allan Hill, *Bail Reform and the (False) Racial Promise of Algorithmic Risk Assessment*, 68 UCLA L. REV. 910 (2021) (describing the use of pre-trial risk assessments); Ifeoma Ajunwa, *The Paradox of Automation as Anti-Bias Intervention*, 41 CARDOZO L. REV. 1671 (2020) (describing algorithmic hiring systems).

62. *See, e.g.*, Ari Ezra Waldman, *Power, Process, and Automated Decision-Making*, 88 FORDHAM L. REV. 613 (2019) (describing algorithmic decision-making and offering illustrative examples); Strandburg, *supra* note 48, at 1856–57 (comparing automated decision tools to delegated, distributed decision procedures without offering a definition). *But see* Aziz Z. Huq, *Racial Equity in Algorithmic Criminal Justice*, 68 DUKE L.J. 1043, 1060–62 (2019) (offering a succinct definition of algorithmic criminal justice with analysis of each definitional component).

63. Witherspoon Council, *Preface: Cloning Then and Now*, NEW ATLANTIS (2015), https://www.thenewatlantis.com/publications/preface-cloning-then-and-now.

64. Witherspoon Council, *Part Four: Cloning Policy in the United States*, NEW ATLANTIS, (2015), https://www.thenewatlantis.com/publications/preface-cloning-then-and-now [hereinafter *Cloning Policy*]; Shaun D. Pattinson & Timothy Caulfield, *Variations and Voids: The Regulation of Human Cloning Around the World*, BMC MED. ETHICS, Dec. 13, 2004.

65. *See Cloning Policy*, *supra* note 64.

66. *Id.*

many countries in an uncertain regulatory position that offers no clear direction for scientists.[67]

With this context in mind, I led a series of workshops with a group of interdisciplinary scholars to develop two nested definitions of ADS (comprehensive and narrow) that would meet the aforementioned policy goals of governments contemplating ADS regulations in addition to providing clarity to the variety of audiences that must comprehend ADS definitions and corresponding laws. Each definition has four components that are necessary to achieve systematic and normatively grounded evaluations to identify ADS, consistent interpretations of ADS for compliance and enforcement, and a more holistic understanding of ADS use and risks for future policy development. Once explicated, the definitional components demonstrate how these nested definitions can enable new modalities of ADS regulation.

First, the definitions clarify that ADS can exist in many forms, but all rely on computation.[68] This is expressed as "*any tool, software, system, process, function, program, method, model, and/or formula designed with or using computation*" in the comprehensive definition and "*any systems, software, or processes that use computation*" in the narrow definition. ADS rely on a variety of computing architectures that can range from simple regression and decision tree models to complex deep learning models. Thus, the configurations of ADS can vary greatly. This fact is often unappreciated or misconstrued because public perceptions of ADS are distorted by which breakthroughs or controversies receive media attention.[69] If the public only hears about robots, iris scanners, virtual reality headsets, and other breakthroughs that bear little relation to what is commonly used in government or typically happens in most research labs or product development teams, then it is less likely that inconspicuous ADS will be identifiable as a spreadsheet,[70] mathematical formulas, or in paper form, like

67. *See id.*; Pattinson & Caulfield, *supra* note 64; *see also* Preetika Rana, *How a Chinese Scientist Broke the Rules to Create the First Gene-Edited Babies*, WALL ST. J. (May 10, 2019, 12:44 PM), https://www.wsj.com/articles/how-a-chinese-scientist-broke-the-rules-to-create-the-first-gene-edited-babies-11557506697.

68. *See* Peter J. Denning, *What Is Computation?: Opening Statement*, UBIQUITY (Nov. 2010), https://dl.acm.org/doi/pdf/10.1145/1880066.1880067.

69. RUSSELL, *supra* note 34, at 62–65.

70. For example, a 2017 class action lawsuit revealed that a computational formula in an Excel spreadsheet was used to cut Medicaid benefits by twenty or thirty percent for 3,600 individuals with developmental and intellectual disabilities. K.W. v. Armstrong, 180 F. Supp. 3d 703 (D. Idaho 2016). The reduction to health care services via Excel worsened the health conditions of some plaintiffs and was ultimately found to be unconstitutional. *Id.* at 720; Jay Stanley, *Pitfalls of Artificial Intelligence Decisionmaking Highlighted in Idaho ACLU Case*, ACLU: FREE FUTURE

some pretrial risk assessments. Thus, clarifying what to look for can aid ADS identification and ensure mundane or passive-appearing ADS are not overlooked.

Second, the definitions clarify the various ways ADS are used by government agencies. This is expressed as "*to automate, analyze, aid, augment, and/or replace government decisions, judgments, and/or policy implementation*" in the comprehensive definition and "*to aid or replace government decisions, judgments, and/or policy implementation*" in the narrow definition. ADS are increasingly adopted by government agencies to support or replace governance functions traditionally performed by humans, in whole or in part.[71] Yet, the role of ADS and the autonomy of government actors can vary significantly, and both aspects are pertinent to understanding and evaluating ADS performance and impact.[72]

Research on human compliance with ADS recommendations note two competing tendencies that stem from the type of task in which ADS are involved and the level of autonomy government actors retain: algorithmic aversion and automation bias.[73] Algorithmic aversion is the tendency to ignore or override ADS recommendations after seeing that they can be erroneous.[74] This problem typically arises from the lack of autonomy government actors retain and the lack of transparency of the ADS.[75] Conversely, automation bias is the tendency to follow the ADS recommendations despite evidence that would indicate the ADS is faulty. This problem arises when the task is complex or high-stakes and when a

(June 2, 2017, 1:30 PM), https://www.aclu.org/blog/privacy-technology/pitfalls-artificial-intelligence-decisionmaking-highlighted-idaho-aclu-case.

71. *See, e.g.*, DAVID FREEMAN ENGSTROM ET AL., *GOVERNMENT BY ALGORITHM*: ARTIFICIAL INTELLIGENCE IN FEDERAL ADMINISTRATIVE AGENCIES (2020), https://www-cdn.law.stanford.edu/wp-content/uploads/2020/02/ACUS-AI-Report.pdf (highlighting AI usage by federal agencies for decision-making, analysis, adjudication, service delivery and other functions); ALGORITHM WATCH, AUTOMATING SOCIETY 2020 (2020), https://automatingsociety.algorithmwatch.org/wp-content/uploads/2020/12/Automating-Society-Report-2020.pdf (detailing the public sector use of automated decision-making across EU member states).

72. Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 GEO. L.J. 1147, 1164–65 (2017).

73. De-Arteaga et al., *supra* note 45; *see also* René F. Kizilcec, *How Much Information? Effects of Transparency on Trust in an Algorithmic Interface*, CHI '16: PROC. 2016 CHI CONF. ON HUM. FACTORS IN COMPUTING SYS. 2390–95 (May 7, 2016), https://dl.acm.org/doi/10.1145/2858036.2858402 (finding that perceived accuracy of ADS can depend on whether explanations of how the ADS work are easily understood).

74. De-Arteaga et al., *supra* note 45.

75. *See* Philip Alston (Special Rapporteur on Extreme Poverty and Human Rights), *Extreme Poverty and Human Rights*, at 9, U.N. Doc. A/74/493 (Oct. 11, 2019) (describing how significantly error-ridden Canadian ADS led caseworkers to take measures to undermine its outcomes to ensure beneficiaries were treated fairly, but this subterfuge made decisions harder to understand).

government actor's autonomy is affected by their lack of experience with the task, high workloads that necessitate multitasking, or overconfidence in the ADS because of its perceived superiority.[76] Both of these problems degrade ADS-related outcomes, but understanding their origins can also inform policy mechanisms for mitigating ADS risk and concerns.[77] Thus, it is important to understand the exact role ADS have in governance to effectively evaluate their use along with relevant laws and regulations.

Third, the definitions clarify what operational actions or functions ADS perform without relying on technical language. This is expressed as "*predicting, scoring, analyzing, classifying, demarcating, recommending, allocating, listing, ranking, tracking, mapping, optimizing, imputing, inferring, labeling, identifying, clustering, excluding, simulating, modeling, assessing, merging, processing, aggregating, and/or calculating*" in the comprehensive definition and "*[a]utomated [d]ecisions [s]ystems can involve predicting, classifying, optimizing, identifying, and/or recommending*" in the narrow definition. Prevailing ADS definitions often list the mathematical or computational models and techniques that undergird ADS, rather than clarify the operational actions or functions those models enable.[78] Yet, this approach continues a problematic tendency of assuming greater public knowledge and comprehension of the underlying logics of each model and their respective theoretical weaknesses.[79]

Relegating the task of determining an accurate understanding of different models, their inherent weaknesses, and potential consequences when operationalized in a specific government context to various audiences with different technical competencies means that important aspects of ADS design, use, and risks often go unappreciated or are consistently under-evaluated.[80] This is, in part, because various actors (e.g., the public,

76. Kate Goddard, Abdul Roudsari & Jeremy C. Wyatt, *Automation Bias: A Systematic Review of Frequency, Effect Mediators, and Mitigators*, 19 J. AM. MED. INFORMATICS ASS'N 121, 124 (2011).

77. *See, e.g.*, Linda J. Skitka et al., *Automation Bias and Errors: Are Crews Better Than Individuals?*, 10 INT'L J. AVIATION PSYCH. 85 (2000) (finding explicit training about automation bias can guard against the phenomenon); De-Arteaga et al., *supra* note 45 (noting that social accountability mechanisms like high public visibility or ensuring government actors using ADS are publicly elected can guard against these problems).

78. *See supra* note 11.

79. Mathematical formulas and models are theoretical so they will produce errors when used in dynamic, real-world circumstances. Additionally, there are no conventional standards for accuracy, so error thresholds can vary greatly and are partial to developer choices. *See* GANDY, JR., *supra* note 16, at 20–25.

80. *Cf.* Hao-Fei Cheng et al., *Explaining Decision-Making Algorithms through UI: Strategies to Help Non-Expert Stakeholders*, CHI '19: PROC. 2019 CHI CONF. ON HUM. FACTORS IN COMPUTING SYS. (2019), https://dl.acm.org/doi/10.1145/3290605.3300789 (observing that improved understanding of ADS logic did not increase participant's trust in ADS making high-

government agencies, judges) with different technical competencies are responsible for having an accurate understanding of different ADS models, their inherent weaknesses, and their potential consequences in a variety of governmental contexts. For instance, many ADS employ computational models that impose correlational analyses on causal decision-making processes, though there is limited scientific support for this approach.[81] Whereas most individuals can comprehend the potential problems that may arise if an ADS is merely listing information when it should be ranking for example, the different types of errors and misinterpretations that stem from more subtle inappropriate applications may not be evident when technical language is used. Model selection often reflects "the interests, background, and goals of the modelers or their clients" and these choices should be visible to or at least weighted against the goals and interests of the different stakeholders using or affected by ADS—i.e., how much error is socially or politically acceptable and how the impact of such errors are distributed in society.[82] But, this is less likely to happen if most relevant actors do not understand what ADS are doing, so it is the work of definitions to help translate these operational actions and functions.

Finally, the definitions acknowledge and name impact. This is expressed as "*[a]utomated decision systems impact opportunities, access, liberties, safety, rights, needs, behavior, residence, and/or status*" in the comprehensive definition and "*impact opportunities, access, liberties, rights, and/or safety*" in the narrow definition. A primary concern with ADS is that they produce unintended, negative outcomes that reproduce and worsen existing structural inequalities. Yet, these impacts may not be readily apparent or identifiable by those empowered to detect and address them, namely developers of ADS and government actors using ADS or enforcing ADS regulations.[83]

---

stakes decisions). *See also* Rechtbank Den Haag [Court of the Hague] 5 februari 2020, Case No. C-09-550982-HA ZA 18-388, m.nt. (NJCM/the Netherlands) para. 6.49 (Neth.) (finding the Dutch law regulating a fraud detection ADS did not clarify how the decision model functions and thus inhibited the Court's ability "assess the correctness of the position of the State of the precise nature of" the ADS).

81. *Cf.* Sendhil Mullainathan & Jann Spiess, *Machine Learning: An Applied Econometric Approach*, 31 J. ECON. PERSPS. 87 (2017) (describing concerns and problems that arise from applying machine learning naively or to inappropriate tasks); Obermeyer et al., *supra* note 3 (finding a hospital algorithm produced racially biased results by inferring a correlational relationship in data was causal).

82. GANDY, JR., *supra* note 16, at 20–25.

83. Alston, *supra* note 75, at 14–15 (highlighting social welfare ADS that were implemented without ensuring legality).

There are several drivers of this problem, but two related sources are relevant for ADS definitions and regulations.[84] The first is that ADS developers often lack sufficient understanding of the relevant sector where their technology will be used and the problems they seek to address, so they fail to fully appreciate and understand the risks and errors associated with their design choices and fail to anticipate negative outcomes.[85] The second is that government actors seeking to use ADS or enforce relevant ADS regulations often overestimate the ability of ADS to solve complex social problems and fail to assess the full social costs and risks associated with ADS use, whether it is ignoring the role of government practices and policies in contributing to the problem ADS seek to address or developers failing to disclose known risks or vulnerabilities.[86] These problems are related because they both demonstrate how information germane to our understanding of ADS' impacts can be overlooked, withheld, misconstrued, and distorted by

84. *See, e.g.*, RUHA BENJAMIN, RACE AFTER TECHNOLOGY: ABOLITIONIST TOOLS FOR THE NEW JIM CODE (2019) (positing that racial inequities are deepening due to discrimination encoded in and amplified through data-driven technologies); ROBERT N. PROCTOR, VALUE-FREE SCIENCE? PURITY AND POWER IN MODERN KNOWLEDGE (1991) (describing how the construct of scientific neutrality advanced as a resolution of social conflict and to serve certain interests); DOROTHY ROBERTS, FATAL INVENTION: HOW SCIENCE, POLITICS, AND BIG BUSINESS RE-CREATE RACE IN THE TWENTY-FIRST CENTURY (2011) (describing how biologically racist logic persists and promotes racial inequality); TUKUFU ZUBERI & EDUARDO BONILLA-SILVA, WHITE LOGIC, WHITE METHODS: RACISM AND METHODOLOGY (2008) (detailing how white methods and white logic shape the production of racial knowledge).

85. *See generally* Ben Green, *"Good" Isn't Good Enough*, AI FOR SOC. GOOD WORKSHOP at NeurIPS (2019) (describing common oversights and naivete exhibited by computer scientists developing ADS for sensitive social issues); Ben Green, *The False Promise of Risk Assessments: Epistemic Reform and the Limits of Fairness*, FAT* '20: PROC. 2020 CONF. ON FAIRNESS, ACCOUNTABILITY, & TRANSPARENCY (2020) (detailing epistemic flaws and oversights in designing risk assessments); Roel Dobbe, Thomas Krendl Gilbert & Yonatan Mintz, *Hard Choices in Artificial Intelligence*, A.I. (Nov. 2021), https://www.sciencedirect.com/science/article/pii/S0004370221001065 (analyzing normative choices made in the ADS design process that are not appreciated by developers and the public); Darshali A. Vyas, Leo G. Eisenstein & David S. Jones, *Hidden in Plain Sight — Reconsidering the Use of Race Correction in Clinical Algorithms*, 383 NEW ENGLAND J. MED. 874 (2020) (highlighting how clinical algorithms employ race correction mechanisms that may worsen racial health disparities while ignoring outdated and racist rationales for including the correction). *See also* Michael D. Cobb & Jane Macoubrie, *Public Perceptions About Nanotechnology: Risks, Benefits and Trust*, 6 J. NANOPARTICLE RSCH. 395 (2004) (finding low public trust in technology business leaders to protect the public from potential risks of nanotechnology).

86. GANDY, JR., *supra* note 16, at 55–76, 146–61. *See generally* Rashida Richardson, Jason M. Schultz & Kate Crawford, *Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice*, 94 N.Y.U. L. REV. ONLINE 15 (2019) (highlighting how some police departments use predictive policing technologies to address bias while ignoring that their current and historical discriminatory police practices and policies may skew the outcomes produced by the technology); Ajunwa, *supra* note 61 (arguing that bias introduced in the hiring process and employment law's deference to employers are not overcome by the use of algorithmic hiring).

the primary actors expected to identify and mitigate ADS-related problems and harms.[87] Since ADS' impacts may not be self-evident, they must be named as a way to provide guidance and accountability.[88]

II. APPLYING THE DEFINITIONS TO REAL-WORLD USE CASES

This Part analyzes the history and practical implementation of two ADS currently used by government agencies: teacher evaluation systems and gang databases. These use cases were chosen because they represent urgent domains for ADS regulation and emphasize the variegated policy uses of ADS in vulnerable public domains. For each use case, I evaluate the social and political conditions that engendered the development of these particular ADS because this context is crucial to understanding how they aid governance as well as evaluating the risks, benefits, and impact of the ADS on society and relevant government institutions. This analysis is coupled with an examination of the practical realities of ADS implementation to demonstrate how social policy can precede and prefigure ADS design and implementation.[89] I then break down the narrow definition into its key components and demonstrate how each ADS meets this definition and how the definitions can enhance ADS laws and regulations. Since the narrow and comprehensive definitions are concentric, I apply these use cases to the narrow definition because it allows for a compendious review.

A. Teacher Evaluation Systems

1. Background

Teacher evaluation systems[90] are used by school and other government officials to inform or make employment decisions (e.g., rewards, promotions,

87. GANDY, JR., *supra* note 16, at 146–61 (discussing the role of information in technology and social policy formulation and evaluation).

88. While the role of data is a common topic in ADS scholarship, it is not a necessary component for ADS' legislative and regulatory definitions. Legal and normative inquiries regarding the role of data in ADS design, use, and outcomes are warranted and should be performed in a sector- or context-specific manner. This can be established or incentivized in the normative provisions of any proposed ADS legislation or regulation.

89. *See* Steven J. Jackson, Tarleton Gillespie & Sandy Payette, *The Policy Knot: Re-integrating Policy, Practice and Design in CSCW Studies of Social Computing*, PROC. 2017 ACM CONF. ON COMPUT. SUPPORTED COOP. WORK & SOC. COMPUTING (2014) (arguing for more scholarship that interrogates how policy is entangled with ADS design and practice).

90. Here and throughout this Article, I use the term teacher evaluation systems to refer to digitized and automated systems of evaluation that were created in response to federal education policies. Conventional teacher evaluations are conducted by principals or other school administrators and can include classroom observations, reviews of lesson plans and records, and student or parent feedback.

termination, disciplinary actions), to evaluate teacher performance, and to implement local, state, or federal education policies. These systems can exist in many forms, but this Article focuses on teacher evaluation systems that are designed to measure teacher performance or contributions to student learning based, at least in part, on large-scale standardized achievement tests.

Teacher evaluation systems came into prominence in the United States following several seismic shifts in federal education policy. In 1983, the National Commission on Education released *A Nation at Risk*, a United States Department of Education ("DOE")-commissioned report that examined the quality of education in the United States.[91] The report suggested that the United States was losing its competitiveness with other industrialized nations because of poorly performing public schools, and though the report's claims were subsequently proven to be erroneous and exaggerated, it nonetheless changed policymakers' and the public's views on the American public school system and provoked an accountability movement in education.[92] Yet, this move towards greater accountability in public education tended to "impose a uniform grid [e.g., homogenized curricula, large-scale standardized testing, rigorous standards for students, educators, and administrators] on diverse circumstances and parental and student cultures without recognizing that local conditions may demand different strategies in implementing changes."[93]

The No Child Left Behind Act of 2001 ("NCLB") represented a major shift in education policy reform towards increased accountability.[94] NCLB used federal funding to pressure schools to improve student proficiency through annual standardized tests and created harsh penalties for noncompliance. Because NCLB did this without creating a national standard, states had flexibility in the selection of tests, standards, evaluation systems and compliance policies, as long as schools were improving.[95] As a result,

91. NAT'L COMM. ON EXCELLENCE IN EDUC., A NATION AT RISK: THE IMPERATIVE FOR EDUCATIONAL REFORM (1983).

92. DAVID C. BERLINER & BRUCE J. BIDDLE, THE MANUFACTURED CRISIS: MYTHS, FRAUD, AND THE ATTACK ON AMERICA'S PUBLIC SCHOOLS (1995) (critiquing the findings of *A Nation at Risk* as creating a manufactured crisis about the American education system that failed to address the real challenges American educators face); *see also* AMREIN-BEARDSLEY, *supra* note 19, at 9–10 (2014) (describing the *A Nation at Risk* report as an impetus for the education accountability movement).

93. TENNER, *supra* note 49, at 101.

94. No Child Left Behind Act of 2001, Pub. L. No. 107-110, 115 Stat. 1425 (2002).

95. Prior to NCLB, education equity and adequacy were primarily promoted and upheld using the state and federal equal protection claims or state education statutes. Teacher quality was performed using classroom observations and salary and employment decisions followed a fixed salary schedule that rewarded experience and credentials. *See* Washington v. Seattle Sch. Dist. No. 1, 458 U.S. 457 (1981) (holding that a state initiative preventing districts from enforcing mandatory busing violated the Equal Protection Clause because it primarily disadvantaged minority students);

many states tied school funding, closures, and teacher and administrator performance evaluations to student test performance,[96] while data analytics companies began lobbying the federal government to use their automated software systems to measure teacher, school, district, and state performance.[97]

Yet another shift occurred just seven years later. In 2009, DOE created a $4.35 billion competition grant, Race to the Top ("RttT"), to incentivize states to adopt common standards, implement performance-based evaluations for teachers and principals, turn around low performing schools, and employ consequential uses of data systems. RttT represented two major shifts in education policy: (1) it moved away from NCLB's focus of holding students accountable for meeting higher standards to holding teachers and administrators accountable for student achievement;[98] and (2) it diverted government money to private enterprise, rather than investing directly in students, teachers, and local communities.[99] However, RttT did not include

---

Pauley v. Kelly, 255 S.E.2d 859 (W. Va. 1979) (holding that the state's education clause required the legislature to enact a school funding system that was fair and equitable); Mills v. Bd. of Educ., 348 F. Supp. 866 (D.D.C. 1972) (finding that the district's exclusionary practices violated the Equal Protection Clause and ordering a school district to provide equal access to education for students with disabilities); SEAN P. CORCORAN, CAN TEACHERS BE EVALUATED BY THEIR STUDENTS' TEST SCORES? SHOULD THEY BE? THE USE OF VALUE-ADDED MEASURES OF TEACHER EFFECTIVENESS IN POLICY AND PRACTICE 1–2 (2010) (describing teacher quality assessments before NCLB).

96. Helen F. Ladd, *No Child Left Behind: A Deeply Flawed Federal Policy*, 36 J. POL'Y ANALYSIS & MGMT. 461, 464 (2017) (finding NCLB's use of "top-down accountability pressure" was a more punitive than constructive approach to education reform); Derek Neal & Diane Whitmore Schanzenbach, *Left Behind by Design: Proficiency Counts and Test-Based Accountability*, 92 REV. ECON. & STAT. 263 (2010) (concluding that stringent proficiency policies led teachers to shift more attention to students near current proficiency standards).

97. *See, e.g.*, *Issues Lobbied by SAS Institute, 2002*, OPENSECRETS, https://www.opensecrets.org/federal-lobbying/clients/issues?cycle=2002&id=D000037384&spec=EDU&specific_issue=Education#specific_issue (last visited Feb. 13, 2022) ("Discussed implementation and administration of accountability and Adequate Yearly Progress as it relates to the No Child Left Behind Act of 2001, Public Law 107-110, to close the achievement gap with accountability, flexibility, and choice.").

98. AMREIN-BEARDSLEY, *supra* note 19, at 19; Bruce D. Baker, Joseph O. Oluwole & Preston C. Green, *The Legal Consequences of Mandating High Stakes Decisions Based on Low Quality Information: Teacher Evaluation in the Race-to-the-Top Era*, EDUC. POL'Y ANALYSIS ARCHIVES, (Jan. 28, 2013), https://epaa.asu.edu/ojs/index.php/epaa/article/view/1298/1043 (summarizing various state laws that require use of student performance data for teacher evaluations).

99. Diane Ravitch, *Education Law Center: States with Most Unequal Funding Won RTTT Grants*, DIANE RAVITCH'S BLOG (Apr. 10, 2014), https://dianeravitch.net/2014/04/10/education-law-center-states-with-most-unequal-funding-won-rttt-grants/ (describing research that found states that won largest share of RttT grants had the least fair and equitable state school finance systems); Mike Simpson, *Latest Race to the Top Grants Go To States at Bottom on School Funding Equity*, BIG EDUC. APE BLOG (Dec. 18, 2012, 11:04 AM), http://bigeducationape.blogspot.com/2013/01/education-justice-december-18-2012.html (finding

explicit guidance on how to implement its policy principles, so many states turned to evaluation systems that linked teacher performance to their students' test scores, resulting in forty states and the District of Columbia using, piloting, or developing such systems by 2014.[100] Despite the enactment of the Every Student Succeeds Act ("ESSA") in 2015, which reduced federal incentives and enforcement of test-based teacher accountability, state and school district reliance on teacher evaluation systems persists due to the preceding decade of financial and public policy investment to develop or acquire such systems.[101]

2. Teacher Evaluation Systems in Practice

The most common teacher evaluation system is the Value-Added Model ("VAM"),[102] and the most common proprietary version of this model is the Education Value-Added Assessment Systems ("EVAAS").[103] VAMs are multivariate statistical tools that attempt to measure and classify the purported effect of an individual teacher on student performance on large-scale standardized achievement tests in certain subject areas over time. VAMs measure a group of students' academic progress using either a predictive model that predicts the average student gains expected and then compares with the actual average gains, or a comparative model that uses a prior or pre-test score to represent student proficiency when they enter the

---

the "RTTT grant process ignores the key precondition for sustaining any meaningful education reform – a fair and equitable state school finance system").

100. Clarin Collins & Audrey Amrein-Beardsley, *Putting Growth and Value-Added Models on the Map: A National Overview*, TCHRS. COLL. REC. (2014), https://www.tcrecord.org/Content.asp?ContentId=17291; KEVIN CLOSE, AUDREY AMREIN-BEARDSLEY & CLARIN COLLINS, NAT'L EDUC. POL'Y CTR., STATE-LEVEL ASSESSMENTS AND TEACHER EVALUATION SYSTEMS AFTER THE PASSAGE OF THE EVERY STUDENT SUCCEEDS ACT: SOME STEPS IN THE RIGHT DIRECTION 8 (2018); Mark A. Paige, Audrey Amrein-Beardsley & Kevin Close, *Tennessee's National Impact on Teacher Evaluation Law & Policy: An Assessment of Value-Added Model Litigation*, 13 TENN. J.L. & POL'Y 523, 534–35 (2019).

101. Kevin Close, Audrey Amrein-Beardsley & Clarin Collins, *Putting Teacher Evaluation Systems on the Map: An Overview of States' Teacher Evaluation Systems Post–Every Student Succeeds Act*, EDUC. POL'Y ANALYSIS ARCHIVES (Apr. 13, 2020), https://epaa.asu.edu/ojs/index.php/epaa/article/view/5252/2423.

102. Student Growth Percentiles ("SGPs") are another common teacher evaluation system. Unlike VAM models, SGPs do not use statistical controls or attribute responsibility for student performance to the teacher or school. SGPs measure the relative change in a student's performance as compared to similarly situated students. Audrey Amrein-Beardsley, *VAMs v. Student Growth Percentiles (SGPs) — Part II*, VAMBOOZLED! (Dec. 3, 2013), http://vamboozled.com/vams-v-student-growth-percentiles-sgps-part-ii/; Bruce D. Baker, *Firing Teachers Based on Bad (VAM) Versus Wrong (SGP) Measures of Effectiveness: Legal Note*, SCH. FIN. 101 BLOG (Mar. 31, 2012), https://schoolfinance101.wordpress.com/2012/03/31/firing-teachers-based-on-bad-vam-versus-wrong-sgp-measures-of-effectiveness-legal-note/.

103. Close et al., *supra* note 101, at 6.

teacher's classroom and then compares with subsequent test scores.[104] Most models control for at least one year of student prior test scores and some models[105] control for external variables (e.g., student background and classroom or school characteristics),[106] but the outcomes of these calculations are used to make inferences about the teacher's effectiveness or impact on student learning and progress.[107] If there is a positive difference (typically one standard deviation above zero), then the teacher is considered effective or having added value to student achievement, and if there is a negative difference (typically below one standard deviation below zero), then the teacher is considered ineffective.[108] The calculations and inferences are then used to make relativistic comparisons of all teachers in a school or school district to create a continuum of high to low value-added classifications.[109]

These outcomes are used to implement teacher accountability policy and thus inform high-stakes employment decisions including but not limited to teacher tenure, compensation, merit pay, disciplinary action, termination, and professional development.[110] Reliance on VAM outcomes for such consequential decisions was incentivized by federal and state policy requirements.[111] For example, Florida "amended [its] teacher evaluation statutes to ensure that VAMs played a controlling role in teacher employment status, including tenure decisions."[112] Additionally, due to automation bias,

104. AMREIN-BEARDSLEY, *supra* note 19, at 21–23.

105. EVAAS is "the only large-scale VAM that intentionally excludes statistical controls for student risk variables." *Id.* at 58. Student risk variables can include student background variables like race, socioeconomic status, levels of English language proficiency, and special education status. *Id.*

106. Kimberly Kappler Hewitt, *Educator Evaluation Policy that Incorporates EVAAS Value-Added Measures: Undermined Intentions and Exacerbated Inequities*, 23 EDUC. POL'Y ANALYSIS ARCHIVES 21–23 (Aug. 10, 2015), https://epaa.asu.edu/ojs/index.php/epaa/article/view/1968/1642 (describing how various external variables affect or bias value-added calculations).

107. AMREIN-BEARDSLEY, *supra* note 19, at 21–23.

108. *Id.*

109. *Id.*

110. Baker et al., *supra* note 98, at 304; Stephanie Banchero & David Kesmodel, *Teachers Are Put to the Test: More States Tie Tenure, Bonuses to New Formulas for Measuring Test Scores*, WALL ST. J. (Sept. 13, 2011), https://www.wsj.com/articles/SB10001424053111903895904576544523666669018; Close et al., *supra* note 101, at 6.

111. Arne Duncan, U.S. Sec'y Educ., Remarks at The Race to the Top Program Announcement: The Race to the Top Begins (July 24, 2009) (on file with Dep't of Educ.) ("We have $200 million in Recovery Act funding for the Teacher Incentive Fund, which supports performance-based teacher and principal compensation systems in high-need schools."); Baker et al., *supra* note 98; Close et al., *supra* note 101, at 5–6 (describing how the federal government required states to adopt rigid accountability practices for teacher evaluations and employment matters to secure waivers from NCLB non-compliance penalties).

112. Paige et al., *supra* note 100, at 528 (citing FLA. STAT. ANN. § 1012.22(1)(c)(5) (West 2013)) (connecting teacher salary to an evaluation system that requires use of VAMs).

VAM outcomes can have undue influence on school administrators' decision-making and there is evidence that school administrators have altered other teacher evaluation indicators to match VAM outcomes or justify controversial decisions.[113]

Despite the prevalence of VAMs, their use, especially for consequential decisions, is heavily criticized and the subject of at least fifteen lawsuits across seven states.[114] VAMs are criticized for being unreliable, invalid, biased, unfair, and opaque, and for producing perverse outcomes. VAMs are criticized as unreliable because they have large error ranges that vary from year to year such that "teachers classified as 'effective' one year will have a 25%–59% chance of being classified as 'ineffective' the next year, or vice versa."[115] Since VAM outcomes are inconsistent and unreliable, they are also considered invalid because they cannot support accurate interpretations of and inferences about teachers' causal effects on student achievement, and there is limited research to support claims of VAM validity.[116] VAMs are considered biased because there are several variables and characteristics of the educational environment that are unpredictable, unobservable, or beyond the control of a teacher or school, and therefore cannot be controlled in a way that mitigates biased outcomes, even with the most sophisticated statistical methods.[117] Additionally, bias may not present in obvious patterns across a dataset, so for many VAMs it remains unclear if the models are measuring a teacher's effect on student achievement or the effect of something else on student achievement.[118] VAMs are considered unfair[119] for several reasons but a chief criticism is that VAM-based estimates, particularly EVAAS, can

113. AMREIN-BEARDSLEY, *supra* note 19, at 45; CORCORAN, *supra* note 95, at 8.

114. Close et al., *supra* note 101, at 7; Stephen Sawchuk, *Teacher Evaluation Heads to the Courts*, EDUC. WEEK (Oct. 8, 2015), https://www.edweek.org/ew/section/multimedia/teacher-evaluation-heads-to-the-courts.html.

115. Close et al., *supra* note 101, at 7; *see also* AMREIN-BEARDSLEY, *supra* note 19, at 33–35.

116. *See* AMREIN-BEARDSLEY, *supra* note 19, at 35–37; Kappler Hewitt, *supra* note 106; *see also* Lederman v. King, 47 N.Y.S.3d 838, 846 (N.Y. Sup. Ct. 2016) (finding government reliance on VAM for teacher evaluations was arbitrary and irrational thus supporting claims of VAM invalidity).

117. Such variables or characteristics can include but are not limited to students' home lives and family situations, modifications, disruptions, non-random student classroom assignments, and missing data. *See, e.g.*, AMREIN-BEARDSLEY, *supra* note 19, at 38–41; Jesse Rothstein, *Student Sorting and Bias in Value-Added Estimation: Selection on Observables and Unobservables*, 4 EDUC. FIN. & POL'Y 537, 565 (2009); Kappler Hewitt, *supra* note 106.

118. Baker et al., *supra* note 98, at 16.

119. *See, e.g.*, Cook v. Bennett, 792 F.3d 1294, 1301 (11th Cir. 2015) ("Without a doubt, the evaluation scheme has led to some unfair results . . . ."); Cook v. Stewart, 28 F. Supp. 3d 1207, 1215 (N.D. Fla. 2014) ("The unfairness of the evaluation system as implemented is not lost on this Court. We have a teacher evaluation system in Florida that is supposed to measure the individual effectiveness of each teacher. But as the Plaintiffs have shown, the standards for evaluation differ significantly.")

only be produced for approximately 30–40% of all public school teachers who teach core subject areas tested[120] using large-scale standardized tests.[121] VAMs are not transparent because VAM outcomes are often not understood or useful for formative purposes to those receiving the results,[122] and vendors of proprietary VAMs are resistant to inspection.[123] Finally, use of VAMs, especially for consequential decisions, can lead to perverse outcomes like teaching to the test, teacher retention issues, or avoiding high-need students and schools.[124]

3. Applying Teacher Evaluations Systems to the Narrow Definition

Despite critical scholarship and litigation challenging their use and formative value, teacher evaluation systems continue to play an important role in education decision-making and policy implementation.[125] This is because their use, negative impacts, and overall qualitative and quantitative futility[126] remain invisible to and misunderstood by federal education policymakers and the public.[127] Because the definitions help bring clarity

120. Collins & Amrein-Beardsley, *supra* note 100 ("100% of the states currently calculating (or with plans to calculate) these data are using (or are planning to use) their large-scale, state-level, standardized test score data, predominantly collected in grades 4–8 in the core subject areas of mathematics and English/language arts.").

121. AMREIN-BEARDSLEY, *supra* note 19, at 41–42; Preston C. Green, Bruce D. Baker & Joseph Oluwole, *The Legal and Policy Implication of Value-Added Teacher Assessment Policies*, 2012 BYU EDUC. & L.J. 1, 14–15 (2012).

122. AMREIN-BEARDSLEY, *supra* note 19, at 42–44; Rachael Gabriel & Jessica Nina Lester, *Sentinels Guarding the Grail: Value-Added Measurement and the Quest for Education Reform*, EDUC. POL'Y ANALYSIS ARCHIVES (Jan. 31, 2013), https://epaa.asu.edu/ojs/index.php/epaa/article/view/1165/1045.

123. LITIGATING ALGORITHMS, *supra* note 38, at 10 ("When [Houston Federation of Teachers] members asked to examine the systems, they were denied with the explanation that the algorithms and code that comprised these systems were the private property of a third-party vendor."); Hous. Fed'n Tchrs., Loc. 2415 v. Hous. Indep. Sch. Dist., 251 F. Supp. 3d 1168 (S.D. Tex. 2017) (denying school district's motion for summary judgment on procedural due process claims, while leaving trade secrets claims intact).

124. Susan Moore Johnson, *Will VAMS Reinforce the Walls of the Egg-Crate School?*, 44 EDUC. RESEARCHER 117, 120–22 (2015); Kappler Hewitt, *supra* note 106, at 24–29; Close et al., *supra* note 101, at 5.

125. Close et al., *supra* note 101, at 20.

126. Qualitative and quantitative futility are terms used in the medical field to categorize treatments or procedures that have an unreasonably low percentage chance of achieving a desired goal (quantitative futility) or where the quality of benefit a particular intervention will produce is exceedingly poor (qualitative futility). Here, I extend these terms to teacher evaluation systems and ADS more generally to demonstrate their shared deficiencies in achieving desired goals or outcomes.

127. *Cf.* Close et al., *supra* note 101 (describing how practitioners and state education officials are shifting away from quantitative test score teacher evaluation systems towards research-based conceptual frameworks with greater local control).

and visibility to the actions performed by teacher evaluation systems, their integral role in governance, and their impacts, the definitions can instigate greater scrutiny regarding their use and urgency for reform. This Section demonstrates how teacher evaluation systems meet our narrow definition, and how policymakers within the education sector should evaluate each component of the definition.

(a) "Any systems, software, or processes that use computation"

In the United States, some states or school districts developed and implemented their own teacher evaluation system. Some are computed using publicly available software,[128] while others turn to one of the eight third-party proprietary software systems.[129]

Most VAMs use regression analysis to compute the value added at the teacher and school level.[130] Other teacher evaluation systems, like Student Growth Percentiles, apply similar statistical models to compute performance metrics and evaluate teachers.[131]

(b) "to aid or replace government decisions, judgments, and/or policy implementation"

Teacher evaluation systems are used to measure teacher effectiveness, implement state or federal education policy, and make employment-related decisions.[132] Most teacher evaluation systems are a byproduct of federal education policy that incentivized their use and state education laws, which in most cases prescribe how teacher evaluation systems should be used or accounted for in decision-making. School and other government officials

128. *See, e.g.*, Elias Walsh & Eric Isenberg, *How Does a Value-Added Model Compare to the Colorado Growth Model?* 2 (Mathematica Pol'y Rsch., Working Paper No. 22, 2013) ("Policymakers may also prefer the [Colorado Growth Model] because student growth percentiles can be computed with publicly available software that does not require extensive customization for use by a state or district.").

129. *See* Close et al., *supra* note 101, at 6 ("The most common proprietary model was the Education Value-Added Assessment System, with five states adopting it statewide (i.e., North Carolina, Ohio, Pennsylvania, South Carolina, and Tennessee)" (citations omitted)); Banchero & Kesmodel, *supra* note 110 ("Rob Meyer, the bowtie-wearing economist who runs the Value-Added Research Center, known as VARC . . . calls his statistical model a 'well-crafted recipe.' VARC is one of at least eight entities developing such models.")

130. AMREIN-BEARDSLEY, *supra* note 19, at 22; Banchero & Kesmodel, *supra* note 110.

131. *Colorado Growth Model FAQs (General)*, COLO. DEP'T OF EDUC., https://www.cde.state.co.us/schoolview/generalgrowthmodelfaq#q22 (last updated Dec. 14, 2016) ("The Colorado Growth Model is a statistical model to calculate each student's progress on state assessments."); *The Use of Multiple Years of Data to Calculate Median Student Growth Percentiles*, N.J. DEP'T OF EDUC. (Sept. 2019), https://www.state.nj.us/education/AchieveNJ/teacher/MultiyearSGPOverview.pdf.

132. *See supra* Section II.A.1.

then use the teacher evaluation system outcomes to aid employment-related decisions for teachers. Some state education laws mandate that teacher evaluation system outcomes are a sole or significant factor in making employment-related decisions for teachers,[133] some state laws dictate what types of decisions teacher evaluation system results can be used,[134] and some states or jurisdictions lack specific statutory stipulations but there is evidence[135] that teacher evaluation systems aided high stakes decisions.[136]

(c) "that impact opportunities, access, liberties, rights, and/or safety"

Teacher evaluation systems impact teachers' opportunities, rights, and liberties. Teachers' access to employment opportunities is impacted because teacher evaluation system results are used to make employment decisions like tenure and reassignment. The results of teacher evaluation systems remain on teachers' permanent professional files, which can prevent or inhibit a teacher's ability to change jobs within a state, or result in designations that hinder job mobility and options.[137] Reliance on teacher evaluation systems for such high-stakes employment decisions also affects student opportunities because their use can lead to perverse outcomes like teachers avoiding high-need students, classrooms, and schools that are more likely to hinder positive evaluation results or principals "'stacking' classes to make sure certain

133. *See, e.g.*, LA. STAT. ANN. § 17:442 (2018); S.B. 10-191, Gen. Assemb., Reg. Sess. (Colo. 2010).

134. In 2008, New York passed a law that prohibited school districts from tying teacher tenure decisions to student test scores, which includes the use of teacher evaluation systems. Since guidelines for RttT funding penalized such laws and New York State lost its first bid for the federal grant program, the New York State Department of Education and the teachers' unions subsequently entered an agreement that linked 40% of a teacher's performance evaluation to student performance measures. Early research following this agreement found that principals changed their evaluations of teachers in response to negative VAM results, and a higher fraction of teachers receiving low VAM results were denied tenure following this policy change. CORCORAN, *supra* note 95, at 6–9.

135. Thomas Dee & James Wyckoff, *Incentives, Selection, and Teacher Performance: Evidence from IMPACT* (Nat'l Bureau of Econ. Res., Working Paper No. 19529, 2013) (finding evidence that teacher evaluation, including VAM results, were used in teacher dismissal decisions and VAM data accounted for 50% of teacher evaluations despite no statutory stipulations).

136. Baker et al., *supra* note 98; Close et al., *supra* note 101, at 11; Collins & Amrein-Beardsley, *supra* note 100, at 1–2.

137. Paige et al., *supra* note 100, at 533; MARK A. PAIGE, BUILDING A BETTER TEACHER: UNDERSTANDING VALUE-ADDED MODELS IN THE LAW OF TEACHER EVALUATION 15, 16 (2016) (warning against use of teacher evaluation systems for high-stakes decisions); Marcus A. Winters, *The Fight over Flunked-Out Teachers*, CITY J., Winter 2018, https://www.city-journal.org/html/fight-over-flunked-out-teachers-15661.html (describing the negative consequences of being included on the Absent Teacher Reserve list used in New York City, and where 12% of the list is comprised of teachers with ineffective performance ratings).

teachers can demonstrate value added or growth or vice versa."[138] These types of perverse outcomes significantly impact the type of education students receive, their overall educational trajectory, and life chances.

Teacher evaluation systems impact teachers' rights and liberties because overreliance on such systems implicates teachers' due process rights[139] and engenders arbitrary decision-making that impedes a teacher's access to certain rights, benefits, or privileges, such as salary increases and merit pay.[140] Reliance on flawed teacher evaluation systems can also produce racially biased outcomes in teacher employment decisions because these systems can "classify teachers of certain races as failing not because of their actual effectiveness but because of the students they were more likely to have served."[141] Even though fewer than one in ten teachers in U.S. public schools are non-white, these teachers tend to work in lower-resourced, high-need schools,[142] where teacher evaluation systems are less precise because the students in these environments have "'harder-to-predict' achievement."[143] In these circumstances, non-white teachers are systemically disadvantaged and it is possible that their civil rights are violated, particularly under Title VII of the Civil Rights Act of 1964.[144]

---

138. AMREIN-BEARDSLEY, *supra* note 19, at 24; *see also* Kappler Hewitt, *supra* note 106, at 24–29 (describing negative consequence produced by reliance on teacher evaluation systems as predicted and observed by educators).

139. Hous. Fed'n of Tchrs., Loc. 2415 v. Hous. Indep. Sch. Dist., 251 F. Supp. 3d 1168, 1180 (S.D. Tex. 2017) (finding violation of plaintiff's procedural due process rights); Leff v. Clark Cnty. Sch. Dist., 210 F. Supp. 3d 1242,1246–47 (D. Nev. 2016) (finding that a change to the state laws governing teaching evaluation and contract status that removed procedural protections and required use of VAMs did not violate the Constitution's Contract Clause); Baker et al., *supra* note 98, at 10 ("[T]here exists significant possibility that where arbitrary distinctions that cannot be made, are made, that the policies in question violate the due process rights of teachers.").

140. Banchero & Kesmodel, *supra* note 110; NAT'L CTR. FOR EDUC. EVALUATION & REG'L ASSISTANCE, STATE REQUIREMENTS FOR TEACHER EVALUATION POLICIES PROMOTED BY RACE TO THE TOP (2014) (describing how teacher evaluation systems are used for decision-making, including performance-based compensation); CORCORAN, *supra* note 95, at 12–13.

141. Baker et al., *supra* note 98, at 16.

142. Katherine Schaeffer, *America's Public School Teachers Are Far Less Racially and Ethnically Diverse than Their Students*, PEW RSCH. CTR. (Dec. 10, 2021), https://www.pewresearch.org/fact-tank/2021/12/10/americas-public-school-teachers-are-far-less-racially-and-ethnically-diverse-than-their-students/ (describing data on the low racial and ethnic diversity amongst U.S. public school teachers and how teachers of different races work in different school environments).

143. AMREIN-BEARDSLEY, *supra* note 19, at 168; *see also* Mariesa Herrmann et al., *Shrinkage of Value-Added Estimates and Characteristics of Student with Hard-to-Predict Achievement Levels* (Mathematica Pol'y Rsch. Working Paper No. 17, 2013) (finding the achievement of particular groups of students—students with low prior achievement and who receive free lunch—are harder to predict using VAM teacher evaluation systems)

144. Civil Rights Act of 1964, Pub. L. No. 88-352, Tit. VII, 78 Stat. 241 (codified as amended at 42 U.S.C. §§ 2000e–2000e-17); *see also* Hazelwood Sch. Dist. v. United States, 433 U.S. 299

(d) "Automated [d]ecision [s]ystems can involve predicting, classifying, optimizing, identifying, and/or recommending"

Teacher evaluation systems involve inferences and classification. Systems like VAMs make inferences about a teacher's impact on student achievement by measuring student performance on large-scale standardized tests. These inferences are then adjusted and aggregated on a continuum to classify all teachers within a school or district according to the teacher performance categories (e.g., "effective" or "ineffective") when stipulated by state law.[145]

B. Gang Databases

1. Background

Gang databases are centralized and decentralized information systems primarily used by criminal justice actors and institutions to compile, analyze, and disseminate information about gangs and alleged gang members for a variety of interests and priorities. They have become more common for national, regional, and local use in recent decades and hold a global presence,[146] but their development and use are determined by jurisdictional laws, politics, and culture, so this Article focuses on digitized gang databases in the United States.

Following two Great Migrations of Black communities escaping the racial terrorism of Jim Crow in southern states and Puerto Ricans seeking economic opportunities, concern about street gangs became a common feature in increasingly segregated cities during the 1940s and 1950s, where groups of young men would engage in turf wars over neighboring ethnic enclaves.[147] In response to rising rates of violent crime in major cities like New York and Los Angeles associated with growing economic inequality in

(1977) (holding Title VII prohibits racial discrimination and that statistical evidence can be used to find a prima facie case of race discrimination).

145. *See* AMREIN-BEARDSLEY, *supra* note 19, at 20–25; Baker et al., *supra* note 98.

146. *See, e.g.*, Ali Winston, *You May Be in California's Gang Database and Not Even Know It*, REVEAL NEWS (Mar. 23, 2016), https://www.revealnews.org/article/you-may-be-in-californias-gang-database-and-not-even-know-it/ (noting that Canada used GangNet, a web-based gang database modeled after CalGang and created by SRA International, Inc); James A. Densely & David C. Pyrooz, *The Matrix in Context: Taking Stock of Police Gang Databases in London and Beyond*, 20 YOUTH JUST. 11, 11–12 (2020) (describing London's Gang Matrix gang databases used by the London Metropolitan Police Services); Betsy Powell, *It Works like Gangbusters*, TORONTO STAR (Sept. 27, 2005), https://www.pressreader.com/canada/toronto-star/20050927/281573761084978 (describing the use of GangNet in Canada).

147. RICHARD C. MCCORKLE & TERANCE D. MIETHE, PANIC: THE SOCIAL CONSTRUCTION OF THE STREET GANG PROBLEM 45–47 (2002).

the late 1950s and 1960s,[148] municipalities created anti-gang units within local police departments.[149] In the mid-1970s, amid deindustrialization[150] and a sharp increase in high school expulsion rates and homicides, particularly amongst young Black and Latinx men, the federal government declared gang violence and suppression a new focal point[151] for federal law enforcement.[152] This new focus also helped fortify the Republican Party's embrace of "tough on crime" rhetoric and policies.[153] Though some local police departments were already engaged in gang suppression efforts, more police departments adopted this federal priority as a result of the Ford Administration's deep commitment to and practice of New Federalism,[154] where federal block grants are used to induce state adoption of federal

148. *Id.*; JUDITH GREENE & KEVIN PRANIS, JUST. POL'Y INST., GANG WARS: THE FAILURE OF ENFORCEMENT TACTIC AND THE NEED FOR EFFECTIVE SAFETY STRATEGIES 13–29 (2007), https://justicepolicy.org/wp-content/uploads/justicepolicy/documents/07-07_rep_gangwars_gc-ps-ac-jj.pdf; MICHAEL K. BROWN ET AL., WHITEWASHING RACE: THE MYTH OF A COLOR-BLIND SOCIETY 154 (2003) (citing Richard Fowels & Mary Merva, *Wage Inequality and Criminal Activity: An Extreme Bounds Analysis for the United States, 1975–1990*, 34 CRIMINOLOGY 163 (1996)) (describing research that demonstrated that rising crime rates were associated with rising economic inequality which confirmed strain theories that suggested crime was most likely to grow from relational socioeconomic inequality).

149. MCCORKLE & MIETHE, *supra* note 147, at 48–50.

150. Deindustrialization is the term used to describe the process and conditions of social and economic change caused by the decline or removal of industrial activity, particularly manufacturing, in a country or region. In the United States, deindustrialization conditions include economic volatility, high and chronic unemployment rates, foreign competition, and suburbanization. *See* WILLIAM JULIUS WILSON, WHEN WORK DISAPPEARS: THE WORLD OF THE NEW URBAN POOR (1996); IRA KATZNELSON, CITY TRENCHES: URBAN POLITICS AND THE PATTERNING OF CLASS IN THE UNITED STATES (1981); JAMES HOWARD KUNSTLER, THE GEOGRAPHY OF NOWHERE: THE RISE AND DECLINE OF AMERICA'S MAN-MADE LANDSCAPE (1993); THOMAS J. SUGRUE, THE ORIGINS OF THE URBAN CRISIS: RACE AND INEQUALITY IN POSTWAR DETROIT (1996).

151. Before this shift in federal law enforcement priorities, federal agency intelligence efforts focused on "political radicals and suspected terrorists." James B. Jacobs, *Gang Databases: Context and Questions*, 8 CRIMINOLOGY & PUB. POL'Y 705, 706 (2009). "Legal challenges to some of these operations resulted in tight controls as to when and what kind of intelligence files could be opened and what use could be made of the information." *Id.*

152. ELIZABETH HINTON, FROM THE WAR ON POVERTY TO THE WAR ON CRIME: THE MAKING OF MASS INCARCERATION IN AMERICA 263–70 (2016).

153. BROWN ET AL., *supra* note 148, at 153–60 (detailing the fallacies of conservative explanations of crime and embrace of "tough on crime" rhetoric and policies).

154. New Federalism is a political ideology practiced by most U.S. presidential administrations since President Richard Nixon. It is an approach that attempts to advance a domestic affairs agenda by sharing priorities and power between the federal government and states, while upholding constitutional principles. The most notable applications of New Federalism are the federal government's efforts to advance school desegregation and urban renewal. *See* Neal Devins & James B. Stedman, *New Federalism in Education: The Meaning of the Chicago School Desegregation Cases*, 59 NOTRE DAME L. REV. 1243 (1984); Bruce Katz, *Nixon's New Federalism 45 Years Later*, BROOKINGS INST. (Aug. 11, 2014), https://www.brookings.edu/blog/the-avenue/2014/08/11/nixons-new-federalism-45-years-later/.

priorities (often racially motivated objectives) while still operating within a states' rights paradigm.[155] This marked a notable shift because law enforcement in the United States is highly decentralized, but during this time period a number of national commissions and police leaders pushed for consolidation that never fully materialized but resulted in more complex interagency cooperation, especially for organized crime efforts.[156]

In 1987, the Los Angeles County Sheriff's Department and the Law Enforcement Communications Network[157] launched the Gang Reporting, Evaluation, and Tracking System ("GREAT"), a decentralized intelligence database for law enforcement agencies (e.g., police, prosecutors, and probation) to identify and investigate street gangs and their members, a first of its kind.[158] In 1993, the California Department of Justice ("Cal DOJ") expressed interest in centralizing and upgrading GREAT, then initiated consultancies with external vendors to develop an improved system.[159] In 1995, Cal DOJ contracted with the private software firm Orion Scientific Systems Inc. to create a prototype of a new unified statewide gang database system to be piloted with the San Diego Police Department.[160] That same year, the Federal Bureau of Investigation Violent Gang and Terrorist Organization File—a database with information on gang and terrorist activity—became operational,[161] and nationally the use of automated systems for storing gang information became more common in police departments

155. HINTON, *supra* note 152, at 263–70. Contemporary research on law enforcement anti-gang efforts have demonstrated that this New Federalism approach to local gang issues has created a perverse feedback loop, where local police departments have inflated gang statistics to obtain federal funds. *See, e.g*, Marjorie Zatz, *Chicano Youth Gangs and Crime: The Creation of a Moral Panic*, 11 CONTEMP. CRISES 129, 129–34 (1987) (noting that the Phoenix Police Department inflated estimates of gangs from five to more than one hundred in a two-year period in order to attract more federal funding).

156. Jacobs, *supra* note 151, at 707–08; Stephen D. Mastrofski & James J. Willis, *Police Organization Continuity and Change: Into the Twenty-First Century*, 39 CRIME & JUST. 55, 59–62 (2010).

157. The Law Enforcement Communication Network is a private, non-profit law enforcement organization. Stacey Leyton, *The New Blacklists: The Threat to Civil Liberties Posed by Gang Databases*, *in* CRIME CONTROL AND SOCIAL JUSTICE: THE DELICATE BALANCE 109, 144 n.20 (Darnell F. Hawkins et al. eds., 2003).

158. U.S. DEP'T OF JUST., BUREAU OF JUST. ASSISTANCE, URBAN STREET GANG ENFORCEMENT 29 (1997); Leyton, *supra* note 157, at 111; CAL. DEP'T OF JUST., TECHNOLOGY ACQUISITION PROJECT CASE STUDY: CALIFORNIA DEPARTMENT OF JUSTICE CAL/GANG SYSTEM 1 (undated) (draft report) (on file with author).

159. Cal DOJ initially engaged a computer consultant using a $300,000 grant from the California Office of Criminal Justice Planning to expand GREAT, but after seeing few results by 1995, Cal DOJ severed ties with the consultant. Later that year, Cal DOJ was introduced to Orion Scientific Systems and requested the firm make a proposal to address their problems with GREAT. CAL. DEP'T OF JUST., *supra* note 158, at 2–3.

160. *Id*. at 3–4.

161. Leyton, *supra* note 157, at 113.

and prosecutors' offices.[162] In 1997, the expansion of interagency gang databases continued with President Clinton announcing the launch of the U.S. Department of Justice ("DOJ")-supported National Gang Tracking Network,[163] and then California Governor Pete Wilson announced plans to spend $800,000 to create CalGang, a fully integrated web-based intranet gang database system that would be accessible to police departments statewide and include new capabilities like automated analysis, report generation, and photographic lineups.[164] During this same period, the DOJ's Bureau of Justice Assistance ("DOJ BJA") created RISSGang, a national network of six regional databases with analytics capabilities to track and support investigations of gang activity, terrorism, and drug trafficking.[165]

Gang databases faced several legal challenges as they became more prevalent on national and local levels. Controversy erupted in Chicago when the Chicago Police Department was barred from joining the statewide gang database and from developing its own intelligence systems because of a consent decree imposed in response to its unlawful practices targeting political activist and community organizations.[166] Then, in *City of Chicago v. Morales*,[167] the Supreme Court struck down Chicago's anti-gang loitering ordinance for violating the Due Process Clause of the Fourteenth Amendment because it was unconstitutionally vague and provided too much discretion to law enforcement to decide what constitutes loitering.[168] However, the *Morales* decision ultimately led law enforcement to rely *further* on gang

---

162.

> In their study of 149 police departments and 191 prosecutors' offices across the nation, Johnson, Webster, Connors, and Saenz (1995) found that 70% of police departments and 20% of prosecutors' offices used an automated system for storing gang information. Additionally, of the police departments that reported a gang problem, 78% used a database.

Julie Barrows & C. Ronald Huff, *Gangs and Public Policy: Constructing and Deconstructing Gang Databases*, 8 CRIMINOLOGY & PUB. POL'Y 675, 683 (2009) (citing CLAIRE JOHNSON ET AL., *Gang Enforcement Problems and Strategies: National Survey Findings*, J. GANG RSCH., Fall 1995, at 1; *see also* IRVING A. SPERGEL, THE YOUTH GANG PROBLEM: A COMMUNITY APPROACH 194 (1995).

163. The National Gang Tracking Network provided grants to states to use gang databases as pilot programs in 1997 in New York, Connecticut, Rhode Island, Massachusetts, and Vermont. Leyton, *supra* note 157, at 147 n.40.

164. *Id.* at 111–13; U.S. DEP'T OF JUST., BUREAU OF JUST. ASSISTANCE, URBAN STREET GANG ENFORCEMENT 29 (1997).

165. U.S. DEP'T OF JUST., BUREAU OF JUST. ASSISTANCE, REGIONAL INFORMATION SHARING SYSTEMS: THE RISS PROGRAM: 1998 3 (1999).

166. All. to End Repression v. City of Chicago, 66 F. Supp. 2d 899, 913 (N.D. Ill. 1999) (denying the City of Chicago's request to overturn consent decree so the police department could maintain files on gangs); Leyton, *supra* note 157, at 113.

167. 527 U.S. 41 (1998).

168. *Id.* at 64.

databases because its use of these databases presumably limited discretion by narrowing enforcement efforts to purported gang members.[169]

The turn of the century marked a significant change in the organizational structure, purpose, and culture of street gangs, in that they became less hierarchical, more fragmented, and driven by different economic interests (i.e., a shift from drug market to music and social media markets).[170] Nevertheless, since 2000, media coverage and public "moral panic"[171] regarding gangs has skyrocketed due to law enforcement and media collusion to commercialize a narrative of increased gang violence, which facilitated new resources for law enforcement, new anti-gang legislation, and public acquiescence to law enforcement intelligence practices following the events of September 11, 2001.[172] In 2003, the DOJ launched the National Criminal Intelligence Sharing Plan to provide resources to federal, regional, and local law enforcement to create or enhance intelligence databases to target criminal (including gangs) and terrorist activities domestically and internationally.[173] In 2005, the FBI established the National Gang Intelligence Center to nationally coordinate intelligence and enforcement efforts targeting violent national and regional gangs, including the creation of a database to centralize federal, state, and local gang intelligence.[174] Throughout the first decade of the twenty-first century, Congress considered, yet failed to pass, several legislative measures targeting gangs and gang activity, including the Gang

169. The decision also led to increasing reliance on "hot spot" policing, where police identify and target high crime areas for suspected gang activity. *See* Rebecca R. Brown, *The Gang's All Here: Evaluating the Need for a National Gang Database*, 42 COLUM. J.L. & SOC. PROBS. 293, 316 (2009); Kim Strosnider, *Anti-Gang Ordinances After* City of Chicago v. Morales*: The Intersection of Race, Vagueness Doctrine, and Equal Protection in the Criminal Law*, 39 AM. CRIM. L. REV. 101, 134–38 (2002).

170. FORREST STUART, BALLAD OF THE BULLET: GANGS, DRILL MUSIC, AND THE POWER OF ONLINE INFAMY 11 (2020).

171. Moral panic refers to an escalation of intense, disproportionate, and typically unfounded concern in response to a perceived social threat posed by an identified group of individuals. *See* K. Babe Howell, *Gang Policing: The Post Stop-and-Frisk Justification for Profile-Based Policing*, 5 U. DENV. CRIM. L. REV. 1, 12–13 (2015); MCCORKLE & MIETHE, *supra* note 147, at 24–29 (describing the evolution of gangs as moral panics); THE ASHGATE RESEARCH COMPANION TO MORAL PANICS (Charles Krinksy ed., 2013) (highlighting the types of moral panics, the role of media, and the impact on governance).

172. Howell, *supra* note 171, at 12–15; GREENE & PRANIS, *supra* note 148, at 3.

173. U.S. DEP'T OF JUST., BUREAU OF JUST. ASSISTANCE, THE NATIONAL CRIMINAL INTELLIGENCE SHARING PLAN 12 (2003).

174. U.S. DEP'T OF JUST., NAT'L DRUG INTEL. CTR., ATTORNEY GENERAL'S REPORT TO CONGRESS ON THE GROWTH OF VIOLENT STREET GANGS IN SUBURBAN AREAS (2008); *SRA International (SRX) Awarded $16M Contract*, STREETINSIDER (Oct. 16, 2007, 4:04 PM), https://www.streetinsider.com/Corporate+News/SRA+International+%28SRX%29+Awarded+%2416M+Contract/3032131.html.

Abatement and Prevention Act of 2007, which directed the Attorney General to create a federally funded national gang database.[175]

In the last decade, law enforcement use of social media for gang and other criminal investigations has become routine because the ubiquity of social media provides law enforcement with a wide spectrum of covert access to content on individuals' and groups' daily experiences, practices, and activities.[176] Indeed, many scholars have noted that "[p]olice penetration and control of communication among community members" through social media monitoring practices and technologies has supplanted community policing approaches, reduces transparency, and can serve to conceal unlawful or discriminatory practices because it increases the power imbalance between police and public.[177]

This shift in the "datafication" of gang policing was notable in New York City, where in 2012, anticipating that its stop and frisk program would be held unconstitutional, the New York Police Department ("NYPD") doubled the size of its Gang division and launched its Operation Crew Cut initiative to monitor gang members' social media.[178]

2. Gang Databases in Practice

Gang databases are one of many law enforcement information technologies used for gang suppression efforts and other law enforcement priorities. They are compiled and used by several law enforcement and criminal justice institutions and actors, based on the belief that they function

175. *See e.g.*, Gang Prevention and Effective Deterrence Act of 2003, S. 1735, 108th Cong. (2003); Gang Deterrence and Community Protection Act of 2005, H.R. 1279, 109th Cong. (2005); Gang Abatement and Community Prevention Act of 2007, H.R. 1582, 110th Cong. (2007); Gang Reduction, Investment, and Prevention Act, H.R. 3922, 110th Cong. (2007); Free Flow of Information Act of 2007, H.R. 2102, 110th Cong. (2007); Gang Abatement and Prevention Act of 2009, S. 132, 111th Cong. (2009).

176. Desmond Upton Patton et al., *Stop and Frisk Online: Theorizing Everyday Racism in Digital Policing in the Use of Social Media for Identification of Criminal Conduct and Associations*, SOC. MEDIA & SOC'Y, July–Sept. 2017, at 1, 2–3; *see also* Memorandum from Charlie Beck, L.A. Chief of Police, Field Interview Report (May 27, 2015) (on file with author) (asking LAPD officers to record social media and email account information when completing field interview cards that are used to record all civilian interactions including those that do not result in arrest or conviction).

177. JEFFREY LANE, THE DIGITAL STREET 157–59 (2019) (noting that law enforcement reliance on online surveillance can result in less careful criminalization with a weaker rationale and structure for investigation); *see also* DANIEL TROTTIER, SOCIAL MEDIA AS SURVEILLANCE: RETHINKING VISIBILITY IN A CONVERGING WORLD 135–54 (2012); Martin A. French & Simone A. Browne, *Profiles and Profiling Technology: Stereotypes, Surveillance, and Governmentality*, *in* CRIMINALIZATION, REPRESENTATION, REGULATION: THINKING DIFFERENTLY ABOUT CRIME 251, 274 (Deborah Brock et al. eds., 2014); Patton et al., *supra* note 176, at 2–3; STUART, *supra* note 170.

178. *See* Howell, *supra* note 171, at 2–14; Patton et al., *supra* note 176, at 4E**rror! Hyperlink reference not valid.**; LANE, *supra* note 177, at 128.

as a "force" or institutional multiplier because they increase the overall efficiency, speed, and performance[179] of all agencies without having to increase staffing or expend additional funds.[180] However, this theory appears to ignore that the development and maintenance of these databases is very costly, even when subsidized by grants or in-kind donations.[181]

Though the specific needs and rationales for use vary, gang databases make intelligence and investigative information accessible to various government actors and institutions. Police rely on gang databases to advance public safety, investigate and arrest persons of interest,[182] and deter new or potential gang members from further engagement or criminal activity.[183] Prison and jail officials rely on gang databases to make appropriate classifications and other decisions for security and institutional order.[184] Prosecutors rely on gang databases to inform and craft criminal charges and plea bargains.[185] Judges rely on gang databases to inform bail and sentencing decisions.[186] School officials, public housing authorities, and other non-law enforcement government actors that have access to or receive information from gang databases use the information for decisions about community safety, tenant applications, and assignment of counseling resources.[187] As a

179. Mark Poster, *Databases as Discourse; or, Electronic Interpellations*, *in* COMPUTERS, SURVEILLANCE AND PRIVACY 175, 189 (David Lyon & Elia Zureik eds., 1996) ("Databases provide contemporary governments with vast stores of accessible information about the population that facilitates the fashioning of policies that maintain stability.").

180. James Lingerfelt, *Technology as a Force Multiplier*, *in* TECHNOLOGY FOR COMMUNITY POLICING: CONFERENCE REPORT 29 (1996); Kenneth L. Kraemer & Jason Dedrick, *Computing and Public Organizations*, 7 J. PUB. ADMIN. RSCH. & THEORY 89, 96 (1997).

181. Samuel Nunn & Kenna Quinet, *Evaluating the Effects of Information Technology on Problem-Oriented-Policing: If It Doesn't Fit, Must We Quit?*, 26 EVALUATION REV. 81, 82 (2002) (arguing that police agencies often lack the willpower to refuse grants to acquire information technology even when technology is less useful than expected or is ill-matched for agency objectives).

182. Ben Popper, *How the NYPD Is Using Social Media to Put Harlem Teens Behind Bars*, VERGE (Dec. 10, 2014, 1:15 PM), https://www.theverge.com/2014/12/10/7341077/nypd-harlem-crews-social-media-rikers-prison (describing the case of Jelani Henry, a young Black man from Harlem who was incarcerated at Rikers Island for nineteen months based on NYPD use of a gang database and social media monitoring to label him as a criminal affiliate).

183. Leyton, *supra* note 157, at 109–12; Jacobs, *supra* note 151, at 705–07; MCCORKLE & MIETHE, *supra* note 147, at 58–72; LANE, *supra* note 177, at 121–28; Charles M. Katz, *Issues in the Production and Dissemination of Gang Statistics: An Ethnographic Study of a Large Midwestern Police Gang Unit*, 49 CRIME & DELINQ. 485, 486 (2003).

184. Jacobs, *supra* note 151, at 705–07; Leyton, *supra* note 157, at 122.

185. Jacobs, *supra* note 151, at 705–07; LANE, *supra* note 177, at 128–49; Leyton, *supra* note 157, at 122.

186. Jacobs, *supra* note 151, at 705–07.

187. Leyton, *supra* note 157, at 122–23; Becki R. Goggins & Dennis A. DeBacco, *Survey of State Criminal History Information Systems, 2016: A Criminal Justice Information Policy Report*, NAT'L CONSORTIUM FOR JUST. INFO. & STATS. 6 (2018),

result, gang databases are typically developed as intranet-based systems that are accessible via a web browser or a shared interface, and some are designed so that new features or third-party applications can be integrated.

There is no federal mandate or guidance on gang databases, so most policies guiding or regulating gang database construction and maintenance occur at the state level. Oversight and enforcement of these laws and administrative rules is difficult because all entries originate at the local level, and local police often have their own formal and informal policies on entering and maintaining gang database information that may not be consistent with statutes.[188] Even when databases are merged at the state, regional, or national level and there are governing statutes, local police often keep their own databases and files, and such redundancies or inconsistent systems and practices can vary in neighboring jurisdictions.[189] Thus, most gang databases are constructed and maintained according to statutory or institutional definitions and/or criteria for designating gangs and gang members.

Yet, defining what constitutes a gang or gang member has been a significant challenge for law enforcement, particularly because law enforcement definitions and practices tend to foreground the criminal activities of gangs, whereas researchers and social welfare practitioners tend to emphasize the social and cultural aspects of gang formation and activity.[190] This schism can be partially attributed to law enforcement's traditional approach to criminal profiling, which "relies on the correlation between

---

https://www.ncjrs.gov/pdffiles1/bjs/grants/251516.pdf (highlighting state and federal practices and laws permitting access to criminal databases for employment or licensing decisions).

188. Jacobs, *supra* note 151, at 707–08; Barrows & Huff, *supra* note 162, at 679–80.

189. Jacobs, *supra* note 151, at 707–08 ("Even if gang databases are combined or merged at a central . . . level, then it is likely that local police departments would keep their own databases and files"); Barrows & Huff, *supra* note 162, at 679 ("Neighboring jurisdictions compile gang information according to their own gang definitions and criteria, which results in the potential for inconsistency in information from one gang database to the next."); Rashida Richardson & Amba Kak, *Suspect Development System: Databasing Marginality and Enforcing Discipline*, 55 U. MICH. J.L. REFORM (forthcoming 2022) (manuscript at 41–42), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3868392 (describing that despite the appearance of centralized data and oversight, gang database practices are diffused at the local level, resulting in duplicative, informal systems).

190. *See* Leyton, *supra* note 157, at 114; *see also* Mercer L. Sullivan, *Maybe We Shouldn't Study "Gangs": Does Reification Obscure Youth Violence?*, 21 J. CONTEMP. CRIM. JUST. 170, 171 (2005) ("Youth violence takes many organizational forms. Lumping these together as 'gang' phenomena carries distracting baggage. . . . It can, and sometimes does, cloud our view of what we should be placing front and center . . . ."); Katz, *supra* note 183, at 487 ("[P]olice do not necessarily document individuals because of their behavior but rather document individuals according to their own ideas and beliefs about gang members. . . . [T]his leads to officers documenting individuals based solely on where individuals live, with whom they associate, what they look like, or what clothes they wear."); Forrest Stuart, *Code of the Tweet: Urban Gang Violence in the Social Media Age*, 67 SOC. PROBS. 191, 194 (2020) (describing how police assign residents to gang and other criminal databases based on social media activity that is misinterpreted as evidence of criminal activity).

behavioral factors and the past experience of law enforcement in discovering criminal behavior associated with those factors; thus, profiling rests on the perceived accuracy of the profile as a predicator of criminality."[191] Unlike other forms of organized crime such as mafias or mobs, which are hierarchical groups with strict codes of conduct that exist for the criminal enterprise, gangs are not necessarily focused only on criminal activity; they are more amorphous and characterized by their fluidity in membership, geographic mobility, and differential organizational structures.[192]

A 2009 study on gang database uses and policies found that "41 states and the District of Columbia provide statutory definitions of a 'gang'" but that most of these definitions are inconsistent and reflect the political, social, and financial pressures of a given jurisdiction.[193] For instance, the statutory definitions have different requirements for how many individuals must participate in criminal activity to qualify as a gang—most states require three or more individuals, some require at least five individuals, and some do not specify a requisite number of members.[194] Overall, the five general elements reflected in statutory gang definitions are: "number of participants, criminal activity, hierarchy, alliance or understanding, and a common name or symbol."[195] The same study found that only fifteen states have statutory definitions for gang members and most of the definitions are relatively generic.[196]

Critics of gang databases note that "because gang membership itself is not illegal, it does not qualify as an underlying criminal predicate and therefore does not justify maintenance of intelligence information."[197] Thus, law enforcement also employs statutory or institutional criteria-based

191. Patton et al., *supra* note 176, at E**rror! Hyperlink reference not valid.**2 (citing William M. Carter Jr., *The Thirteenth Amendment and Constitutional Change*, 38 N.Y.U. REV. L. & SOC. CHANGE 583 (2014)).

192. Barrows & Huff, *supra* note 162, at 678–79; MALCOLM W. KLEIN, *Introduction to* THE MODERN GANG READER viii (1995) (noting distinctions between gangs and criminal syndicates); MCCORKLE & MIETHE, *supra* note 147, at 202–09; GREENE & PRANIS, *supra* note 148, at 10 ("Most experts agree that drug trafficking is a secondary interest for street gang members . . . ."); Leyton, *supra* note 157, at 115 ("Most gangs are loosely structured, and many young people may join solely for safety or acceptance reasons rather than to participate in the gang's criminal activities.").

193. Barrows & Huff, *supra* note 162, at 683–85.

194. *Id.*

195. *Id.* at 684.

196. *Id.* at 685. *Compare* Leyton, *supra* note 157, at 115 ("The varied motivations and activities of gang members renders identification of gang members difficult and highly dependent upon the definition of the level of involvement that qualifies an individual as a gang 'member.'"), *with* Sullivan, *supra* note 190 (criticizing the use of monolithic terms like gangs that nullify careful distinctions between youth gangs and group criminal activities that may not be related to gang membership).

197. Leyton, *supra* note 157, at 114.

classifications to guide gang database designation and limit police officer discretion. Similar to gang and gang member definitions, the criteria for gang designations vary significantly, which means that in practice a gang member in a given state, region, or municipality may not be designated as a gang member in a neighboring jurisdiction. At least ten states provide statutory criteria for gang database designation, though the criteria and requirements for designation differ.[198] Amongst these state statutes there are over twenty-two different criteria of gang membership identified, with self-admission being the only consistent criterion.[199]

Although these criteria-based classifications were established to limit law enforcement discretion and quell legal challenges, "[c]ompliance depends entirely on the good faith and competence of local police officials who are more likely to fear the negative consequences of failing to identify a gang member who later engages in violent crime than the consequences (of which there are none) of erroneously labeling someone a gang member."[200] This concern of overinclusion is exacerbated by the fact that individuals added to gang databases are not entitled to notice,[201] few gang database policies have purging or audit requirements, and even when they exist, compliance and active oversight are rare. For instance, CalGang guidelines include records purging requirements,[202] but a 2016 audit found that the database was rife with errors, unsubstantiated entries, and names that should have been purged.[203] Again in 2020 the Cal DOJ initiated an investigation of the LAPD's use of the database following several reports of falsified or inaccurate records.[204]

Despite the growing prevalence of gang databases and the exorbitant amount of public funds spent on law enforcement gang suppression efforts, the state of the "gang problem[]"[205] and the efficacy of the gang database

198. Barrows & Huff, *supra* note 162, at 685–87.

199. *Id.*

200. JAMES B. JACOBS, THE ETERNAL CRIMINAL RECORD 24 (2015).

201. There are some exceptions. California law enforcement agencies are required to give written notice to a minor's parents or guardian before including the individual in a shared database. CAL. PENAL CODE § 186.34(b) (West 2014).

202. CAL. CODE REGS. tit. 11 § 754.4 (2020).

203. CAL. STATE AUDITOR, REPORT NO. 2015-130, CALGANG CRIMINAL INTELLIGENCE SYSTEM 3 (2016). For example, forty-two people in the database were younger than one year of age at the time of entry and some entries had record purge dates set for more than 100 years in the future. *Id.*

204. Gabrielle Canon, *California Department of Justice to Investigate LAPD for Falsifying Gang Database Records*, USA TODAY (Feb. 10, 2020, 4:05 PM), https://www.usatoday.com/story/news/politics/2020/02/10/californias-gang-database-under-investigation/4715847002/.

205.

solution remains unclear and debatable.[206] This is because public understanding of the problem and law enforcement's attention to it have almost always been outsized and driven by political pressure,[207] financial interests,[208] moral panics,[209] misrepresentations in media,[210] and an overreliance on "therapeutic policing."[211] As a result, gang databases are rife with many problems such as dirty data, racial bias, interminable collateral consequences, and counterproductive outcomes.

Research and legal challenges have demonstrated that police data collection and maintenance practices are severely flawed; thus, dirty data is endemic in most police datasets and databases.[212] Dirty data is a term that refers to the various inaccuracies, flaws, and misrepresentations reflected in police data that are "derived from or influenced by corrupt, biased, and unlawful practices, including data that has been intentionally manipulated or 'juked,' as well as data that is distorted by individual and societal biases."[213] While many of the problems that lead to dirty data are systemic, the political and social dynamics surrounding law enforcement gang suppression efforts make the prevalence and permanence of dirty data in gang databases seem

---

> Los Angeles taxpayers have not seen a return on their massive investments over the past quarter century: law enforcement agencies report that there are now six times as many gangs and at least double the number of gang members in the region. In the undisputed gang capital of the U.S., more police, more prisons, and more punitive measures haven't stopped the cycle of gang violence.

GREENE & PRANIS, *supra* note 148, at 3; *see also* Joshua D. Wright, *The Constitutional Failure of Gang Databases*, 2 STAN. J. C.R. & C.L. 115, 118–19 (2005).

206. CHI. OFFICE OF INSPECTOR GENERAL, FOLLOW-UP INQUIRY ON THE CHICAGO POLICE DEPARTMENT'S "GANG DATABASE" 29 (2021) (questioning the value of gang databases in addressing violent crime since they do not remain up-to-date and "cannot effectively track the shifting alliances and conflicts across many small gang factions" that currently exist in Chicago).

207. GREENE & PRANIS, *supra* note 148, at 3–7; Katz, *supra* note 183, at 489.

208. Majorie Zatz, *Chicano Youth Gangs and Crime: The Creation of a Moral Panic*, 11 CONTEMP. CRISES 129, 130, 153 (1987) (finding a police department purposefully manipulated estimate of gang membership to receive federal funding); Katz, *supra* note 183, at 489.

209. MCCORKLE & MIETHE, *supra* note 147, at 15–17, 58–60.

210. Richardson & Kak, *supra* note 189 (manuscript at 47–48).

211. Forrest Stuart established therapeutic policing as when cops diagnose and implement ideas about residents and their problems while relying on the threat or use of criminal sanctions. FORREST STUART, DOWN, OUT, AND UNDER ARREST: POLICING AND EVERYDAY LIFE IN SKID ROW 6 (2016).

212. *See, e.g.*, Richardson et al., *supra* note 86, at 16–26; Katz, *supra* note 183, at 511 ("Police researchers have long recognized that police record-keeping practices regularly yield unreliable data."); Henry H. Brownstein, *The Social Production of Crime Statistics*, 2 JUST. RSCH. & POL'Y 73 (2000) (finding many flaws with the quality of police data and that police have manipulated crime statistics because of political and social pressure).

213. Richardson et al., *supra* note 86, at 18; *see also* MCCORKLE & MIETHE, *supra* note 147, at 57–60 (describing how criminal justice data and statistics are misleading because police "routinely overcharge" arrestees, a majority of cases are never prosecuted, and law enforcement may need high crime statistics to justify budget requests); Leyton, *supra* note 157, at 118.

fated.[214] Police departments have inflated statistics on gang-related crime or activity to receive federal grants[215] and invented gangs to unlawfully target and harass groups.[216] Also, poorly constructed definitions and criteria for designating gangs and gang members increase the risks of police officers relying on stereotypes and biases to determine gang activity.[217] Indeed, gang databases also exhibit extreme racial biases, with Black and Latinx people making up over 90% of people included in the databases nationally,[218] even

214. *See* Albert J. Meehan, *The Organizational Career of Gang Statistics: The Politics of Policing Gangs*, 41 SOCIO. Q. 337, 362 (2000) (describing how the record-keeping practices that produce gang-related statistics are a byproduct of social and political pressures and practical decisions and actions); G. David Curry, Richard A. Ball & Scott H. Decker, *Estimating the National Scope of Gang Crime from Law Enforcement Data*, NAT'L INST. OF JUST.: RSCH. IN BRIEF 3 (Aug. 1996), https://www.ncjrs.gov/pdffiles1/Digitization/161477NCJRS.pdf ("The capacity to report gang crime statistics was significantly related to city size . . . ."); Katz, *supra* note 183, at 489 ("[G]ang statistics are constructed by the police in response to more insidious political and financial pressures."); Leyton, *supra* note 157, at 118 ("The high potential for inaccuracy is particularly problematic when funding for anti-gang initiatives creates incentives to be over- rather than under-inclusive.").

215. Zatz, *supra* note 208, at 153 (finding the Phoenix Police Department exaggerated the severity of its gang problems to receive federal funding); Robert J. Bursik & Harold G. Grasmick, *Defining and Researching Gangs*, *in* THE MODERN GANG READER (Cheryl L. Maxson et al. eds., 3d ed. 2005) (suggesting that local police departments may have a vested interest in demonstrating a gang problem or gang activity to access federal grants); Nunn & Quinet, *supra* note 181, at 82 ("Few agencies have the fiscal willpower to refuse grants to purchase equipment, especially in police agencies that have been traditional targets of money from the old Law Enforcement Assistance Administration, the National Institute of Justice, or the Office of Law Enforcement Technology Commercialization.").

216. Dave Biscobing, *'Prime for Abuse': Lack of Oversight Lets Phoenix Police Add Protesters to Gang Database*, ABC 15 ARIZ. (June 5, 2021, 3:08 PM), https://www.abc15.com/news/local-news/investigations/protest-arrests/prime-for-abuse-lack-of-oversight-lets-phoenix-police-add-protesters-to-gang-database.

217. Katz, *supra* note 183, at 489 ("The confusion over such terms may put officers and agencies in the position of having to label gang members, gangs, and gang crime according to their own preferences and ideas rather than by any established and clear set of criteria that can be agreed on by all."); Decker & Kempf-Leonard, *supra* note 15, at 286 ("[P]olicy responses to gang activity are in large part dependent upon socially constructed definitions. The absence of an agreed upon working definition can lead either to minimizing the problem or to over-estimating its incidence.").

218. GREENE & PRANIS, *supra* note 148, at 4; Daryl Khan, *New York City's Gang Database Is 99% People of Color, Chief of Detectives Testifies*, JUV. JUST. INFO. EXCH. (June 14, 2018), https://jjie.org/2018/06/14/new-york-citys-gang-database-is-99-people-of-color-chief-of-detectives-testifies/; Richard Winton, *California Gang Database Plagued with Errors, Unsubstantiated Entries, State Auditor Finds*, L.A. TIMES (Aug. 11, 2016, 9:10 PM), https://www.latimes.com/local/lanow/la-me-ln-calgangs-audit-20160811-snap-story.html ("The database is overwhelmingly male—some 93.1%—and disproportionately minority—64.9% Latino and 20.5% black."); CITIZENS FOR JUV. JUST., WE ARE THE PREY: RACIAL PROFILING AND POLICING OF YOUTH IN NEW BEDFORD 20 (2021) (finding that the New Bedford Police Department's gang database is overrepresented with young Black and Latino men and alleging that the police department's gang identification practices are subjective); Chris Gelardi, *More Kids and Overwhelmingly Black: New Records Show Concerning Trends in D.C. Gang Database*, INTERCEPT (Jan. 9, 2022), https://theintercept.com/2022/01/09/dc-police-gang-database-mpd/ ("Metropolitan

though research suggests that at least 25% of gang members generally and 40% of adolescent gang members are white.[219] Such disparities are likely indicative of racial profiling police practices and racially biased police priorities,[220] but also demonstrate that gang databases constitute what surveillance scholar Simone Browne terms "racializing surveillance—when enactments of surveillance reify boundaries along racial lines, thereby reifying race, and where the outcome of this is often discriminatory and violent treatment."[221]

The discriminatory outcomes of racialized surveillance are not limited to the racial disparities within gang databases; they also have widespread, cumulative effects on individuals and their communities,[222] particularly

---

Police Department's gang database almost tripled in size over eight years, and nearly nine out of 10 entries with a race listed are Black people, who make up 46 percent of D.C.'s population . . . .").

219. *See* GREENE & PRANIS, *supra* note 148, at 4; A.C. Thompson, Ali Winston & Darwin BondGraham, *Racist, Violent, Unpunished: A White Hate Group's Campaign of Menace*, PROPUBLICA (Oct. 19, 2017, 2:01 PM), https://www.propublica.org/article/white-hate-group-campaign-of-menace-rise-above-movement (profiling the scope and severity of white hate groups and gangs in the United States and the lack of law enforcement suppression efforts targeting these groups); *see also* Donald Ladd, *Only Black People Prosecuted Under Mississippi Gang Law Since 2010*, JACKSON FREE PRESS (Mar. 29, 2018, 1:32 PM), https://www.jacksonfreepress.com/news/2018/mar/29/only-black-people-prosecuted-under-mississippi-gan/ (finding that between 2010 and 2017, only Black people were arrested under the Mississippi Gang Law, even though the Mississippi Association of Gang Investigators declared that 53% of verified gang members are white).

220. MCCORKLE & MIETHE, *supra* note 147, at 201 ("Hate groups—such as KKK or Skinheads—are recognized as gangs in some places, but not others."); Leyton, *supra* note 157, at 120 ("[S]ince law enforcement's definition of a gang is broad enough to encompass many groups of white persons . . . these statistics clearly reflect the officers' racially-based preconceptions of gang members, rather than any objective of carefully applied criteria." (quoting Letter from Edward M. Chen et al., ACLU, to Representative Don Edwards, Chair, Committee on the Judiciary, Subcommittee on Civil & Constitutional Rights, U.S. House of Representatives 26 (Aug. 6, 1993)); Scot Wortley & Julian Tanner, *Data, Denials, and Confusion: The Racial Profiling Debate in Toronto*, 45 CANADIAN J. CRIMINOLOGY & CRIM. JUST. 367, 369–70 (2003) (arguing that racial profiling typically comes to light through racial disparities in police practices).

221. SIMONE BROWNE, DARK MATTERS: ON THE SURVEILLANCE OF BLACKNESS 8 (2015).

222. Joe R. Feagin, *The Continuing Significance of Race: Antiblack Discrimination in Public Places*, 56 AM. SOCIO. REV. 101, 115 (1991) ("The cumulative impact of racial discrimination accounts for the special way that blacks have of looking at and evaluating interracial incidents. . . . [B]lacks look at white-black interaction through a lens colored by personal and group experience with cross-institutional and cross-generational discrimination. . . . What many whites see as black 'paranoia' . . . is simply a realistic sensitivity to white-black interaction created and constantly reinforced by the two types of cumulative discrimination . . . ."); GREENE & PRANIS, *supra* note 148, at 6 ("Communities of color suffer not only from the imposition of aggressive police tactics that can resemble martial law, but also from the failure of such tactics to pacify their neighborhoods.").

reinforcing distrust of the police[223] and exacerbating the collateral consequences of the criminal justice system in addition to the unique consequences of gang designation.[224] For instance, even when gang databases have policies with purging requirements, compliance is rare and there is typically no requirement to notify individuals for an opportunity to correct misclassification. This means that a gang database designation can have a *perpetual blacklist effect* on individuals, thus leading to differential treatment by private and public actors and inhibiting or completely foreclosing housing, educational, employment, financial, immigration, public benefits, and social opportunities for a significant period of time, if not indefinitely.[225] These cumulative effects can be taken up by feedback loops where the norms and conditions of systemic racism and social inequities are validated by selective observations and dirty data, which serve to concretize and justify the discriminatory practices, policies, and even technologies that created or at least perpetuate underlying conditions.[226]

3. Applying Gang Databases to the Narrow Definition

The definitions help clarify gang databases as ADS. Gang databases currently evade scrutiny because they are seen as passive or technologically primitive, even though they employ similar computational methods, perform similar functions, inform governance, and produce negative outcomes like other technologies that are indubitably considered ADS, like predictive policing.[227] The clarity offered by these definitions also helps overcome

223. *See, e.g.*, GREENE & PRANIS, *supra* note 148, at 6; Leyton, *supra* note 157, at 121 ("Some warn that mistaken inclusion reinforces distrust of the police by young people of color and that the police harassment may actually push youth into gangs.").

224. JACOBS, *supra* note 200, at 227–74; GREENE & PRANIS, *supra* note 148, at 5 ("[M]any gang control policies make the process of leaving more rather than less difficult by continuing to target former members after their gang affiliation has ended.").

225. Leyton, *supra* note 157, at 120–23; JACOBS, *supra* note 200, at 227–74; POLICING IN CHI. RSCH. GRP., TRACKED AND TARGETED: EARLY FINDINGS ON CHICAGO'S GANG DATABASE 10 (2018), http://erasethedatabase.com/wp-content/uploads/2018/02/Tracked-Targeted-0217-r.pdf; Katz, *supra* note 185, at 513.

226. French & Browne, *supra* note 177, at 274–77; GREENE & PRANIS, *supra* note 148, at 6 ("One researcher argues that in Chicago, for example, a cycle of police suppression and incarceration, and a legacy of segregation, have actually helped to *sustain* unacceptably high levels of gang violence."); DAVID LYON, SURVEILLANCE STUDIES: AN OVERVIEW 76 (2007) ("[T]oday's information technologies 'embed and inscribe work' in ways that are hard to see but freeze values, opinions and rhetoric in technology."); RICHARD JENKINS, SOCIAL IDENTITY 192–96 (Routledge ed., 2d ed. 2004) (arguing that reliance on stereotypes is an inherent function of bureaucratic classification practices because it enables the exercise of discretion by enhancing group identification and a sense of predictability).

227. Rashida Richardson & Amba Kak, *It's Time for a Reckoning About This Foundational Piece of Police Technology*, SLATE (Sept. 11, 2020, 1:38 PM), https://slate.com/technology/2020/09/its-time-for-a-reckoning-about-criminal-intelligence-

subversive rhetorical tactics used by law enforcement officials to obscure public perceptions about ADS, such as referring to ADS use as "intelligence-driven" or "precision" policing.[228] This Section demonstrates how gang databases meet the narrow definition and how policymakers within the criminal justice sector should evaluate the components of the definitions.

(a) "Any systems, software, or process that use computation"

Gang databases, and most commonly used databases today, are designed using a relational model,[229] which is encoded into a software system format for commercial sale or internal use. Some gang databases are designed for interoperability so that additional applications or software can be integrated to provide new features or modules, like map displays to visually display and track patterns of violence in an area.

Most gang databases are software systems that rely on some form of computation to function, but some databases also include features or modules that rely on advanced mathematical models to perform a specific task (e.g., data visualizations) or explicitly provide statistical analysis.[230]

Additionally, some gang database policies that provide criteria for designating individuals as gang members require law enforcement personnel to perform basic computations to make a designation. For example, the Providence Police Department's previous gang database policy included a list of fourteen weighted criteria for designating a person as a gang member

databases.html ("[D]atabases are typically considered simple record repositories, often seen as the 'first stage' in the creation of more high-tech A.I. systems. But these databases perform varied and advanced functions of profiling, not unlike systems of predictive policing."); Richardson & Kak, *supra* note 189 (manuscript at 13–16) (describing how databases are presented as bureaucratic systems of record-keeping and classification, but in practice they are used by governments for profiling and social control).

228. Pervaiz Shallwani & Julian Cummings, *In Letter to Uniformed Members, NYPD Commissioner Says They Will Have to Fight Crime Differently and with Fewer Street Stops*, CNN (June 17, 2020, 5:14 AM), https://www.cnn.com/2020/06/17/us/nypd-commissioner-letter-crime-less-street-stops/index.html ("That means for the NYPD's part, we'll redouble our precision-policing efforts."); *Mayor De Blasio Appoints Dermot Shea New York City Police Commissioner*, N.Y.C. POLICE DEP'T, (Nov. 4, 2019), https://www1.nyc.gov/site/nypd/news/p1104a/mayor-de-blasio-appoints-dermot-shea-new-york-city-police-commissioner ("Shea was appointed Chief of Crime Control Strategies and Deputy Commissioner for Operations, where he oversaw the CompStat system and honed a new generation of precision approaches that helped drive crime to record lows. He focused the Department not just around arrests, but around intelligence-driven prosecutions . . . .").

229. CAL. DEP'T OF JUST., *supra* note 158, at 2. A relational model is an approach to managing and structuring data in the form of relations.

230. *See, e.g.*, SRA INT'L INC., 2008 ANNUAL REPORT 2 (2008), https://www.annualreports.com/HostedData/AnnualReportArchive/s/NYSE_SRX_2008.pdf ("Our GangNet® database system is a browser-based investigative, analysis, and statistical resource used by law enforcement officials to record and track gang members and their activities.").

and each criterion was given a point value.[231] The policy provided that anyone with ten or more points should be included in the gang database and police officers would compute the matching criteria, except for self-admission, which had an automatic point value of ten.[232]

(b) "to aid or replace government decisions, judgments, and/or policy implementation"

Gang databases aid government decisions and judgments, as well as policy implementation, depending on a jurisdiction's policy priorities. As referenced above, most criminal justice actors and institutions use gang databases to aid various decisions, and other non-criminal justice government officials use the databases or information shared from gang databases to aid decisions regarding institutional safety and resource allocation. In fact, after the Supreme Court decision in *Morales*, government actors have increased their reliance on gang databases to avoid legal challenges, though subsequent federal district and state court decisions have questioned or invalidated the use of certain gang database criteria as a predicate for police action.[233]

Gang databases can also be used to aid policy implementation, particularly after a crisis[234] or in jurisdictions that have identified targeting gang activity as a priority. This is because law enforcement considers gang databases as one of several techniques and tools employed for gang suppression efforts.[235] Reliance on gang databases for policy implementation is also more likely in police departments with a history of civil rights violations. For example, in *Gang Policing: The Post Stop-and-Frisk*

231. *Intelligence Assessment Database Policy*, PROVIDENCE POLICE DEP'T (2018), https://upriseri.com/wp-content/uploads/2018/01/2018-01-01-PPD-Gang-database-policy.pdf; *see also* Steph Machado, *Community Group Files Suit over Providence 'Gang Database,'* WPRI (Jul. 23, 2019, 9:59 PM), https://www.wpri.com/news/local-news/providence/community-group-files-suit-over-providence-gang-database/.

232. *Intelligence Assessment Database Policy*, *supra* note 231; Machado, *supra* note 231.

233. *See, e.g.*, NAACP Anne Arundel Cnty. Branch v. City of Annapolis, 133 F. Supp. 2d 795, 808 (D. Md. 2001) (holding that making hand signals associated with drug-related activity as a predicate for dispersal order was unconstitutionally vague and infringed on First Amendment rights); Hodge v. Lynd, 88 F. Supp. 2d 1234, 1244–45 (D.N.M. 2000) (holding that wearing clothing perceived to be gang-related as a predicate for dispersal order violated vagueness doctrine); Johnson v. Athens-Clark Cnty., 529 S.E. 2d 613, 616 (Ga. 2000) (holding that using a person's presence in a known drug area as a predicate for police action is unconstitutionally vague).

234. Crises, whether real or fabricated, fuel moral and crime panics that law enforcement institutions leverage for more resources and political support. Criminologists Richard C. McCorkle and Terance D. Miethe note that "[a]fter the crisis, there is little retrenchment [in police budgets and power] because the public and elected officials have come to believe that an increased police presence is required to sustain the peace, a perception nurtured by law enforcement bureaucrats interested in maintaining funding levels." MCCORKLE & MIETHE, *supra* note 147, at 59.

235. Leyton, *supra* note 157, at 110.

Justification for Profile-Based Policing, legal scholar K. Babe Howell details how in 2013, the NYPD increased use of its gang database and covert surveillance to advance a new policy priority of policing "crews," a law enforcement term for gangs that are loosely organized, neighborhood-based, and primarily comprised of young people.[236] She argues that this increased reliance on gang databases was intentional because their use was less likely to be subject to review or legally challenged since they are not governed by constitutional or statutory requirements like the NYPD's recently invalidated stop-and-frisk regime.[237]

(c) "that impact opportunities, access, liberties, rights, and/or safety"

Gang databases impact individuals' and communities' civil rights and liberties, access to opportunities, and safety. Though law enforcement's gang database practices vary greatly, research on and legal challenges to gang databases have asserted and in some cases demonstrated that government use of gang databases impacts rights to equal protection, due process, association, privacy, freedom from unreasonable searches and seizures, freedom from unwanted false-light publicity, and freedom from racial harassment and intimidation.[238] Gang database designation is also stigmatizing, therefore limiting or completely foreclosing educational, employment, housing, social, immigration, and economic opportunities for individuals in the database.[239] Moreover, since most gang databases are disproportionately composed of Black and Latinx people, the aforementioned collateral consequences of gang database designation reproduce and compound the social, economic, and political disparities and disadvantages endured by these communities because of centuries of structural and institutional racism.[240]

236. Howell, *supra* note 171, at 4–6.

237. *Id.* at 14.

238. *See e.g.*, Leyton, *supra* note 157, at 122–40; Wright, *supra* note 205, at 117–18.

239. *See, e.g.*, Irene Romulo, *'Gang Contracts' in Cicero and Berwyn Schools Raise Concerns About Criminalization of Youth*, INJUSTICE WATCH (May 26, 2021), https://www.injusticewatch.org/news/juvenile-justice/2021/cicero-gang-contracts/ (describing the use of a gang database by schools and police departments in Cicero, Illinois, to "force students into alternative schools or push them out of school completely"); Letter from Zoey Chenitz et al., Co-Chair, Civil Rights Committee, to Philip Eure, Inspector General, Office of the Inspector General 3 (Apr. 27, 2021) ("Gang database policing also dehumanizes members of Black and Latinx communities and severely restricts their freedom of association and their right to express themselves . . . because most gang raids take place in low-income communities, typically targeting [New York City Housing Authority] public housing developments, the practice effectively criminalizes poverty . . . .").

240. NAT'L RSCH. COUNCIL, MEASURING RACIAL DISCRIMINATION 223–40 (Rebecca M. Blank et al. eds., 2004) (explaining theories and consequences of cumulative disadvantage); GANDY, JR.,

Gang database use also has individual and community-wide consequences on safety. Not only are individuals identified in gang databases subjected to increased police scrutiny and harassment, but so are their family members, neighbors, and other individuals that share any characteristics (e.g., race, age, height, gender presentation).[241] Indeed, criminology scholars have indicated "[t]he absence of a clear and substantive definition of gangs and gang members may also serve to focus police attention on poor minority youth, who follow normative systems different from those held by a majority of police officers."[242] Research has also demonstrated that this heightened scrutiny is often accompanied by more excessive force by police officers, which directly impacts the safety of designated individuals and their community.[243] Finally, when gang database information is leaked or otherwise revealed to non-governmental actors, individuals or areas can be targeted by rival gangs for violence.[244]

(d) "Automated [d]ecision [s]ystems can involve predicting, classifying, optimizing, identifying, and/or recommending"

Gang databases involve classification and identification. Though classification is an inherent function of any database that organizes information,[245] it is an explicit function of gang databases because law enforcement uses statutory, formal, and informal policies and criteria to determine what individuals and information to include. Further, law enforcement has full discretion in how it characterizes[246] individuals (e.g.,

---

supra note 16, at 81 (arguing that the widespread use of ADS automates and reproduces discrimination, thus negatively affecting the life chances of Black people).

241. *See, e.g.*, Complaint at 3, Chicagoans for an End to the Gang Database et al. v. City of Chicago, No. 18-cv-04242 (N.D. Ill. June 19, 2018) (alleging the Chicago Police Department relied on gang database designations to "harass, falsely arrest, and falsely imprison class members"); CITIZENS FOR JUV. JUST., *supra* note 218, at 22 (highlighting that the New Bedford Police Department used gang labels of individuals to stop and harass their family members).

242. MCCORKLE & MIETHE, *supra* note 147, at 208; *see also* LANE, *supra* note 177, at vii–xi (detailing the street and social media practices of young people in Harlem, New York, to avoid, diffuse, or walk away from violence and gang activity and how several criminal justice actors misinterpret this behavior because of their own biases, lack of cultural context, and different normative systems); Stuart, *supra* note 190, at 194 ("[L]aw enforcement personnel overwhelmingly lack the cultural competencies and knowledge necessary to accurately comprehend and regulate the cultural practices of urban youth. Criminal justice actors are particularly prone to misidentify and thus criminalize non-violent interactions and ordinary behaviors, especially those related to expressions of black cultural identity . . . .").

243. Katz, *supra* note 183, at 490.

244. Barrows & Huff, *supra* note 162, at 678.

245. LYON, *supra* note 226, at 73.

246. "The act of classification is a moral one because each standard or category valorizes one viewpoint and silences another; it can create advantage or suffering." *Id.* (citing BOWKER & STAR, *supra* note 15, at 5–6 (1999)).

gang member, gang affiliate, or person of interest) and information (e.g., labeling social media activity as gang or criminal activity). Once added, database subjects are reduced to the fixed classifications of the gang database. These fixed classifications are a byproduct of database design, the routine surveillance practices that precede gang database designations, and institutional priorities related to gangs.[247]

In a similar vein, gang databases also involve identification, though as with many ADS, such identifications may not reflect reality. Gang databases allow law enforcement to identify individuals and groups as gangs, gang members, gang affiliates, or other persons of interest classifications, and information or observations as gang or criminal activity and areas. Since all of these labels are based on unstable legal classifications and subjective normative judgments, the identification enabled by gang databases is dubious despite being heavily relied upon by various government actors and institutions for decision-making.[248]

III. EXEMPTIONS TO THE ADS DEFINITIONS

Most modern software, systems, and processors used by governments rely on algorithms and statistical techniques to perform their intended function, so while the definitions are intentionally comprehensive, they are not intended to subject every technical system used in government to regulation. For this reason, it is important for policymakers to identify systems exempt from the ADS definitions. Exemptions provide more clarity for oversight and enforcement of ADS laws and regulations, as well as quell claims that an ADS law or rule is overbroad or vague.

---

247. *Id.* at 74 ("On a much larger scale, bureaucracies also use lists as a means of organizing reality according to organizational priorities, and . . . surveillance categories make people up to fit them . . . ."); Poster, *supra* note 179, at 185 (describing how database subjects lack agency to know or correct entries so their identity and relevant narratives reflect database rules of formation or underlying policy objectives); French & Browne, *supra* note 177, at 275 ("This routine surveillance work is structured in relation to the knowledge needs of other risk-managing organizations. Accordingly, police use categories like 'age, race, gender, and ethnicity' to describe their observations and to build risk profiles of populations—this activity 'forces people into specific institutional identities.'").

248. JACOBS, *supra* note 200, at 24–25; LANE, *supra* note 177, at 141–42 (recounting how prosecutors use gang database identification to create or support criminal conspiracy charges); Leyton, *supra* note 157, at 114–20 (describing how the difficulty in identifying gang members can lead to inaccurate entries, and the challenges of compliance and quality control undermine the accuracy of gang databases); Marjorie S. Zatz & Richard P. Krecker, Jr., *Anti-Gang Initiatives as Racialized Policy*, *in* CRIME CONTROL AND SOCIAL JUSTICE: THE DELICATE BALANCE, *supra* note 157, at 173, 176–78 (highlighting the broad discretion police have in making youth gang designations and how these identifications influence risk assessment scores and juvenile court decisions).

Exemptions are not universal and require local and context-specific evaluation about how the system is operationalized by government agencies, the history of the system's use in government, and its impact. Such analysis is necessary because cursory reviews that merely rely on marketing materials or agency declarations can lead to false conclusions that exempt systems may appear innocuous but pose serious risks to the public or threaten the integrity of government agencies. Additionally, blanket exemptions can create a perverse incentive for ADS developers to design or reproduce technologies in a way that can evade scrutiny or regulation.[249] The following Sections evaluate two technical systems commonly used by government agencies and offer explanations on whether they should be exempted from the ADS definitions.

A. Email Spam Filters

Email filtering is a process of organizing or inspecting email according to a specified criterion, which can be performed manually by a human or automated processing.[250] The most common form of automated email filtering is the detection and removal of unsolicited, unwanted, or computer virus-affected messages (spam), which are colloquially known as spam filters.[251] Spam filters employ several heuristic methods that rely on probabilistic classifiers to detect and distinguish spam emails from desired emails, and they typically apply to inbound email.[252] Probabilistic classifiers are a statistical technique that calculates the probability of a specified observation or event,[253] so in this case it calculates the probability that an email is or is not spam. Heuristic methods are the different types of predefined criteria or rules about the content or other email features that guide

249. The Anh Han et al., *To Regulate or Not: A Social Dynamics Analysis of an Idealised AI Race*, 69 J. A.I. RSCH. 881 (2020) (finding that the AI arms race narrative can lead AI developers to ignore ethical and safety precautions in order to attain or maintain a dominant position); Meredith Whittaker, *The Steep Cost of Capture*, INTERACTIONS (Nov.–Dec. 2021), https://interactions.acm.org/archive/view/november-december-2021/the-steep-cost-of-capture (arguing that technology companies are incentivized to push for regulations that aid their concentration of power rather than democratic values or outcomes); Yochai Benkler, *Don't Let Industry Write the Rules for AI*, NATURE (May 1, 2019), https://www.nature.com/articles/d41586-019-01413-1 (arguing that the technology industry's participation in policy and regulatory discourse is harmful because it frames AI research and regulation to benefit its interest over societal interests).

250. Emmanuel Gbenga Dada et al., *Machine Learning for Email Spam Filtering: Review, Approaches and Open Research Problems*, HELIYON (June 2019), https://www.sciencedirect.com/science/article/pii/S2405844018353404; *Spam Filtering*, FORTINET, E**rror! Hyperlink reference not valid.**https://www.fortinet.com/resources/cyberglossary/spam-filters (last visited Mar. 13, 2022).

251. Dada et al., *supra* note 250; *Spam Filtering*, *supra* note 250.

252. Dada et al., *supra* note 250.

253. *Id.*

the filtering process.[254] For example, content spam filters evaluate the content of an email by scanning for words that are common in spam emails. These filters typically employ a natural language processing algorithm known as "bag-of-words" to identify the occurrence or presence of words in a predefined corpus.[255]

Though spam filters are a common built-in feature in all commercial emails, spam filters are important for government agency emails because of harmful effects spam can have on government information technology infrastructure.[256] In general, spam negatively affects an individual user's computer storage capacity and network bandwidth. However, a "huge volume of spam mails flowing through the computer networks have destructive effects on the memory space of email servers, communication bandwidth, CPU power and user time."[257] Additionally, malicious spam emails can lead to data breaches at organizations.[258]

While spam filters meet most of the technical aspects of the ADS definitions, in that they are systems that use computation and involve functions like classification, they do not inform government decision-making or impact the public, except when they fail to work. For example, an aggressive or flawed spam filter could improperly block important government emails, which can affect decision-making or policy implementation in a manner that impacts the public. Yet, even in this predicament the spam filter and its flawed outcomes are not designed or used for aiding government decision-making or policy implementation, and the connection between government action and societal impact is conjectural. Thus, spam filters can be exempted from the ADS definitions.

254. *Id.*

255. Nikita Sharma, *Spam Filtering Using Bag-of-Words: Guide to Building Your Own Spam Filter in Python*, HEARTBEAT (May 12, 2020), https://heartbeat.fritz.ai/spam-filtering-using-bag-of-words-1c5484ff07f1.

256. *Anti-Spam Toolkit: Governments*, INTERNET SOC'Y, https://www.internetsociety.org/spamtoolkit/governments/ (last visited Mar. 6, 2022) (describing how spam can be harmful to government infrastructure and offering guidance on how governments can combat these risks).

257. Dada et al., *supra* note 250.

258. Brian Krebs, *Florence, Ala. Hit by Ransomware 12 Days After Being Alerted by KrebsOnSecurity*, KREBSONSECURITY (June 9, 2020), https://krebsonsecurity.com/2020/06/florence-ala-hit-by-ransomware-12-days-after-being-alerted-by-krebsonsecurity/; Andrew Westrope, *L.A. County Confirms Phishing Attack, No Services Disrupted*, GOVTECH (Jan. 10, 2020), https://www.govtech.com/security/la-county-confirms-phishing-attack-no-services-disrupted.html.

B. Accounting Software

Accounting software systems have become an integral information technology for private and public institutions. Accounting software typically includes various modules dealing with different aspects of accounting like recording and processing financial transactions (e.g., expenses and payments received), tracking and overseeing funds and finances, managing payroll, and budgeting. Some accounting software also includes enterprise resource planning ("ERP") applications, which integrate and include financial management and operations functions.[259] Accounting software can be developed in-house, purchased from a third-party vendor,[260] or be a combination of both, and the software can be internet-enabled or intranet-based, both allowing for optimal accessibility. In the United States, accounting software used by state and local governments often comply with standards established by the Governmental Accounting Standards Board ("GASB"), a private non-profit and non-governmental organization that establishes government accounting and financial reporting standards.[261] In fact, thirty-two states mandate compliance with GASB standards by statute, and thirteen states and the District of Columbia comply without statutory mandate, but in hopes of receiving favorable audits.[262]

A cursory review would suggest that accounting software systems should be exempted from our ADS definitions; however, I recommend that these systems require context and system specific analysis to make an appropriate determination. While most accounting software is used for financial management tasks, some systems, particularly those including ERP applications, can be leveraged for identification and classification purposes, in addition to informing government decisions and judgments that impact government employees and constituents. This is because these more comprehensive or advanced accounting software systems are better understood as management accounting tools, which seek to improve the efficiency and productivity of an existing operation while still providing

259. For example, Oracle makes enterprise resource planning applications, modules, and all-inclusive systems. Oracle's "Financials" products include traditional accounting functions and services. Oracle also offers other products that perform more advanced features and analytics for human resources, supply chain, business planning, competition strategy, and compliance. *See Oracle Fusion Cloud Enterprise Resource*, ORACLE, https://www.oracle.com/erp/ (last visited Feb. 19, 2022).

260. For example: Intuit's Quickbooks, SAP's Business One, or Accufund's Municipal Accounting Software.

261. *About the GASB*, GOVERNMENTAL ACCT. STANDARDS BD., https://www.gasb.org/aboutgasb (last visited Feb. 19, 2022).

262. Emilia Istrate, Cecilia Mills & Daniel Brookmyer, NAT'L ASS'N FOR COUNTIES, COUNTING MONEY: STATE & GASB STANDARDS FOR COUNTY FINANCIAL REPORTING 2 (2016), https://www.naco.org/sites/default/files/documents/CountingMoney_report_FINALv2.pdf.

traditional accounting modules.[263] This distinction is significant, since many of the methods and practices that inform modern management accounting, including its software applications, emanate from slavery.[264] Indeed, the systematic accounting practices developed and advanced on antebellum plantations blended record keeping, data analysis, surveillance, and experimentation with the distribution of incentives and punishment in a way that transformed industrial management and the global commodity economy.[265]

Accounting software systems can function as private rulemaking, in that record keeping and data analysis can be used to covertly and informally surveil employees, contractors, or populations whose information is particularly visible and accessible through software modules, as well as inform sophisticated systems of incentives and penalties to manipulate conduct and operations.[266] When understood in this context, government agencies' use of accounting software can involve classification or optimization when an agency tries to lower operating expenses, which can in turn inform decisions about resource allocation or austerity measures,[267] or involve identification for employment decisions such as hiring, layoffs,

---

263. *See* Elisabetta Mafrolla, *Management Accounting as a Science: From Costs and Benefits Analysis of Productions to Strategic Planning of Uncertainty*, 12 J. MOD. ACCT. & AUDITING 577, 577–78 (2016) (describing management accounting in relation to the more colloquially understood financial accounting); She-I Chang et al., *A Delphi Examination of Public Sector ERP Implementation Issues*, 2000 PROC. 21ST INT'L CONF. ON INFO. SYS. 494–95 (describing ERP use by government agencies in Queensland); GLENDALE, CALIFORNIA, ENTERPRISE RESOURCE PLANNING (ERP) SYSTEM PROCUREMENT AND IMPLEMENTATION SERVICES RFP "ERP-2014" 5 (2014), http://www.glendaleca.gov/home/showdocument?id=19250 [hereinafter ERP-2014].

264. CAITLIN ROSENTHAL, ACCOUNTING FOR SLAVERY: MASTERS AND MANAGEMENT xii–xiii (2018); EDWARD E. BAPTIST, THE HALF HAS NEVER BEEN TOLD: SLAVERY AND THE MAKING OF AMERICAN CAPITALISM xxiii (2014).

265.

> Their practices rapidly transformed the southern states into the dominant force in the global cotton market, and cotton was the world's most widely traded commodity at the time, as it was the key raw material during the first century of the industrial revolution. The returns from cotton monopoly powered the modernization of the rest of the American economy, and by the time of the Civil War, the United States had become the second nation to undergo large-scale industrialization. In fact, slavery's expansion shaped every crucial aspect of the economy and politics of the new nation—not only increasing its power and size, but also, eventually, dividing US politics, differentiating regional identities and interests, and helping to make civil war possible.

BAPTIST, *supra* note 264, at xxi; *see also* ROSENTHAL, *supra* note 264, at 94–120.

266. ROSENTHAL, *supra* note 264, at 94–100.

267. David Heald & David Steel, *The Governance of Public Bodies in Times of Austerity*, 50 BRIT. ACCT. REV. 149, 150 (2018) (describing the use of accounting practices and systems during a period of fiscal austerity).

scheduling, and government contracting.[268] Such decisions can impact constituent access to government services and resources, especially when use of accounting software informs austerity measures. When the impact of such decisions are not evenly distributed across a community (e.g., school or fire department closures) the effects are not only immediate and long-term[269] but compounded, thus impeding or at least posing a risk to safety, civil rights, and civil liberties.[270] Additionally, when accounting systems fail they can affect a municipality's overall budgeting process.[271] Thus, policymakers must assess not only what type of accounting software is being used, but how it is being used to determine whether it should be exempted from the ADS definition.

CONCLUSION

In order for an ADS law to be successfully complied with, enforced, and interpreted, various audiences must understand what ADS are and their impact. Yet, this can only be accomplished if there is shared meaning that does not require or presume particular knowledge, expertise, or experience. The comprehensive and narrow ADS definitions achieve this goal by clarifying the various forms ADS can take, the role of computation, their relationship to governance, the actions or functions they are performing, and naming their impact in a sector and discipline agnostic manner. In addition to providing shared meaning, this definitional approach makes legislative and regulatory definitions more adaptable so that they can be adopted across jurisdictions that have different legal frameworks for addressing legal issues presented by emergent technologies.

These definitions also help demystify ADS as objective or neutral tools. The definitions and the "real world" use cases demonstrate that ADS are social and political artifacts as much as they are technical, in that they reflect

---

268. ERP-2014, *supra* note 263, at 21–22 (detailing several module design requirements that are used to inform employment decisions and judgments).

269. Aldo Toledo, *San Mateo County Court to Cut 20 Positions, Reduce Office Hours by Half Amid Budget Cuts*, MERCURY NEWS (Aug. 6, 2020, 4:23 AM), https://www.mercurynews.com/2020/08/05/san-mateo-county-court-to-cut-20-positions-reduce-office-hours-by-half-amid-budget-cuts/ (detailing various consequences of large reduction in county court staff due to layoffs and furloughs).

270. *See generally* FLOOD, *supra* note 2 (describing long-term consequences and safety problems created by closure of New York City fire departments in primarily lower-income and more diverse communities).

271. *See, e.g.*, Ben Tansey, *Council Adopts Provisional Budget: Finance Department Receives $80,000 to Clean Up Books*, S. PASADENAN. (June 25, 2020), https://southpasadenan.com/council-adopts-provisional-budget-finance-department-receives-80000-to-clean-up-books/ (cleaning up accounting system failure has used significant resources and caused delays in South Pasadena's annual audit and other budgeting projects).

and concretize the public policies and practices that preceded their development and use. The education policies that gave rise to teacher evaluation systems reflect the misguided logic of the education accountability movement that preceded their development, and their continued use contributes to growing educational inequities in American public schools. It is also not a coincidence that gang database designations produce a perpetual blacklist effect, since the intelligence practices that preceded and influenced the development and use of gang databases, especially law enforcement targeting of political activists or alleged Communists, yielded similar outcomes. Since public discourse about ADS often ignores these histories and the full extent of their social consequences, the tendency for ADS to enable or facilitate government subjugation is often rendered banal or normalized. Therefore, the ADS definitions and analytical framework offered in this Article can serve as an important intervention in public policy and scholarly discourse by grounding future ADS policies in the world of practice they intend to govern.

The use cases and definitional analysis also demonstrate that the motivations to create ADS, their design, and how they are ultimately used are inextricably linked to policy, social interests, and how these interests are renegotiated overtime. Both use cases reveal that despite good faith motivations, ADS can and do produce counterproductive and negative outcomes, and such outcomes are more likely when: (1) ADS development or use derives from public policies used to govern social marginality;[272] and (2) when the ADS disproportionately targets or affects communities of color and poor people.[273] Thus, the ADS definitions help clarify the function and process of these technologies as a prominent mode of governance, and this understanding can better enable systemic evaluation of ADS, their relevant social domains, and broader public policy needs.

The definitions account for the variation and uncertainty of ADS in practice, and their embedded nature in modern politics and society. Often these systems are ill-defined and are operating on already amorphous and subjective categories without regard for social or economic costs, such as the inconsistent definitions of "gangs" in gang databases and measures of "value added" in standardized teacher evaluations. Yet, my definitions ground these governing technologies by acknowledging and emphasizing their capacity to

272. Here I am referring to public policy regimes that are more punitive in effect and tend to stigmatize individuals and groups to justify differential treatment. The use cases demonstrate one or both of these elements. For example, gang database designation results in more punitive criminal charges or sanctions. *See* Richardson & Kak, *supra* note 189.

273. *See e.g.*, AMREIN-BEARDSLEY, *supra* note 19, at 25–28 (evaluating VAM use in the Houston Independent School District and noting that terminated teachers were predominantly women and racial minorities).

transform liberties, rights, access, safety, and other social outcomes. The application of the use cases to the narrow definition demonstrates that even a more constrained definition that prioritizes impact over process or technical specificity can do better work in regaining accountability for the actors and institutions that support and use ADS. The analysis of ADS exemptions showed the technical, social, and political considerations that must be assessed to avoid exclusion of consequential technologies.

Though my analysis of ADS is critical, I remain optimistic about their potential as tools for social change. Data-driven solutions should not foreclose opportunities for systemic re-evaluation of how society is governed, and the roles of government and technology. Indeed, a more critical examination of the history, politics, and social dynamics associated with any ADS and its relationship to governance is crucial for identifying meaningful pathways forward. The definitions and analytical framework provided in this Article can aid in identifying appropriate laws, regulations, and other safeguards for ADS use, such as the types of training government actors using ADS should receive to better mitigate errors from flawed ADS or consequences that stem from ADS-human interactions, cumulative disadvantage, or related social policies.[274] This Article can also serve as an analytical guide for advocates and local communities seeking to evaluate what social problems can benefit from government or technological interventions versus community-based solutions.

274. *See, e.g.*, De-Arteaga et al., *supra* note 45, at 9 (noting that an unanswered question from research is whether prior experience in the role before ADS use and training can affect government actors' behavior and ADS outcomes).