

Remedying Public-Sector Algorithmic Harms: The Case for Local and State Regulation via Independent Agency

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Algorithms increasingly play a central role in the provision of public benefits, offering government entities previously unimaginable ways of optimizing public services, but they also pose risks of error, bias, and opacity in government decision-making. At present, many publicly-deployed algorithms are created by private companies and sold to government agencies. Given robust protections for trade secrets in the courts and feeble state open records laws, such algorithms, even those with fundamental flaws or biases, may escape regulatory scrutiny. If state and local governments are to avail themselves of the benefits of algorithmic governance without triggering its potential harms, they will need to act quickly to design regulatory systems that are flexible enough to respond to continual innovation yet durable enough to withstand regulatory capture. This Note proposes a novel regulatory solution in the form of a new, independent agency at the state or local level — an Algorithmic Transparency Commission — devoted to the regulation of publicly-deployed algorithms. By establishing such an agency, tailored to the needs of each jurisdiction, state and local governments can continue to enhance their efficiency and safeguard companies' proprietary information, while also fostering a greater degree of algorithmic transparency, accountability, and fairness.

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I. INTRODUCTION

Over the past few decades, state and local agencies have increasingly begun employing algorithms¹ to optimize the provision of government services. In many jurisdictions, automated decision systems² now determine the priority and timing of building inspections,³ whether someone is eligible for Medicaid benefits,⁴ and whose food subsidies will be terminated.⁵ They sort students into schools,⁶ allocate public housing for homeless individuals,⁷ and estimate the public health dangers posed by individuals at risk of contracting infectious diseases.⁸ They are used by judges in criminal justice proceedings,⁹ by law enforcement for predictive policing¹⁰ and facial recognition,¹¹ by child welfare caseworkers to

1. An algorithm is a sequence of instructions consisting of a set of steps or rules used to perform specific calculations or problem-solving operations.

2. Automated decision systems (also known as automated decision-making systems or ADS) include a broad set of technological systems, namely algorithms, designed to aid or replace human decision-making. Although automated decision systems can incorporate many algorithms, this Note follows much of the literature in using these two terms interchangeably.

3. Brian Heaton, *New York City Fights Fire with Data*, GOV'T TECH. (May 15, 2015), <https://www.govtech.com/public-safety/New-York-City-Fights-Fire-with-Data.html> [<https://perma.cc/2ZHX-MYRL>].

4. Natasha Singer, *Bringing Big Data to the Fight Against Benefits Fraud*, N.Y. TIMES (Feb. 20, 2015), <https://www.nytimes.com/2015/02/22/technology/bringing-big-data-to-the-fight-against-benefits-fraud.html> [<https://perma.cc/PZV3-GMTK>].

5. H. Claire Brown, *How an Algorithm Kicks Small Businesses Out of the Food Stamps Program on Dubious Fraud Charges*, INTERCEPT (Oct. 8, 2018), <https://theintercept.com/2018/10/08/food-stamps-snap-program-usda/> [<https://perma.cc/2NDB-HN7Z>].

6. Tracy Tullis, *How Game Theory Helped Improve New York City's High School Application Process*, N.Y. TIMES (Dec. 5, 2014), <https://www.nytimes.com/2014/12/07/nyregion/how-game-theory-helped-improve-new-york-city-high-school-application-process.html> [<https://perma.cc/3YVY-PU46>].

7. Halil Toros & Daniel Flaming, *Prioritizing Homeless Assistance Using Predictive Algorithms: An Evidence-Based Approach*, 20 CITYSCAPE 117 (2018).

8. Miranda S. Moore et al., *A Surveillance-Based Hepatitis C Care Cascade, New York City, 2017*, 133 PUB. HEALTH REPS. 497 (2018).

9. Julia Angwin et al., *Machine Bias: There's Software Used Across the Country to Predict Future Criminals. And It's Biased Against Blacks*, PROPUBLICA (May 23, 2016), <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing> [<https://perma.cc/G2J5-ENQK>].

10. Predictive policing is “the application of analytical techniques — particularly quantitative techniques — to identify likely targets for police intervention and prevent crime or solve past crimes by making statistical predictions” (citation omitted). Kristian Lum & William Isaac, *To Predict and Serve?*, SIGNIFICANCE MAG. 14, 16 (Oct. 2016), <https://rss.onlinelibrary.wiley.com/doi/epdf/10.1111/j.1740-9713.2016.00960.x> [<https://perma.cc/5GD2-948D>]; see also Steven Melendez, *NYPD Unveils Controversial Algorithm to Track Crime Patterns*, FAST COMPANY (Mar. 20, 2019),

determine when interventions might be necessary,¹² and by ICE to identify targets for immigration investigation and removal.¹³ In fact, these examples — all of which can be found in New York City alone¹⁴ — merely scratch the surface of the dramatic twenty-first century shift toward algorithmic governance. And while this shift creates extraordinary opportunity, the widespread automation of public functions has remained largely immune from regulatory oversight. This lack of regulatory scrutiny magnifies concerns that automated decisions suffer from unchecked bias, are not adequately rooted in good public policy, and deprive individuals of due process.

This Note is primarily concerned with the automation of *public* functions at the *state and local* level. Over the past several years, there has been increasing discussion about how algorithms used by large *private* companies might be regulated.¹⁵ These efforts are promising, but they do not address the concerns articulated in this Note. For a number of reasons, chiefly the constraints imposed by federalism, the algorithms used by large tech companies like Facebook, Google, and Amazon are amenable to

<https://www.fastcompany.com/90321778/nypd-unveils-controversial-algorithm-to-track-crime-patterns> [https://perma.cc/SVW3-M57C].

11. *NYPD Questions and Answers: Facial Recognition*, N.Y. CITY, <https://www1.nyc.gov/site/nypd/about/about-nypd/equipment-tech/facial-recognition.page> [https://perma.cc/DJ3H-HPDU] (last visited Dec. 2, 2020).

12. Dan Hurley, *Can an Algorithm Tell When Kids Are in Danger?*, N.Y. TIMES (Jan. 2, 2018), <https://www.nytimes.com/2018/01/02/magazine/can-an-algorithm-tell-when-kids-are-in-danger.html> [https://perma.cc/Q2JP-HWEZ].

13. Chris Welch, *NYCLU Sues ICE Over Changes to Immigrant Risk Assessment Algorithm*, VERGE (Dec. 12, 2018), <https://www.theverge.com/2018/12/12/18138243/nyclu-lawsuit-ice-immigration-risk-assessment-tool> [https://perma.cc/V3UR-Z5VX].

14. *Automated Decision Systems: Known New York City Use Cases*, AI NOW INST., <https://ainowinstitute.org/nycadschart.pdf> [https://perma.cc/54AZ-PA35] (last visited Dec. 2, 2020).

15. In 2016, the European Union adopted the General Data Protection Regulation (GDPR), regulating the ownership and processing of personal data to protect privacy; in 2018, California followed suit with a similar measure. California Consumer Privacy Act (CCPA) of 2018, Cal. Civ. Code §§ 1798.100–1798.199 (2018). At the federal level in the United States, large tech companies have come under increasing scrutiny. In April 2019, federal lawmakers introduced the Algorithmic Accountability Act, a bill that, if passed, would empower the FTC to promulgate regulations requiring large companies to assess algorithmic bias. Algorithmic Accountability Act of 2019, H.R. 2231, 116th Cong. (2019), <https://www.congress.gov/bill/116th-congress/house-bill/2231/text> [https://perma.cc/SME8-TW3Y]. Notably, the legislation is designed to target the Amazons and Facebooks of the world, and would not apply to government entities or small companies. Under the Act, covered entities include “any person, partnership, or corporation over which the Commission has jurisdiction under section 5(a)(2) of the Federal Trade Commission Act,” provided such entities also have greater than \$50 million in annual gross receipts or possess the personal information of more than one million consumers or consumer devices. *Id.* § 2(5).

federal regulation in a way that algorithms used by state and local governments are not.¹⁶ As this Note argues, however, regulating local and state actors' role in the proliferation of algorithmic harms is just as necessary.¹⁷ And since courts currently offer insufficient avenues to secure the transparency needed to identify and evaluate such harms,¹⁸ states and localities must address these issues by turning to legislation and regulation. By establishing an independent Algorithmic Transparency Commission, this Note argues, state and local governments can maximize the benefits of algorithmic governance while minimizing the costs.

Viewed optimistically, automation offers local and state agencies previously unimaginable ways of improving government services. Not all types of agency decisions are amenable to automation, but for agencies facing budgetary constraints, the automation of public functions has become an attractive and even necessary option to manage increasingly complex government decision-making across many domains. Through automation, proponents argue, agencies can allocate resources more efficiently and fairly, making local governments more fiscally sustainable.¹⁹ By contracting with private vendors to create automated decision systems, agencies can set priorities and administer unwieldy programs in a manner that improves efficiency and saves taxpayer money.²⁰ But as scholars have increasingly begun to suggest, these tools also carry the potential to exacerbate inequality and, if left unchecked, may pose substantial threats to democratic governance.²¹ Algorithms, like the humans who program them, can be flawed.²² Without robust oversight, they remain vulnerable to

16. See *infra* Part IV.A.

17. The impacts of local and state government policy on everyday people can be just as significant as federal regulation, but state and local algorithmic governance remains much less studied.

18. See *infra* Part II.C.

19. See *infra* Part II.A.

20. See, e.g., Jens Riis Andersen et al., *How Governments Can Harness the Power of Automation at Scale*, MCKINSEY (Feb. 1, 2019), <https://mckinsey.com/industries/public-and-social-sector/our-insights/how-governments-can-harness-the-power-of-automation-at-scale#> [<https://perma.cc/8NX3-5MSH>].

21. See generally CATHY O'NEIL, *WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY* (2016) (documenting how algorithms increasingly operate to reinforce inequality).

22. Karen Hao, *This Is How AI Bias Really Happens and Why It's So Hard to Fix*, MIT TECH. REV. (Feb. 4, 2019), <https://www.technologyreview.com/s/612876/this-is-how-ai-bias-really-happens-and-why-its-so-hard-to-fix/> [<https://perma.cc/8PLJ-VCMC>]; AI Now Institute, Comment Letter on HUD's Proposed Rule to Amend its Interpretation of the Fair Housing Act's Disparate Impact Standard (Oct. 18, 2019), at 5,

many sources of error — errors that can inhibit effective and efficient governance, perpetuate institutional discrimination, and cause devastating harm to people’s lives. This Note argues that as the automation of public functions accelerates, government entities must act quickly to curb these threats.²³

Algorithmic harms can take several forms, but this Note is concerned with three primary types. First, there are simple programming errors.²⁴ Second, there are harms caused by algorithmic bias.²⁵ As discussed in Part II.B, *infra*, these two categories overlap — some types of programming errors can manifest as algorithmic bias — and both types of errors can corrupt an algorithm at many stages of the programming process. Third, there are transparency and democratic accountability harms.²⁶ These harms often sound in due process: namely, the inability to challenge an adverse algorithmic decision or to understand what role an algorithm had in a particular decision and how that decision was made. In many cases, each of these harms may be implicated, but in the absence of regulations aimed at algorithmic transparency and accountability, the first two types of harm can go undetected.²⁷ Without laws requiring algorithmic transparency and administrative opportunities to contest algorithmic decision-making, FOIA and states’ open records laws remain the imperfect alternative — “imperfect because government responses to re-

<https://ainowinstitute.org/ainow-cril-october-2019-hud-comments.pdf> [https://perma.cc/AHG3-R3VA] (“Individual and institutional bias can be introduced at many different stages [of algorithmic programming], including framing the problem that the algorithm is designed to solve, choosing what metrics to optimize for, collecting and preparing the data, developing the model that guides the performance of the tool, and deciding how to present that information to practitioners.”).

23. See Mark Fenwick et al., *Regulation Tomorrow: What Happens When Technology Is Faster than the Law?*, 6 AM. U. BUS. L. REV. 561, 561 (2017) (arguing that “lawmaking and regulatory design needs to become more proactive, dynamic, and responsive”).

24. See, e.g., Christian Chessman, Note, *A “Source” of Error: Computer Code, Criminal Defendants, and the Constitution*, 105 CAL. L. REV. 179, 186–96 (2017) (discussing the many structural sources of error inherent to computer programming).

25. See, e.g., Sandra G. Mayson, *Bias In, Bias Out*, 128 YALE L.J. 2218, 2218 (2019) (responding to the racial bias problems inherent in algorithmic risk assessment, and arguing that the proffered solutions — making algorithms race neutral, adopting some kind of algorithmic affirmative action, or rejecting algorithmic methods altogether — each fail to adequately respond to the issue, which is “the nature of prediction itself” in a racially stratified society).

26. See *infra* Part II.A.

27. As discussed in Part II.B, *infra*, many such harms are never even discovered, let alone remedied.

quests for source codes²⁸ and other relevant data are typically slow, incomplete, or nonresponsive.”²⁹ Moreover, due to courts’ persistent application of trade secret protections to privately-created, publicly-deployed algorithms, these errors may never come to light.³⁰

The effects of errors that *have* come to light have often been sweeping and disastrous. In Colorado, over 900 mistakes were found in an algorithm designed to administer the state’s public benefit system, leading to “hundreds of thousands of incorrect Medicaid, food stamp, and welfare eligibility determinations.”³¹ But programming errors are only part of the issue. The harmful effects of poorly designed or biased algorithms are not equally distributed; algorithmic injustice is borne disproportionately by underprivileged communities.³² Indeed, as Virginia Eubanks writes,

[m]arginalized groups face higher levels of data collection when they access public benefits, walk through highly policed neighborhoods, enter the healthcare system, or cross national borders. That data acts to reinforce their marginality when it is used to target them for suspicion and extra scrutiny. Those groups seen as undeserving are singled out

28. An algorithm’s “source code” consists of the programmer’s human-readable instructions, written in a programming-language, for actions to be executed by the computer program.

29. *Testimony of the New York Civil Liberties Union before the New York City Council Committee on Technology regarding Automated Processing of Data (Int. 1696-2017)*, N.Y. CIVIL LIBERTIES UNION (Oct. 16, 2017), <https://www.nyclu.org/en/publications/nyclu-testimony-nyc-council-committee-technology-re-automated-processing-data> [<https://perma.cc/Z778-ZVXW>]; see also Robert Brauneis & Ellen P. Goodman, *Algorithmic Transparency for the Smart City*, 20 YALE J.L. & TECH. 103, 109–10 (2018) (indicating that most states’ open records laws mandate disclosure of contracts with third-party vendors, although such laws may not extend to trade secrets). FOIA, for its part, also exempts “trade secrets” from the Act’s requirements. 5 U.S.C. § 552(b)(4) (2018).

30. See *infra* Part II.C.

31. Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249, 1256, 1268–69 (2007).

32. See generally VIRGINIA EUBANKS, *AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR* (2018) (discussing the impacts of automated decision-making on poor and working class people in the United States); see also Nick Thieme, *We Are Hard-Coding Injustices for Generations to Come*, UNDARK (Feb. 20, 2018), <https://undark.org/2018/02/20/ai-watchdog-computational-justice/> [<https://perma.cc/4D2X-T8SS>] (“It is a grim truism of modern life that everything from civil rights violations and health crises to environmental degradation and educational barriers are disproportionately suffered by the people least financially and socially equipped to deal with them.”).

for punitive public policy and more intense surveillance, and the cycle begins again.³³

As communities around the country take steps to address racial justice and policing reform, algorithmic transparency must play an integral role in those efforts.

Even when local or state governments manage to implement an algorithm that largely avoids programming errors or algorithmic bias, they sometimes fail to ensure sufficient due process protections. In Michigan, an algorithm administering the state's "fugitive felon" policy improperly disqualified more than 19,000 residents from receiving food assistance benefits without sufficient notice or an opportunity to be heard.³⁴ These examples illustrate the disastrous effects unregulated algorithmic governance can have — not only on the people individually impacted, but also on jurisdictions as a whole.³⁵ Moreover, these are just known examples, and there is reason to believe that these problems may be endemic to algorithmic governance.³⁶

The prospect of reforming algorithmic governance has begun attracting the attention of legislators and regulators. In 2017, the New York City Council became the first legislative body in the United States to pass an algorithmic transparency law ("Local Law 49"), requiring a comprehensive review of its automated decision systems.³⁷ Initially, some advocates viewed this law as a

33. EUBANKS, *supra* note 32, at 6–7.

34. Under Michigan's fugitive felon policy, the state's algorithm automatically disqualified any person with an outstanding felony warrant from receiving benefits under the federal Supplemental Nutrition Assistance Program (SNAP). See Letter of Testimony in Support for S.1876/H.2701, to Joint Committee on State Administration and Regulatory Oversight, MA Leg. (Oct. 1, 2019), <https://ainowinstitute.org/ainow-et-al-ma-testimony-191001.pdf> [<https://perma.cc/NZD7-N8JU>]; see also *Barry v. Lyon*, 834 F.3d 706, 717 (6th Cir. 2016) (holding that the SNAP Act conferred an individual right to receive food assistance benefits enforceable by 42 U.S.C. § 1983 and that the Due Process clause of the Fourteenth Amendment required that the Michigan agency administering the program provide for notice and a fair hearing before denying or terminating such benefits).

35. See *Testimony of the New York Civil Liberties Union*, *supra* note 29 ("[T]his [Colorado algorithm] resulted in cancer patients and pregnant women being falsely denied Medicaid benefits, and eligible food stamp recipients having their benefits discontinued. These mistakes affected hundreds of thousands of people, wasted several hundred million dollars, and resulted in litigation as well as a federal probe." (citations omitted)).

36. See *infra* Part II.A.

37. See N.Y.C. LOCAL LAW NO. 49 (2018); see also *Legislation Details of Local Law No. 49*, N.Y.C. COUNCIL, <https://legistar.council.nyc.gov/LegislationDetail.aspx?ID=3137815&GUID=437A6A6D-62E1-47E2-9C42-461253F9C6D0> [<https://perma.cc/TE27-WWYQ>] (last visited Dec. 2, 2020).

step in the right direction.³⁸ Several additional states and municipalities have since considered similar measures.³⁹ Despite their promise, however, transparency and oversight measures have largely failed to produce any substantive changes in algorithmic governance, let alone the comprehensive administrative and legislative response that this set of problems demands.⁴⁰

The purpose of this Note is to conceptualize a robust framework for legislative and regulatory action that would better equip governments and citizens to address algorithmic harms. More specifically, this Note argues that by establishing new independent agencies — Algorithmic Transparency Commissions — at the state and local level, devoted to regulating publicly-deployed algorithms, government entities can implement efficient automated solutions without sacrificing transparency, accountability, and fairness. Part II discusses the potential benefits of algorithmic governance, the prominent sources of algorithmic harm, and some of the obstacles to reform. Using the story of New York City’s Local Law 49 as a framing device, Part III examines state and local proposals to address harms in public sector algorithmic decision-making, underscoring their relative strengths and weaknesses. Part IV articulates a vision for algorithmic accountability and regulation in the form of a local or state independent agency armed with regulatory, adjudicatory, and enforcement powers. It then explores how such agencies might be designed and their powers exercised, making the case for why this is the best regulatory approach among available alternatives. Part V concludes by reviewing, as a normative matter, what legislative, regulatory, and policy controls would best serve the public interest.

38. See Linda Henry, *NYC’s Task Force to Tackle Algorithmic Bias: A Study in Inertia*, JD SUPRA (May 2, 2019), <https://www.jdsupra.com/legalnews/nyc-s-task-force-to-tackle-algorithmic-51991/> [<https://perma.cc/9JSE-WTC5>].

39. See, e.g., H.B. 378, 91st Leg., Reg. Sess. (Vt. 2018), <https://legislature.vermont.gov/bill/status/2018/H.378> [<https://perma.cc/Z6RJ-WDDP>]; H.B. 2701, 191st Leg., Reg. Sess. (Mass. 2019), <https://malegislature.gov/Bills/191/H2701> [<https://perma.cc/FD27-6BKV>]; H.B.1655, 66th Leg., Reg. Sess. (Wash. 2019), <http://lawfilesexternal.wa.gov/biennium/2019-20/Pdf/Bills/House%20Bills/1655.pdf> [<https://perma.cc/S5XX-LLA5>].

40. See *infra* Part III.

II. PUBLIC SECTOR ALGORITHMIC HARMS AND THE OBSTACLES TO REFORM

This Part proceeds in three sections. Part II.A discusses the potential benefits of algorithmic governance and the need for transparency. Part II.B then examines the features of algorithms that make them susceptible to bias and error. Finally, Part II.C explores the obstacles to reform, arguing that neither state open records statutes nor the courts offer sufficient protections against the algorithmic harms identified in this Note.

A. THE DATAFICATION OF GOVERNMENT AND THE NEED FOR TRANSPARENCY

Just as the use of exceedingly powerful algorithmic decision-making tools has grown in the private sector,⁴¹ governments have increasingly sought them out.⁴² For several reasons, publicly-deployed algorithms have the potential to do a lot of good. First, the automation of public functions can allow agencies to administer unwieldy programs in a manner that improves efficiency and saves taxpayer money. Second, automation is incredibly versatile. Administrative complexity tends to invite automation, but

41. Many corporations have taken advantage of increasingly powerful data collection and automated decision-making tools to target consumers. In the Big Data economy, credit card companies use “behavioral-scoring algorithms to rate consumers’ credit risk because they used their cards to pay for marriage counseling, therapy, or tire-repair services.” Danielle Keats Citron & Frank A. Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 4 (2014). Companies like Google and Facebook track their users’ online behavior and use algorithms to sell targeted advertising, ads served only to the consumers most likely to purchase a particular good or service. Nathalie Maréchal, *Targeted Advertising Is Ruining the Internet and Breaking the World*, VICE (Nov. 16, 2018), https://www.vice.com/en_us/article/xwjden/targeted-advertising-is-ruining-the-internet-and-breaking-the-world [<https://perma.cc/TK4S-VMBA>]. Insurance companies use algorithms and publicly available data to assess risk and determine premiums. Rick Swedloff, *Algorithms and AI Are Radically Changing Insurance. Regulators Are Behind the Curve*, PROMARKET (June 5, 2019), <https://promarket.org/algorithms-and-ai-are-radically-changing-insurance-regulators-are-behind-the-curve/> [<https://perma.cc/XGV7-89R5>] (“[I]n the context of interactive life insurance policies, insurers using AI know more about their policyholders’ personal lives than ever before; those who have no extra time in their schedules for exercise and no easy access to healthier food options will have to pay more for insurance.”); see also Shoshana Zuboff, *Big Other: Surveillance Capitalism and the Prospects of an Information Civilization*, 30 J. INFO. TECH. 75 (2015) (discussing the mass collection, repackaging, and commodification of personal data).

42. See Brauneis & Goodman, *supra* note 29, at 111 (“Algorithmic governance is made possible by vast increases in computing power and networking, which enable the collection, storage, and analysis of large amounts of data.”).

even where government agencies determine that human input is essential to a particular administrative task, some automation can prove useful. Indeed, automated decision systems (“ADS”) can be classified as low, medium, or high automation systems.⁴³ In a low automation ADS, an algorithm might analyze a data set later used to inform a human decision.⁴⁴ In a medium automation ADS, an algorithm might produce an advisory decision subject to human review about whether to implement it.⁴⁵ In a high automation ADS, an algorithm might make decisions without any human input, and the agency official might simply implement the decision.⁴⁶

Third, public sector algorithms — when properly designed and subject to regular audit or review — can help make systems fairer and, perhaps just as significantly, maintain the appearance of fairness. With the appropriate regulations, these systems have the potential to eliminate arbitrary decision-making from the administrative process. Naturally, groups may continue to disagree about the principles behind a particular algorithm’s design, the weight it assigns to various factors or data, and the degree to which its decisions should be subject to review by a government official or a court. But, as discussed in Part II.B, *infra*, when these aspects of automated decision systems are made transparent to the public, algorithmic governance can bolster democratic legitimacy and increase trust in public institutions.

At present, however, algorithmic transparency simply does not exist. Although some states and municipalities have begun to pass laws regulating government surveillance and the use of facial recognition technology,⁴⁷ jurisdictions have not yet examined the plethora of automated decision systems used by public agencies. Nor have they enacted regulations that would identify what, if any, sources of error or bias such systems may currently have. As a result, very little public information exists about how many algorithms are used in a given jurisdiction or by a given

43. See Aki Younge et al., AUTOMATING NYC, <https://automating.nyc/#design-decisions-header> [https://perma.cc/QF7D-Y8J8] (last visited Dec. 2, 2020).

44. *Id.* (“Imagine a dashboard that tells you what percentage of reported potholes have been filled this month without suggesting a specific next action.”).

45. *Id.* (“Imagine a scoring system that prioritizes buildings to inspect for fire risk.”).

46. *Id.* (“Imagine a traffic light system that sends you a ticket when it detects that you ran a red light.”).

47. See, e.g., Russell Brandom, *Portland, Maine Has Voted to Ban Facial Recognition*, VERGE (Nov. 4, 2020), <https://www.theverge.com/2020/11/4/21536892/portland-maine-facial-recognition-ban-passed-surveillance> [https://perma.cc/E6ZR-V6VN].

agency, what types of algorithms are in use, what decisions they are tasked with making, how they are programmed and audited, who designed them, and what principles governed their design.⁴⁸ This opacity casts doubt on the potential benefits of publicly-deployed algorithms. Without insight into how much algorithms cost to design or purchase, their effectiveness, or their susceptibility to error, neither governments nor advocates can determine whether they are efficient or fair. Thus, any successful regulatory intervention must begin with transparency. Only then can jurisdictions ensure that they are minimizing algorithmic harm without squandering the capacity of well-designed algorithms to improve the way public agencies operate.

B. BIAS, ERROR, AND THE ALGORITHMIC DIFFICULTY

Algorithms are sequences of steps or rules programmed to solve a specific problem or perform a specific calculation. At each step in the sequence, the person programming the algorithm must ask a series of questions, weigh trade-offs, and make choices, many of which may have a substantial effect on the outcome. She must determine, as an initial matter, the purpose for which the algorithm is being designed. Does she want to solve a specific problem or perform a specific task? How can the algorithm best perform its designated function? What principles lie behind the programmer's desired approach to the task or problem? In answering these questions, programmers make decisions about which variables to prioritize and what instructions to give, as well as what data to train the algorithm on.⁴⁹

Algorithms come in an extraordinary range of shapes and sizes, and with the advent of machine learning, the “development of ever-more-abstract and sophisticated learning algorithms is hap-

48. For a list of known New York City uses of automated decision systems, see *supra* note 14.

49. See FACEBOOK'S CIVIL RIGHTS AUDIT — FINAL REPORT 77 (2020), <https://about.fb.com/wp-content/uploads/2020/07/Civil-Rights-Audit-Final-Report.pdf> [<https://perma.cc/Y7V2-8DAG>] (“One source of bias can be the underlying data used in building and training the algorithm; because algorithms are models for making predictions, part of developing an algorithm involves training it to accurately predict the outcome at issue, which requires running large data sets through the algorithm and making adjustments. If the data used to train a model is not sufficiently inclusive or reflects biased or discriminatory patterns, the model could be less accurate or effective for groups not sufficiently represented in the data, or could merely repeat stereotypes rather than make accurate predictions.”).

pening at an accelerating pace.”⁵⁰ In spite of this incredible versatility, the decision about whether to automate at all can be complicated. Algorithms are often designed with the object of lowering the cost of decision-making, but when achieving fair administrative outcomes in a particular area requires certain types of complexity and nuance, human decisionmakers may be superior. In deciding whether and how to automate, striking the appropriate balance between efficiency and fairness can be difficult.⁵¹

Like human decision-making, algorithms are subject to many sources of bias and error.⁵² These two categories of harm — bias errors and programming errors — are overlapping, and both types of errors can corrupt an algorithm at each of the above-mentioned stages of the programming process. First, simple programming errors can and do cause substantial problems, and even experienced coders make technical mistakes.⁵³ Second, if an algorithm’s data inputs are poorly selected, the outputs may be misleading, if not wrong. These errors can sometimes manifest as algorithmic bias. If the data sets on which algorithms are trained reflect societal discrimination, such algorithms may replicate that discrimination⁵⁴ — a phenomenon one scholar calls “bi-

50. Andrew Tutt, *An FDA for Algorithms*, 69 ADMIN. L. REV. 83, 99 (2017). As one artificial intelligence expert puts it, “[a]ny two AI designs might be less similar to one another than you are to a petunia.” Eliezer Yudkowsky, *Artificial Intelligence as a Positive and Negative Factor in Global Risk*, GLOBAL CATASTROPHIC RISKS 308, 313 (Nick Bostrom & Milan M. Ćirković eds., 2008). Any effective agency overseeing automated decision systems would necessarily have to contend with the unique regulatory challenges posed by different kinds of algorithms, but a precise analysis of the different available approaches is beyond the scope of this Note.

51. Many legal rules, similarly, including the procedural protections guaranteed by Due Process, can be characterized as evolving out of an attempt to balance two (sometimes) competing principles: fairness and efficiency. See, e.g., *Mathews v. Eldridge*, 424 U.S. 319, 332–33 (1976).

52. See Chessman, *supra* note 24, at 186–96.

53. See *Testimony of the New York Civil Liberties Union*, *supra* note 29 (“One study found that even highly experienced programmers failed to identify or correct technical mistakes when coding, which resulted ‘in almost 1% of all expressions contained in source code being wrong.’” (citing Chessman, *supra* note 24, at 186)).

54. See, e.g., SAFIYA U. NOBLE, ALGORITHMS OF OPPRESSION: HOW SEARCH ENGINES REINFORCE RACISM (2018) (demonstrating how search algorithms, which reflect the biases of the people who program and use them, often perpetuate racial bias); Alistair Barr, *Google Mistakenly Tags Black People as ‘Gorillas,’ Showing Limits of Algorithms*, WALL ST. J. (Jul. 1, 2015), <https://blogs.wsj.com/digits/2015/07/01/google-mistakenly-tags-black-people-as-gorillas-showing-limits-of-algorithms/> [<https://perma.cc/23K8-NRQY>] (discussing Google’s flawed image recognition algorithms); HUD’s Implementation of the Fair Housing Act’s Disparate Impact Standard, 84 Fed. Reg. 42854 (proposed Aug. 19, 2019) (to be codified at 24 C.F.R. pt. 100); AI Now Institute, *supra* note 22 (“[W]hile some argue that

as in, bias out.”⁵⁵ For risk-assessment tools in the criminal justice system, for example, “risk has collapsed into prior criminal history, and prior criminal history has become a proxy for race.”⁵⁶ Similarly, law enforcement agencies relying on historical data for predictive policing end up targeting people and communities that have historically been over-policed, and thereby reproduce institutional discrimination against poor people and communities of color.⁵⁷ Without accounting for these historical facts, risk-assessment tools and predictive policing practices are likely to reproduce the biases of the data on which they are based.⁵⁸ As state and local governments continue to acquire new automated decision systems and seek to evaluate and improve upon their current ones, they must not overlook these realities.

A third category of algorithmic harms, sounding in democratic accountability, derives from a lack of transparency. And when government decision-making remains both opaque and unreviewable, the opportunities for bias and error are heightened. Algorithms are often opaque not only to the public, but to govern-

algorithms are favorable because they are trained on extensive, empirically accurate, and objective data, such data actually reflect existing and historical social inequities as well as discriminatory institutional values, systems, and practices.”).

55. Mayson, *supra* note 25, at 2224.

56. Bernard E. Harcourt, *Risk as a Proxy for Race* 2 (Univ. Chi. L. & Econ. Olin Working Paper No. 535, 2010; Univ. Chi. Pub. L. Working Paper No. 323, 2010), [https://chicagounbound.uchicago.edu/cgi/](https://chicagounbound.uchicago.edu/cgi/viewcontent.cgi?article=1265&context=public_law_and_legal_theory)

[viewcontent.cgi?article=1265&context=public_law_and_legal_theory \[https://perma.cc/G9T4-695T\]](https://perma.cc/G9T4-695T); see also Megan T. Stevenson & Jennifer L. Doleac, *Algorithmic Risk Assessment in the Hands of Humans*, IZA Discussion Paper No. 12853 (Dec. 2019) (evaluating impacts of algorithmic risk assessment on felony sentencing).

57. One prominent example is New York City’s “stop-and-frisk” policy. See *Stop-and-Frisk Data*, N.Y. CIVIL LIBERTIES UNION, <https://www.nyclu.org/en/stop-and-frisk-data> [<https://perma.cc/3YJ4-F5KB>] (last visited Dec. 2, 2020) (“Black and Latinx communities continue to be the overwhelming target of these tactics. At the height of stop-and-frisk in 2011 under the Bloomberg administration, over 685,000 people were stopped. Nearly 9 out of 10 stopped-and-frisked New Yorkers have been completely innocent.”).

58. See, e.g., Rashida Richardson et al., *Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems and Justice*, 94 N.Y.U. L. REV. 193, 199–203, 218–19 (2019) (examining how predictive policing systems are built with data derived from “documented periods of flawed, racially biased, and sometimes unlawful practices and policies”); Lum & Isaac, *supra* note 10, at 15 (“Because these predictions are likely to over-represent areas that were already known to police, officers become increasingly likely to patrol these same areas and observe new criminal acts that confirm their prior beliefs regarding the distributions of criminal activity. The newly observed criminal acts that police document as a result of these targeted patrols then feed into the predictive policing algorithm on subsequent days, generating increasingly biased predictions. This creates a feedback loop where the model becomes increasingly confident that the locations most likely to experience further criminal activity are exactly the locations they had previously believed to be high in crime: selection bias meets confirmation bias.”).

ments themselves. Since most state and local governments are not equipped with the resources or expertise necessary to develop automated decision systems for their agency functions, many jurisdictions contract with private vendors to create automated decision systems for public use.⁵⁹ Outsourcing the creation of publicly-deployed algorithms to private companies may save agencies money, but without regulatory oversight and transparency, these public-private partnerships can come at a cost: the loss of democratic accountability and public trust.⁶⁰

Indeed, some “principles of government, like transparency and accountability, conflict with those of the private sector, like maintaining commercial secrecy for competitive advantage.”⁶¹ When governments purchase these systems, “private entities assume a significant role in public administration.”⁶² And until now, this role has largely escaped public accountability.⁶³ Privately developed automated decision systems increasingly shape local government decision-making in ways that neither public officials nor members of the public fully understand. Even the public officials responsible for contracting with private vendors may not have the technical expertise to understand what they are getting.⁶⁴ And

59. See Brauneis & Goodman, *supra* note 29.

60. See Gillian E. Metzger, *Privatization as Delegation*, 103 COLUM. L. REV. 1367, 1408 (2003) (“Privatization holds the potential to yield more efficient and innovative government programs, by allowing the government to harness private expertise, flexibility, and market competition to its advantage. Yet privatization can also lead to abuse and exploitation, because the financial incentives of private companies and organizations often run counter to the public interest and the interests of program participants.” (citations omitted)).

61. David S. Levine, *The People’s Trade Secrets?*, 18 MICH. TELECOMM. & TECH. L. REV. 61, 68 (2011).

62. Brauneis & Goodman, *supra* note 29, at 109 (“What is smart in the smart city comes to reside in the impenetrable brains of private vendors while the government, which alone is accountable to the public, is hollowed out, dumb and dark. The risk is that the opacity of the algorithm enables corporate capture of public power.”).

63. Traditionally, such private action would not constitute state action for constitutional purposes. *But see* Metzger, *supra* note 60, at 1406 (“That private entities play a central role in a program’s implementation may well counsel for application of different constitutional requirements, but the danger is that privatization will remove what are essentially government programs from all judicial constitutional review. The question thus becomes whether it is possible to preserve both the principle of constitutionally constrained, accountable government and constitutional law’s public-private divide in the face of the move to privatized governance.”).

64. Rebecca Heilweil, *New York City Couldn’t Pry Open Its Own Black Box Algorithms. So Now What?*, VOX (Dec. 18, 2019), <https://www.vox.com/recode/2019/12/18/21026229/nyc-ai-algorithms-shadow-report> [<https://perma.cc/S9WX-BXU2>] (“Often, people within agencies really don’t understand how these systems make decisions. They’re mar-

since these private companies often market off-the-rack automated decision systems to a wide variety of jurisdictions, the algorithms may not be tailored to jurisdiction-specific needs.⁶⁵

Suggestions that local and state governments could “avoid the trade secret issue entirely by directly funding the development of open-source computer program” fail to appreciate the lack of resources and expertise that leads agencies to seek out private vendors in the first place.⁶⁶ Although some states, including Minnesota and Arizona, have in some cases “contractually purchase[d] intellectual property rights in an existing proprietary program’s source code,” this solution remains financially unsustainable for many government entities, particularly given how many privately-developed automated decision systems are currently in use.⁶⁷ Other legislatively-created financial and legal incentives to encourage vendors to disclose their source code to agencies — e.g., tax credits, exclusivity agreements, and copyright or patent protection⁶⁸ — can be useful. But by no means do these incentives ensure that a vendor will be willing to disclose this information for an affordable price. In sum, for all their potential benefits, these vendor contracts suffer from two distinct but related oversight gaps: the public’s lack of transparency into government decision-making and the government’s lack of transparency into the algorithms marketed to them by contractors.⁶⁹ Without robust transparency and accountability mechanisms to close both of these gaps, governments and citizens alike will continue to have very little insight into the basis for decisions made or supported by automated decision systems.

keted to by vendors behind-the-scenes, who come with proprietary tools that aren’t available for scrutiny or [aren’t] capable of being scrutinized.”)

65. See, e.g., Brauneis & Goodman, *supra* note 29, at 129 n.89.

66. Chessman, *supra* note 24, at 223–25 (noting that governments could, for instance, develop their own automated decision systems, purchase the rights to a private vendor’s source code, or provide other legal or financial incentives for companies to consent to disclosure of their proprietary information).

67. *Id.* at 224 (Moreover, “purchasing a license in an existing program empirically ends up costing significantly more than simply developing open-source software.”).

68. *Id.* at 224–25.

69. Brauneis & Goodman, *supra* note 29, at 109 (“When a government agent implements an algorithmic recommendation that she does not understand and cannot explain, the government has lost democratic accountability, the public cannot assess the efficacy and fairness of the governmental process, and the government agent has lost competence to do the public’s work in any kind of critical fashion.”).

C. OBSTACLES TO TRANSPARENCY: WHY WE NEED TO LOOK
BEYOND THE COURTS

To minimize the costs of algorithmic governance and maximize the benefits, local and state governments first need significant transparency reforms. As this Part discusses, state open records laws and courts offer insufficient means to achieve algorithmic transparency. Insofar as individuals and groups have tried to rely on open records requests to reveal information about government contracts for automated decision systems, the laws have proven ineffective at securing transparency into the algorithms bought and sold as part of these contracts. Although state open record laws require differing amounts of disclosure, they are generally written broadly enough that “contracts and related correspondence with vendors will almost always be ‘public records’ that must be disclosed.”⁷⁰ Nevertheless, even where local governments are responsive to open records requests, the information sought may not be available — perhaps having never been retained — or it may include trade secrets subject to legal protection.

In *Algorithmic Transparency for the Smart City*, for example, Robert Brauneis and Ellen P. Goodman “set out to test just how opaque local government predictive algorithms are by identifying some of the most common uses of big data prediction in that sector.”⁷¹ By filing forty-two open records requests for six predictive algorithms in twenty-three states, they identified three principal obstacles to transparency: “(1) the absence of appropriate record generation practices around algorithmic processes; (2) insufficient government insistence on appropriate disclosure practices; and (3) the assertion of trade secrecy or other confidential privileges by government contractors.”⁷² In other words, both parties to automated decision system contracts were complicit in maintaining the opacity of such systems. Local governments failed to keep records and insist on vendor disclosure,⁷³ and private contractors

70. *Id.*

71. *Id.* “We identified algorithms developed by foundations, private corporations, and government entities and those used in criminal justice and in civil applications.” *Id.*

72. *Id.* at 110.

73. Absent public pressure, local governments have incentives *not* to insist on vendor disclosure. When an automated decision system does come under public scrutiny, the agency can rely on the trade secret protections afforded to private vendors to avoid responsibility.

avoided disclosure to local governments or the public to protect their proprietary information.⁷⁴ As Brauneis and Goodman's study reveals, states' open records laws are insufficient to detect and deter the harms that publicly-deployed algorithms can cause.⁷⁵ Indeed, in the face of exemptions for trade secrets, open records laws are effectively useless.⁷⁶

Courts and scholars alike recognize that private companies have an intellectual property interest in their algorithms.⁷⁷ At present, "twenty-one states have codified a trade secret privilege in their evidence rules" and "[c]ourts in many of the remaining jurisdictions recognize some common law variation of it."⁷⁸ Indeed, one of the primary reasons to prioritize legislative and administrative reforms to automated decision systems is that courts have not proven hospitable to claims or defenses that rely on revealing proprietary algorithmic information, particularly where a colorable trade secret claim exists.⁷⁹ Ideally, "courts should determine [in each case] — rather than assume — whether programs are reliable, whether they are accurate, whether they have errors, and whether they constitute trade secrets."⁸⁰ But in practice, contractors make broad claims that information is proprie-

74. Proprietary information, like a trade secret, involves information that a company wishes to keep confidential to maintain a business advantage over its competitors. If private vendors were required to disclose the source code of their algorithms, they might have fewer incentives to create the programs in the first place.

75. Brauneis & Goodman, *supra* note 29, at 110.

76. States have the ability to enact legislation that overrules common law trade secret protections, but such a statute would necessarily be over-inclusive in terms of the harms it aims to remedy, and states would be loath to pass it.

77. See, e.g., Rebecca Wexler, *Life, Liberty, and Trade Secrets: Intellectual Property in the Criminal Justice System*, 70 STAN. L. REV. 1343, 1346 (2018) (collecting cases); *id.* at 1352–53 ("Today, the general view among legislators, judges, and scholars alike is that some form of trade secret evidentiary privilege both does and should exist, at least in civil proceedings . . . [and s]ome commentators have also presumed that the privilege should apply to criminal as well as civil cases.").

78. *Id.* at 1352.

79. See *id.* at 1346; see also Chessman, *supra* note 24, at 183 ("Both state and federal courts have issued decisions that presume the reliability, objectivity, credibility, and accuracy of evidence produced by computers."); cf. David S. Levine, *Secrecy and Unaccountability: Trade Secrets in Our Public Infrastructure*, 59 FLA. L. REV. 135, 135 (2007) (arguing that "trade secrecy must give way to traditional notions of transparency and accountability when it comes to the provision of public infrastructure").

80. Chessman, *supra* note 24, at 221 (arguing that defendants in criminal trials should have a right — deriving from the Confrontation Clause, Due Process Clause, and evidentiary doctrines such as *Daubert* — to examine, test, and challenge the source code of algorithms used against them in court).

tary and that its disclosure would damage their business, and judges often defer to these claims.⁸¹

One of the reasons for the judicial disinclination to scrutinize algorithms more closely may be that “people have ‘automation bias’ and, therefore, place their trust in computer-generated assessments even when faced with evidence of the systems’ inaccuracies.”⁸² Judges, like most people, may not be sufficiently aware of the infirmities of algorithmic decision-making. In any event, as long as courts remain reluctant to strike a different balance between transparency and commercial secrecy with respect to these government contracts,⁸³ advocates of transparency in government contracting must turn to legislative and regulatory responses instead.⁸⁴

III. ALGORITHMIC ACCOUNTABILITY IN PRACTICE: ATTEMPTS AT REGULATION

This Part discusses state and local efforts to address public sector algorithmic harms through legislation and regulation. Part III.A examines New York City’s Local Law 49, the country’s first algorithmic transparency law, analyzing its successes and failures. Part III.B examines other attempts at regulation in the United States.

A. NEW YORK CITY LOCAL LAW NO. 49

When the New York City Council passed Local Law 49 in 2017,⁸⁵ some hailed the new algorithmic transparency law as a

81. See, e.g., *id.* at 205 (“The majority of courts attempt to offer some rationale for denying defendants access to source code. These rationales fall broadly into three categories: (1) the source code is irrelevant; (2) the source code is a trade secret; and (3) the state does not possess the source code.” (footnotes omitted)).

82. Citron, *supra* note 31, at 1271 (arguing that automation bias, which can affect a judge’s decision-making process, presents the need for new due process protections that account for this perception). “Automation bias effectively turns a computer program’s suggested answer into a trusted final decision.” *Id.* at 1272.

83. *But see, e.g.,* K.W. v. Armstrong, 180 F. Supp. 3d 703, 717 (D. Idaho 2016) (applying the test established by the Supreme Court in *Mathews v. Eldridge*, 424 U.S. 319 (1976), and finding a substantial risk of “mathematical, clerical, or substantive” error in Idaho’s algorithmic process for determining Medicaid eligibility).

84. See Chessman, *supra* note 24, at 223 (“Legislatures are most effectively situated to address the economic and business considerations that attend the production and disclosure of source code.”).

85. N.Y.C. LOCAL LAW NO. 49 (2018).

progressive and promising development.⁸⁶ Others were significantly less optimistic.⁸⁷ But at the very least, its implementation was certain to exert a strong influence on other jurisdictions across the country.⁸⁸ As the first legislatively enacted algorithmic transparency law in the United States, Local Law 49 serves as a valuable case study. Despite its promise, however, a series of missteps in the Law's drafting and implementation prevented it from producing meaningful reform. The Council passed Local Law 49 with the purpose of establishing an Automated Decision Systems Task Force,⁸⁹ which was to be comprised of eighteen members representing a wide-variety of nonprofit, private sector, advocacy, and academic stakeholders, but led by members of the Mayor's Office.⁹⁰ The Law directed the Task Force to produce a report providing recommendations on six key issues.⁹¹

Even from the beginning, it was clear that the Task Force could not fulfill this mandate. First, the Task Force lacked suffi-

86. See *Mayor de Blasio Announces First-In-Nation Task Force To Examine Automated Decision Systems Used By The City*, N.Y.C. (May 16, 2018), <https://www1.nyc.gov/office-of-the-mayor/news/251-18/mayor-de-blasio-first-in-nation-task-force-examine-automated-decision-systems-used-by> [<https://perma.cc/T5LR-KJ8F>].

87. See Julia Powles, *New York City's Bold, Flawed Attempt To Make Algorithms Accountable*, NEW YORKER (Dec. 21, 2017), <https://www.newyorker.com/tech/annals-of-technology/new-york-citys-bold-flawed-attempt-to-make-algorithms-accountable> [<https://perma.cc/Z894-BK5F>] ("For a government body without real legal powers, this will be a Herculean, or perhaps Sisyphian, undertaking.")

88. *Id.* ("The task force will be the first city-led initiative of its kind in the country, and it is likely to have a significant impact, nationally and internationally, when it reports its findings, in late 2019.")

89. N.Y.C. LOCAL LAW NO. 49 (2018).

90. The Task Force was chaired by Jeff Thamkittikasem, Director of the Mayor's Office of Operations, and co-chaired by Kelly Jin, Chief Analytics Officer and Director of the Mayor's Office of Data Analytics, and Brittny Saunders, Deputy Commissioner of Strategic Initiatives at the N.Y.C. Commission on Human Rights. N.Y.C. AUTOMATED DECISION SYS. TASK FORCE, NEW YORK CITY AUTOMATED DECISION SYSTEMS TASK FORCE REPORT (2019), at 6–7, <https://www1.nyc.gov/assets/adstaskforce/downloads/pdf/ADS-Report-11192019.pdf> [<https://perma.cc/WJG2-XT6J>].

91. The law required the Task Force report to detail: (1) the development of criteria for identifying which automated decisions should be subject to the law; (2) the development of a procedure through which a person can receive explanation of agency automated decision affecting them; (3) the development of a procedure to determine whether an agency automated decision system causes disproportionate impacts on certain categories of persons; (4) the development of a procedure for addressing instances in which a person is harmed by an agency automated decision system if any such system is found to disproportionately impact certain categories of persons; (5) the development of a process for making information publicly available about each agency automated decision system; and (6) the feasibility of the development of a procedure for archiving agency automated decision systems and data. *Id.* at 12–13.

cient information to make a proper evaluation.⁹² Because the city administration was unwilling to provide basic information about what automated decision systems were currently in use,⁹³ members had “to rely on voluntary disclosures as [they] studie[d] how automated systems are designed, procured, and audited.”⁹⁴ Ultimately, the Task Force’s access was limited to generalized briefings by city agencies where they received presentations about just *four* of the city’s automated decision systems.⁹⁵ Second, Local Law 49’s definition of “automated decision system” was overbroad,⁹⁶ and a year after the Task Force was formed, it had yet to reach consensus on which systems would be subject to the law’s requirements.⁹⁷ Third, rather than creating a permanent body to study and regulate the issue, the legislation provided for the termination of the Task Force two months after submitting its report.⁹⁸ The New York City Council may have conceived of Local Law 49 as a first investigatory step in anticipation of further legislation. But the Law made the Task Force’s recommendations advisory rather than binding, failed to provide the Task Force the necessary material to make informed recommendations, created a

92. See Powles, *supra* note 87 (“There is no readily accessible public information on how much the city spends on algorithmic services, for instance, or how much of New Yorkers’ data it shares with outside contractors. Given the Council’s own struggle to find answers, the question now is whether the task force will do any better.”).

93. Shirin Ghaffary, *New York City Wants to Make Sure the AI and Algorithms It Uses Aren’t Biased. That’s Harder Than It Sounds*, VOX (Apr. 11, 2019), <https://www.vox.com/2019/4/11/18300541/new-york-city-algorithms-ai-automated-decision-making-sytems-accountable-predictive-policing> [<https://perma.cc/D9V2-2DJ7>] (“Despite repeated requests, the [Task Force] hasn’t been able to get hold of a list of all the types of automated decision-making technologies being used by city agencies.”).

94. Powles, *supra* note 87.

95. N.Y.C. AUTOMATED DECISION SYS. TASK FORCE, *supra* note 90, at 28 (“Ultimately, we were able to develop a set of protocols for legal review and obtained approvals for and did reviewed [sic] four specific agency examples from the Department of Transportation, the Police Department, the Department of Education, and the Fire Department.”).

96. See N.Y.C. LOCAL LAW NO. 49 § 1(a) (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.”).

97. See N.Y.C. AUTOMATED DECISION SYS. TASK FORCE, *supra* note 90, at 19 (“The ADS Task Force found the broad statutory definition of ADS provided in [Local Law No. 49] difficult to work with as a practical matter, as its breadth made it hard to clearly identify which tools and systems could, in fact, be considered an ADS. This broad-sweeping definition also implicated a potentially unmanageable number of tools and systems, including some that simply perform ministerial functions that could be subject to further review without a compelling reason to do so. The limitations of this definition thus posed challenges for our work in developing the mandated recommendations, as well as for envisioning what ADS management will look like in the future.”).

98. N.Y.C. LOCAL LAW NO. 49 § 1(b)(4) (2018).

sunset on the Task Force shortly after its report was produced, and has failed to produce any subsequent legislation.

In November 2019, the Task Force released its public report, but the report did little to evaluate New York City's use of algorithms or need for reform.⁹⁹ Indeed, without the benefit of actual data sets — apart from four generalized case studies presented by the city — the report could only offer generic recommendations.¹⁰⁰ Had the legislation forced the public disclosure of automated decision system source codes¹⁰¹ or granted the Task Force the authority to compel disclosure from other city agencies, the Task Force could have acquired the information it needed, but both proposals were stripped from the bill. Although the initial draft of the bill would have made the source code of all New York City automated decision systems fully public, that requirement was quickly abandoned after pressure from private vendors.¹⁰² And another draft of the bill that would have created extensive reporting requirements for city agencies was rejected by the city administration.¹⁰³ As a result, the Task Force did not wield sufficient legal authority to compel agencies to disclose the relevant information, and the law did nothing to push back against the city administration's ongoing practice of protecting the proprietary and contractual prerogatives of private vendors.

This outcome is especially disheartening because no city has more leverage than New York City. New York City's "size, wealth, and high-quality demographic data make it a more desirable client than most cities."¹⁰⁴ As a professor researching city-vender contracts put it, "For many of these vendors, it's the biggest customer they'll get. . . . If New York doesn't use that power to make systems accountable, who will?"¹⁰⁵ Concededly, even

99. N.Y.C. AUTOMATED DECISION SYS. TASK FORCE, *supra* note 90, at 17–25.

100. *See infra* note 113.

101. *See supra* note 28.

102. *See Powles, supra* note 87 ("[The proposed requirement] invited strong resistance from some policy experts, who warned that such openness might create security risks and give bad actors an easy way to game the public-benefits system, and from tech companies, which argued that it would force them to disclose proprietary information, supposedly harming their competitive advantage.").

103. *Id.* ("An intermediate draft of [New York City Council member James] Vacca's bill included extensive reporting requirements, which would have compelled agencies to provide the task force with relevant information. But that draft, like the August version, was rejected by the city administration, and now the task force will have to rely on voluntary disclosures as it studies how automated systems are designed, procured, and audited.").

104. *Id.*

105. *Id.*

New York City may be neither willing nor able to compel private vendors to publicly disclose their source code without driving them away from the bargaining table. But, as discussed in Part IV.B, *infra*, there are ways for New York City to audit vendor services and secure transparency into automated decision systems without disclosing algorithms' source codes.¹⁰⁶

Due to the flawed drafting of Local Law 49, the flaws in execution were as predictable as they were insurmountable. First, since the Task Force had not been afforded access to information about the city's vendor contracts — e.g., the quantity, type, cost, and decision-making authority of the city's automated decision systems — they were not able to develop effective criteria for determining which systems should be regulated. The Task Force could not even agree whether it had the legal authority to review actual examples of automated decision systems.¹⁰⁷ Second, throughout the Task Force's tenure, participation by community stakeholders was limited and granted begrudgingly.¹⁰⁸ Third, according to some members of the Task Force, the final report was drafted and produced primarily by City employees on the Task Force who stifled dissenting perspectives.¹⁰⁹ As noted, the legislation granted New York City's mayor the authority to appoint the chair and members of the Task Force,¹¹⁰ and the Mayor appointed members of his office as chair and co-chair of the Task Force.¹¹¹

106. See Pauline T. Kim, *Auditing Algorithms for Discrimination*, 166 U. PENN. L. REV. 189, 202 (2017).

107. N.Y.C. AUTOMATED DECISION SYS. TASK FORCE, *supra* note 90, at 28 ("Some members strongly believed that we needed to review some, if not all, examples of ADS currently in use by the City as part of our deliberative work in forming recommendations. Others believed that reviewing examples posed challenges, both in terms of being able to identify tools or systems in use that met the broad definition of 'ADS' provided in the Local Law, as well as ensuring that reviewing examples with Task Force members would be permissible given any legal, privacy, proprietary, and security considerations relevant to specific technical tools and systems.")

108. AI NOW INSTITUTE, *CONFRONTING BLACK BOXES: A SHADOW REPORT OF THE NEW YORK CITY AUTOMATED DECISION SYSTEM TASK FORCE* (Rashida Richardson, ed., Dec. 4, 2019), <https://ainowinstitute.org/ads-shadowreport-2019.html> [<https://perma.cc/GDC4-RZ4L>].

109. Beryl Lipton, *With Task Force Finished, New York City Looks to Next Steps for AI Regulation*, MUCKROCK (Dec. 3, 2019), <https://www.muckrock.com/news/archives/2019/dec/03/nyc-ads-task-force-final-report-next-steps/> [<https://perma.cc/E9AU-9KH2>].

110. See N.Y.C. LOCAL LAW NO. 49 (2018) ("Such task force and the chair thereof shall be appointed by the mayor or a designee thereof[.]").

111. See *supra* note 90.

These were not trivial decisions. In the name of reaching “consensus,”¹¹² the Task Force produced a report that purported to satisfy its legal obligations while failing to provide the specific recommendations required by Local Law 49.¹¹³ For example, the Task Force’s report shied away from some of the transparency concerns central to the law’s mandate.¹¹⁴ Most strikingly, the report declined to address with any specificity the transparency challenges that arise when private vendors market their automated decision systems to city agencies.¹¹⁵ Ultimately, none of the recommendations were responsive to New York City’s specific needs, and likely could have been made without convening a Task Force.

This is not to say that nothing of value can be gleaned from New York City’s efforts. The entire process has been instructional for any jurisdiction seeking to establish algorithmic transparency, and parts of the Task Force’s report offer a plausible, albeit non-specific, roadmap to achieve this goal. The report’s most valuable set of recommendations proposed that the City “institutionalize an Organizational Structure within City government that would serve as a centralized resource for guiding agency management of ADS and carrying out citywide management functions.”¹¹⁶ Citing disagreement among Task Force members,

112. N.Y.C. AUTOMATED DECISION SYS. TASK FORCE, *supra* note 90, at 28 (“[S]ome members favored reporting a highly detailed set of data elements related to ADS tools and systems, including a rationale for their use, technical features, and evaluations.” But rather than go into detail about particular automated decision systems or provide details about what might make for a beneficial regulatory structure, the Task Force “chose to take an approach that focused on the structures of governance, existing legal and policy frameworks, and feasibility of operationalization. This allowed our recommendations to reflect where we reached consensus among the diverse perspectives represented on the Task Force, and to have the greatest potential for effective implementation.”).

113. *Id.* at 30 (“Ultimately, we chose not to emphasize any specific types of systems or tools within our recommendations, to ensure applicability for the wide range of current technology and expectations of new systems and technology in the future.”).

114. *Id.* (“As a Task Force, we faced challenges in working to develop recommendations for protocols that promoted public transparency in government use of ADS, considering the City’s duties to protect the privacy of the personally identifying information of its residents, public safety, the security of City infrastructure and technical assets, and certain proprietary and other sensitive types of City information.”).

115. *Id.* (“During our meetings, we often specifically discussed the challenges that emerge when government agencies procure services or materials related to ADS from private entities. Most members agreed that proprietary restrictions can make certain key ADS information less available to the public, and given the complexities of procurement within government, that this important topic requires further review beyond the Task Force process.”).

116. *Id.* at 18.

the report offered little insight into how such an entity might be structured and how much authority the organization would exercise over other agencies.¹¹⁷ Nevertheless, the report contemplated that “certain information about agency ADS [would] be compiled at the agency level and, when possible given relevant legal and security considerations, reported centrally to the Organizational Structure.”¹¹⁸

To carry out its mandate, the Organizational Structure would develop policies and best practices around citywide procurement and implementation of automated decision systems, creating a prioritization framework “for agency reporting and publishing of certain information related to ADS, informed by the principle of promoting transparency.”¹¹⁹ In other words, this new, centralized body would establish reporting standards for city agencies and require some degree of algorithmic transparency for certain high-priority automated decision systems.¹²⁰ Moreover, the Organizational Structure would take a lead role in public education regarding automated decision systems;¹²¹ involve impacted communities in discussions about developing or procuring certain systems;¹²² make agency reports on the city’s use of such systems publicly available “[f]ollowing an internal City and agency process for legal and security review and approval”;¹²³ offer training for city agency staff on how “concepts of fairness, accountability and transparency relate to ADS management”;¹²⁴ and “develop protocols to respond to instances where an assessment of an ADS indicates that there may be an unintended or unjustifiable disproportionate impact or harm upon any individual, group, or community.”¹²⁵ Collectively, these recommendations envision a

117. *Id.* at 28 (“While some members wanted to recommend greater authority for the Organizational Structure, including enforcement and compliance powers, other members disagreed. Given the continued divergence of perspectives among Task Force members, our recommendations on this issue reflect those proposed Organizational Structure functions and duties about which we could achieve consensus.”).

118. *Id.* at 23.

119. *Id.*

120. *Id.* (“To facilitate the management of ADS on a citywide level and to foster public discourse, agencies should, when possible given relevant legal and security considerations, report certain information about highest-priority ADS to the Organizational Structure, and, when possible, make certain information about the ADS publicly available.”).

121. *Id.* at 22.

122. *Id.* at 23.

123. *Id.* at 24.

124. *Id.* at 21.

125. *Id.* at 25.

regulatory body that takes meaningful steps toward algorithmic transparency and accountability.

Thus far, however, New York City has failed to make any of the substantive changes contemplated by the report. In November 2019, Mayor Bill de Blasio created a senior-level position in the Mayor's office to manage the city's use of algorithms.¹²⁶ But whether this new position can effect meaningful reform remains doubtful.¹²⁷ The Task Force was unable to produce a report responsive to Local Law 49's questions precisely because the Task Force was led by city officials — officials who appeared unable or unwilling to acquire the necessary information or make specific recommendations.¹²⁸ After all, the Mayor's Office has obvious incentives to maintain the status quo, and will not be inclined to implement regulations that impose significant disclosure or transparency requirements on city agencies. This stubborn obstacle to reform reinforces the necessity of an independent regulator whose interests remain uncaptured by private vendors, the Mayor, or other city agencies.¹²⁹

Subsequent developments in New York City and New York State have sparked some optimism that the Task Force's recommendations will inspire further legislation. In 2019, a New York

126. *New York City Creates Chief Algorithms Officer Position*, GOVERNMENT TECHNOLOGY (Nov. 20, 2019), <https://www.govtech.com/products/New-York-City-Creates-Chief-Algorithms-Officer-Position.html> [<https://perma.cc/244Z-8PJ5>].

127. *Id.* ("The new position, which will operate out of Mayor Bill de Blasio's office, will lead the development of guidelines and best practices surrounding the use of algorithm-based tools by city agencies. . . . The officer will work with and report to the director of the Mayor's Office of Operations," who was also the chair of the Task Force.).

128. Indeed, of the six topics about which Local Law 49 required the Task Force to produce recommendations, the Task Force only produced an answer to the first. *See* N.Y.C. LOCAL LAW NO. 49 (2018) (stating that "[n]o later than 18 months after such task force is established, it shall electronically submit to the mayor and the speaker of the council a report that shall include, at a minimum, recommendations on": (1) the development of criteria for identifying which agency automated decision systems should be subject to the law; (2) the development of a procedure through which a person can receive explanation of agency automated decision affecting them; (3) the development of a procedure to determine whether an agency automated decision system causes disproportionate impacts; (4) the development of a procedure for addressing instances in which a person is harmed by an agency automated decision system if any such system is found to disproportionately impact persons; (5) the development of a process for making information publicly available about each agency automated decision system; and (6) the feasibility of the development of a procedure for archiving agency automated decision systems and data).

129. *See infra* Part IV.A. In theory, this could pose a structural problem: having an algorithmic transparency agency at the same level of government as the automated decision systems it seeks to regulate. But, as discussed below, by establishing an independent agency whereby a jurisdiction can regulate itself, the city or state can regulate its agencies' use of these systems without falling prey to established interests.

City Council member introduced a bill requiring, among other things, that each city department generate an annual list of the automated decision systems it uses.¹³⁰ The bill would require agencies to disclose how each automated decision system is used, what decisions are made based on the system, and the name of the vendor or entity who developed the system.¹³¹ In turn, the bill would make public some of the information the Task Force was unable to acquire or examine — a valuable first step.

New York's State Senate, meanwhile, has proposed legislation similar to Local Law 49 that would create a task force to examine automated decision systems used by state agencies and produce a report within two years.¹³² Hopefully, the State learns from New York City's legislation — and the shortcomings of New York City's Task Force — and decides to grant its task force more substantial investigatory powers. As discussed in Part IV, *infra*, New York State could simply create a regulatory body whose recommendations carry the force of law, and begin pursuing more specific and substantial avenues for reform. But if the State wants to first take a more preliminary investigative step, it will need to arm its task force with a degree of information and independence that the New York City Task Force did not have.

B. OTHER PROPOSED AND ENACTED LEGISLATION

This Part briefly examines legislative attempts at algorithmic transparency reform in Vermont, Massachusetts, and Washington State. Five months after Local Law 49's enactment, Vermont created a statewide Artificial Intelligence Task Force.¹³³ Although the Task Force's agenda placed a greater emphasis on public hearings and engaging the community than New York City's did, it suffered from an overly broad mandate.¹³⁴ As opposed to a

130. *Int. 1806-2019*, 2019 N.Y. City Council (N.Y. 2019), <https://legistar.council.nyc.gov/LegislationDetail.aspx?ID=4265421&GUID=FBA29B34-9266-4B52-B438-A772D81B1CB5&Options=Advanced&Search=> [https://perma.cc/M9V3-SZ63].

131. *Id.*

132. See Heilweil, *supra* note 64.

133. H.B. 378, 2018 Gen. Assemb., Reg. Sess. (Vt. 2018), <https://legislature.vermont.gov/bill/status/2018/H.378> [https://perma.cc/7N6B-NQS4].

134. *Id.*; see also ARTIFICIAL INTELLIGENCE TASK FORCE: FINAL REPORT, 2020 Gen. Assemb., at 32 (Vt. 2020), <https://legislature.vermont.gov/assets/Legislative-Reports/Artificial-Intelligence-Task-Force-Final-Report-1.15.2020.pdf> [https://perma.cc/7UTL-2NHS] (“Note that the mandate of [the New York City Automated Decision] Task Force is

focus on algorithmic transparency, the Vermont bill directed the Task Force to study the entire field of artificial technology and produce a report within eighteen months.¹³⁵ The Massachusetts and Washington State bills, by contrast, avoid this problem. While the Massachusetts bill represents a more preliminary step than the Washington bill, both are geared specifically toward algorithmic transparency, and would create permanent executive branch authority to study the issue statewide. In these respects, both bills offer more promising models for reform than Vermont or New York City's laws.

The Massachusetts bill would establish a commission to conduct “a complete and specific survey of all uses of automated decision systems by the commonwealth of Massachusetts and the purposes for which such systems are used.”¹³⁶ Then, in view of the transparency, explicability, auditability, and accountability of each system, the commission would establish guidelines for training, procurement, implementation, and review.¹³⁷ The commission would also examine how data is protected, used, and shared by agencies using automated decision systems; how the Due Process rights of individuals are affected by automated decision systems; how to mitigate uses of automated decision systems that may result in disparate impacts; and how legal limitations may affect the commission's access to the data or other technical information necessary to audit or evaluate the state's systems.¹³⁸ Notably, the legislation specifically calls on the commission to examine state agency contracts for such systems — with special attention to any intellectual property provisions that bear upon

much narrower than that of the Vermont Artificial Intelligence Taskforce because the inquiry was only into the effects of use of A.I. by New York City Agencies.”).

135. ARTIFICIAL INTELLIGENCE TASK FORCE: FINAL REPORT, *supra* note 134, at 24 (This act creates the Artificial Intelligence Task Force to “investigate the field of artificial intelligence; and make recommendations on the responsible growth of Vermont's emerging technology markets, the use of artificial intelligence in State government, and State regulation of the artificial intelligence field.”). The Task Force unsuccessfully sought to postpone its statutory sunset, citing insufficient time to investigate and make recommendations in the time allotted by the law. *Id.* at 8, 16. Ultimately, the Task Force did “not recommend the promulgation of new, specific State regulations of artificial intelligence at this time.” *Id.* at 4.

136. H.B. 2701, 191st Leg. § 11(b), Reg. Sess. (Mass. 2019) (“There shall be a commission within the executive office of technology services and security for the purpose of studying and making recommendations relative to the use by the commonwealth of automated decision systems that may affect human welfare, including but not limited to the legal rights and privileges of individuals.”).

137. *Id.*

138. *Id.*

non-disclosure agreements, trade secret claims, or other proprietary interests — and the impacts of such provisions on transparency, explicability, auditability, accountability, and Due Process.¹³⁹

Rather than creating a task force or commission to study the issue and recommend further legislative action, the Washington bill would empower the state's chief privacy officer¹⁴⁰ to promulgate rules “regarding the development, procurement, and use” of automated decision systems by state agencies.¹⁴¹ Various provisions in the bill would prohibit agency automated decision systems from discriminating against any individual, abridging constitutional or other legal rights, and deploying or triggering any weapon.¹⁴² The bill would also establish a preclearance process for any new agency automated decision system, making the development or procurement of such a system contingent on the chief privacy officer's approval of an algorithmic accountability report to be prepared by the contracting agency.¹⁴³ Additionally, agencies would have to give notice to affected individuals about the system in use, explain how the system makes decisions and how to contest those decisions, and provide decisions that are both explainable and subject to appeal.¹⁴⁴ Agencies would also need to ensure that their systems and data are available for test-

139. *Id.*

140. In Washington State, the chief privacy officer is an executive in the state's technology services agency. See *About*, WASH. TECH. SOLUTIONS, <https://watech.wa.gov/about> [<https://perma.cc/HY7D-C33R>] (last visited Dec. 2, 2020).

141. H.B.1655, 66th Leg. § 3, Reg. Sess. (Wash. 2019) (A bill “establishing guidelines for government procurement and use of automated decision systems in order to protect consumers, improve transparency, and create more market predictability[.]”).

142. *Id.* § 4; see also *id.* § 1 (“Reliance on automated decision systems without adequate transparency, oversight, or safeguards can undermine market predictability, harm consumers, and deny historically disadvantaged or vulnerable groups the full measure of their civil rights and liberties.”).

143. Such a report would have to include information about the automated decision system's name, vendor, version, and capabilities; the types of data inputs (and their sources) and outputs; what decisions the automated decision system will make and the policies around those decisions; the factors that will be used to determine where, when, and how the technology is deployed; whether the technology will be operated continuously or used only under specific circumstances; how the data will be securely stored and accessed; how personnel operating the automated decision system will be trained and comply with policy; a description of any potential impacts of the automated decision system on civil rights and liberties as well as potential disparate impacts on marginalized communities and a mitigation plan; and a description of the fiscal impact of the automated decision system, including acquisition costs, operating costs, cost savings, and funding. *Id.* § 5.

144. *Id.* § 4.

ing and research,¹⁴⁵ and in any procurement contract, vendors would have to waive any legal claims that would impair these standards.¹⁴⁶ Finally, the bill would create a private right of action, whereby any individual injured by a violation could seek injunctive relief against the offending public agency.¹⁴⁷

The Massachusetts and Washington State bills, if passed, would both represent promising steps forward on the road to algorithmic transparency and accountability. Both have the virtue of arming their state's executive branch, either an individual or a commission, with a very specific set of investigatory goals. While the Massachusetts bill represents a more preliminary, exploratory step, one hopes it will be followed by further legislation and regulation. Although it would have the legal authority to request and acquire data from other agencies,¹⁴⁸ the commission's recommendations would not have the force of law.¹⁴⁹ Instead, the commission would be required to submit an annual report with recommendations for legislative and regulatory action, and to report on timelines and cost-estimates for proposed automated decision systems.¹⁵⁰ The Washington State bill, by contrast, grants an executive branch officer the legal authority to implement rules requiring that an agency adjust or discard an automated decision system.¹⁵¹ In other words, this bill envisions the ongoing regulation of publicly-deployed algorithms, and represents a much more significant step.

As these bills demonstrate, legislatures seeking to regulate algorithmic transparency may take a broad range of approaches. First, they may opt for more preliminary efforts to study the issue, as in the New York City and Vermont laws. Such legislation has the potential to be very effective, but only insofar as the body

145. *Id.* (Public agencies must “[e]nsure the automated decision system and the data used in the system are made freely available by the vendor before, during, and after deployment for agency or independent third-party testing, auditing, or research to understand its impacts, including potential bias, inaccuracy, or disparate impacts.”).

146. *Id.* § 1 (recognizing “automated decision systems are often deployed without public knowledge, are unregulated, and vendors selling the systems may require restrictive contractual provisions that undermine government transparency and accountability.”).

147. *Id.* § 6. Under the law, an automated decision system may not discriminate against an individual, or treat an individual less favorably than another. *Id.* § 7.

148. H.B. 2701, 191st Leg. § 11(b), Reg. Sess. (Mass. 2019).

149. *Id.* § 11(e). The commission established by H.B. 2701 must submit recommendations to the state legislature, but the legislature is under no obligation to implement any of the commission's recommendations. *Id.*

150. *Id.*

151. H.B.1655, 66th Leg. § 5, Reg. Sess. (Wash. 2019).

charged with studying the issue can access the relevant information, and only insofar as its initial recommendations lead to further legislative and regulatory action. The Massachusetts bill, by creating a permanent commission with the legal authority to seek the information it needs, may be able to achieve these preliminary goals more effectively. Second, at the other end of the spectrum, a legislature may opt to issue detailed ex ante rules governing the use of automated decision systems by state agencies. However, this remains an undesirable approach, as legislatures often lack the time and expertise to continually monitor all of the automated decision systems in the state.¹⁵² Third, the legislature may create a regulatory body with the power to promulgate and enforce such ex ante rules, or may grant this power to an existing regulatory body or executive official.

This third category lends itself to various approaches. Some legislatures might elect, as the Washington bill does, to write many of the rules themselves, and in effect delegate enforcement authority around an already existing framework for regulation detailed in the legislation.¹⁵³ The benefits of this approach include cabining the regulatory body's authority to a very specific set of parameters and establishing explicit guidelines for regulation that may bolster efficiency and help resist regulatory capture.¹⁵⁴ For example, this approach makes sense with respect to how "automated decision systems" are defined. If the legislature explicitly delimits which automated decision systems will be subject to regulation, the legislature can leapfrog what might otherwise become a long, contentious regulatory process to establish an acceptable definition.¹⁵⁵ Moreover, once the legislature settles on a definition, agencies can avoid a great deal of uncertainty and

152. See *infra* Part IV.A (discussing why algorithms in particular require flexible regulation and continuous reexamination).

153. H.B.1655, 66th Leg. § 3, Reg. Sess. (Wash. 2019) ("By January 1, 2020, the chief privacy officer appointed in RCW 43.105.369 shall adopt rules pursuant to chapter 34.05 RCW regarding the development, procurement, and use of automated decision systems by a public agency. *These rules must incorporate the minimum standards and procedures set forth in sections 4 and 5 of this act with respect to automated decision systems.*" (emphasis added)).

154. See Justin Rex, *The Federal Banking Regulators: Agency Capture, Regulatory Failure, And Industry Collapse During The 2008 Financial Crisis*, 38–39 (2013) (Ph.D. dissertation, Wayne State University) (Although "there is no commonly accepted definition [of regulatory capture] among scholars . . . most agree that capture includes influence over, or control of, agency decisions by a group regulated by the agency.").

155. See *supra* Part III.A (discussing how New York City's Task Force spent significant time and resources struggling to agree on a definition of "automated decision system").

hand-wringing. This concern is entirely legitimate. An overly broad definition may invite resistance from agency officials afraid that every spreadsheet or Internet search will be subject to the law.¹⁵⁶ As a result, legislatures may want to address this issue directly rather than delegating it to a regulatory body or executive official.

Despite the potential benefits of delegating regulatory authority around a detailed legislative framework of *ex ante* rules, there may be drawbacks to this approach. In particular, as discussed further in Part IV, algorithms require flexible and adaptive regulation, and an overly rigid legislative structure may inhibit a regulatory authority from being sufficiently responsive. Public agencies currently employ an incredibly broad range of algorithms in an incredibly broad range of ways — each carrying its own security, privacy, and proprietary concerns — and an adept regulatory body may need to fashion specific rules for specific types of algorithms and risk.¹⁵⁷

If legislators fail to build this kind of flexibility into a bill, industry actors and public agencies alike may oppose the legislation altogether. For instance, the Washington bill would require that vendors waive any legal claims or nondisclosure agreements that would impair any of the bill's minimum standards.¹⁵⁸ This requirement would fundamentally change the nature of the relationship between vendors and the state's agencies, requiring that vendors be willing to make almost everything about their automated decision systems public, including the system and data used in the system itself.¹⁵⁹ Despite the virtues of the Washing-

156. See Heilweil, *supra* note 64 (discussing the Washington State bill: “[T]he definition of automated decision-making systems used in the bill will likely be changed and possibly narrowed in order to make the legislation easier for agencies to understand and comply with.”).

157. See N.Y.C. AUTOMATED DECISION SYS. TASK FORCE, *supra* note 90, at 19–20 (conceptualizing a prioritization framework for algorithmic regulation, with high-, medium-, and low-priority automated decision systems).

158. H.B.1655, 66th Leg. § 4, Reg. Sess. (Wash. 2019).

159. *Id.* (“[T]he public agency must, at a minimum: . . . (a) Give clear notice to an individual impacted by the automated decision system of the fact that the system is in use; the system’s name, vendor, and version; what decision or decisions it will be used to make or support; whether it is a final or support decision system; what policies and guidelines apply to its deployment; and how the individual can contest any decision made involving the system; (b) Ensure the automated decision system and the data used in the system are made freely available by the vendor before, during, and after deployment for agency or independent third-party testing, auditing, or research to understand its impacts, including potential bias, inaccuracy, or disparate impacts; (c) Ensure that any decision made or informed by the automated decision system is subject to appeal, immediate

ton bill, it is doubtful that requiring every single automated decision system in the state to conform to these *ex ante* rules is good public policy.¹⁶⁰ As a result, some legislatures may elect instead to delegate more general grants of power to a regulatory body or executive official. But again, allowing for too much regulatory flexibility can create inefficiency and expose the delegatee to regulatory capture. Accordingly, legislatures following this third approach will need to strike a delicate balance between writing the rules themselves and delegating regulatory power to an executive commission or official.

IV. THE CASE FOR LOCAL AND STATE ALGORITHMIC GOVERNANCE VIA INDEPENDENT AGENCY

This Part argues that state and local algorithmic harms can best be regulated by a centralized, independent commission established at the state and local level, and dedicated to administering durable yet flexible rules around automated decision systems. Part IV.A discusses the reasons for regulating algorithmic governance via an independent regulatory agency and suggests how such an agency might be structured. Part IV.B then discusses a potential model for regulation, adjudication, and enforcement, considering how state and local governments can increase algorithmic transparency and public accountability without sacrificing security or proprietary interests.

A. A STRUCTURE FOR ALGORITHMIC GOVERNANCE

This Note argues that state and local governments should develop independent regulatory agencies equipped with sufficient authority to make publicly-deployed algorithms both transparent and publicly accountable. Properly constituted, such an agency

suspension if a legal right, duty, or privilege is impacted by the decision, and potential reversal by a human decision maker through a timely process clearly described and accessible to an individual impacted by the decision; and (d) Ensure the agency can explain the basis for its decision to any impacted individual in terms understandable to a layperson including, without limitation, by requiring the vendor to create such an explanation.”).

160. Unless, of course, legislators clearly cabined the bill’s definition of automated decision system in a manner that avoided subjecting low-risk algorithms, for example, to disclosure requirements that could result in over-inclusive and unnecessarily burdensome regulations.

— or, Algorithmic Transparency Commission (ATC)¹⁶¹ — would serve several roles. The ATC would promulgate jurisdiction-specific rules to curtail algorithmic harms; promote transparency through required agency disclosures; achieve compliance through audits, investigations, subpoenas, and enforcement proceedings; issue formal and informal advisory opinions; serve as a resource for other agencies and a leader in public education around algorithmic accountability; and establish minimum fairness and due process protections for those harmed by an algorithmic decision. By taking robust legislative and regulatory action in this vein, state and local governments can both remedy existing harms and identify and prevent harms now hidden from the public eye.

For many states, this is not an unfamiliar regulatory structure. Indeed, all but a handful have some form of statewide ethics commission, many of which have investigatory, advisory, regulatory, and enforcement powers with respect to other state agencies.¹⁶² In New York State, for example, the Joint Commission on Public Ethics (“JCOPE”) “has jurisdiction over more than 250,000 officers and employees at State agencies and departments.”¹⁶³ JCOPE “was created to restore public trust in government by ensuring compliance with the State’s ethics and lobbying laws and regulations,”¹⁶⁴ and exercises, among other powers, the ability to “promulgate rules . . . ; administer and enforce ethics provisions; conduct investigations as necessary; administer oaths or affirmations, subpoena witnesses, compel attendance and require document production.”¹⁶⁵ In the context of algorithmic accountability — or, perhaps, algorithmic ethics — ATCs vested with similar

161. This Note will use “Algorithmic Transparency Commission” or “ATC” as a stand-in name for the agency it is proposing.

162. See *State Ethics Commissions: Powers and Duties*, NAT’L CONF. OF STATE LEGISLATURES (Sept. 4, 2020), <https://www.ncsl.org/research/ethics/50-state-chart-state-ethics-commissions-powers-a.aspx> [<https://perma.cc/GZ46-JFLX>] (“All ethics commissions perform the same basic function of encouraging ethics in government, but the powers and duties of individual commissions vary widely. Some states grant commissions substantial authority and independence, while others serve in a more limited or advisory capacity. Commissions might also have different combinations of responsibilities. Commissions may have the power to issue subpoenas, judicially enforceable orders, make rules, conduct ethics trainings, or more.”).

163. *About the New York State Joint Commission on Public Ethics*, N.Y. STATE JOINT COMM’N ON PUB. ETHICS, <https://jcope.ny.gov/about-new-york-state-joint-commission-public-ethics> [<https://perma.cc/K8NT-5E28>] (last visited Dec. 2, 2020).

164. *Id.*

165. *State Ethics Commissions: Powers and Duties*, *supra* note 162 (citing N.Y. EXEC. LAW § 94).

powers would further some of the same principles that animated the creation of JCOPE and other state ethics commissions.

Creating independent commissions at the local and state level — dedicated exclusively to the regulation of publicly-deployed algorithms — makes sense for several reasons.¹⁶⁶ First, a commission would likely regulate algorithms more effectively than a legislature.¹⁶⁷ For algorithmic governance in particular, regulation needs to be flexible enough to respond to continual innovation yet durable enough to withstand regulatory capture. And aside from the fact that algorithmic technology is constantly evolving, automated decision systems require ongoing maintenance and supervision, making regular audits and disclosures necessary¹⁶⁸ — tasks that legislatures are often ill-positioned to undertake.¹⁶⁹ In such circumstances, administrative action must be agile and iterative, repeatedly setting and revising frameworks for acceptable action.

In *Minimalism and Experimentalism in the Administrative State*, Charles Sabel and William Simon argue that “experimentalist regimes are especially well suited for circumstances in which effective public intervention requires local variation and adaptation to changing circumstances.”¹⁷⁰ Administrative experimentalism, like responsive regulation, contemplates a symbiotic relationship between the regulator and the regulated, wherein a cycle of feedback produces mutual cooperation and benefit.¹⁷¹ As

166. As discussed in Part II.C (discussing trade secret protections and state open records laws), state law systems are currently ill-equipped to remedy algorithmic harms — and state open records laws do not fare much better.

167. See *supra* Part III.B.

168. Kim, *supra* note 106, at 202 (“Auditing is an essential strategy for detecting unintended bias and prompting the reexamination and revision of algorithms to reduce discriminatory effects.”).

169. See *supra* Part III.B.

170. Charles F. Sabel & William H. Simon, *Minimalism and Experimentalism in the Administrative State*, 100 GEO. L.J. 53, 56 (2011). “Experimentalism takes its name from John Dewey’s political philosophy, which aims to precisely accommodate the continuous change and variation that we see as the most pervasive challenge of current public problems. Policies should be ‘experimental in the sense that they will be entertained subject to constant and well-equipped observation of the consequences they entail when acted upon, and subject to ready and flexible revision in the light of observed consequences’” (citing JOHN DEWEY, THE PUBLIC AND ITS PROBLEMS 203 (1927)). *Id.* at 78.

171. See *id.* at 79 (“We start with a relatively abstract model of experimentalism in which the basic constituents are a ‘center’ and a set of ‘local units.’ In practice, the center is sometimes the national government, and the local units its federated states or municipalities. Or the center could be a government agency, and the local units the private actors it regulates or the public or private service providers with which it contracts.” (emphasis added)).

discussed in Part III.B, *supra*, the nature of algorithmic governance does not lend itself well to piecemeal legislation. Legislatures, unlike regulatory commissions, may not have the time or expertise to engage in any kind of experimentalist exchange. An independent ATC, on the other hand — staffed with experts and devoted exclusively to these issues — could likely strike a more appropriate, ongoing balance between transparency and accountability, on one side, and commercial secrecy and security on the other. An ATC “could act as a standards-setting body that coordinates and develops classifications, design standards, and best practices,”¹⁷² and that stands ready to adapt and revise these standards and practices in an agile, ongoing way.

Second, establishing the ATC as a single, centralized commission — as opposed to dividing authority between existing agencies — would be more conducive to achieving robust regulatory action.¹⁷³ Making the case for the creation of the Consumer Financial Protection Bureau (CFPB), Oren Bar-Gill and Elizabeth Warren argued that a “litany of agencies [with overlapping authority], limits on rulemaking authority, and divided enforcement powers results in inaction.”¹⁷⁴ Housing algorithmic regulatory power in a single, centralized agency would avoid this collective action problem. For algorithmic regulation in particular, a centralized agency would play the essential role of concentrating expertise, which is especially important in areas of rapid innovation. To be sure, some states might elect to situate an ATC under the umbrella of an already-existing statewide ethics commission. Whether this structure can produce meaningful regulation and reform in such states depends in large part on the priorities and independence of the existing agency.

Institutional design can have a significant impact on the effectiveness of a regulatory body. A number of initial questions may shape an agency’s actions and effectiveness: who will lead the agency; whether it will be structured as a commission; how, and

172. Tutt, *supra* note 50, at 106.

173. See Fenwick et al., *supra* note 23, at 561 (“In an age of constant, complex and disruptive technological innovation, knowing what, when, and how to structure regulatory interventions has become more difficult. Regulators find themselves in a situation where they believe they must opt for either reckless action (regulation without sufficient facts) or paralysis (doing nothing). Inevitably in such a case, caution tends to trump risk. But such caution merely functions to reinforce the status quo. . .”).

174. Oren Bar-Gill & Elizabeth Warren, *Making Credit Safer*, 157 U. PA. L. REV. 1, 97 (2008).

by whom, the directors will be appointed and removed; and to what degree the agency will have regulatory, adjudicatory, and enforcement powers. Each question also carries tradeoffs. For instance, an agency structured as a multi-member commission may be better able to represent a range of stakeholders than one with a single director. On the other hand, a multi-member commission may be less accountable for its decisions and less agile than an organization with a single head.¹⁷⁵ Ultimately, which regulatory structure a given jurisdiction chooses may be less important than who leads the agency or the commission, how they are appointed, and their degree of independence from industry actors and executive officials.¹⁷⁶ Different jurisdictions may have different needs, not to mention different state constitutional constraints, but any effective agency or commission must be organized such that it retains its independence — both from political figures in the executive branch¹⁷⁷ and from the industry actors and agencies it aims to regulate.

Third, due to the constitutional restraints imposed on the federal government by federalism, regulating the administration of state and local government at the state and local level is the only viable option. Many commentators and even members of Congress have proposed regulating certain kinds of algorithms at the federal level, but while federal regulation of *privately*-deployed algorithms, particularly those affecting interstate commerce, may be desirable, the federal government cannot dictate, for example, the content of an algorithm a state or local government elects to

175. *But see* PHH Corp. v. CFPB, 881 F.3d 75, 165 (D.C. Cir. 2018) (Kavanaugh, J., dissenting) (“Multi-member independent agencies do not concentrate all power in one unaccountable individual, but instead divide and disperse power across multiple commissioners or board members. The multi-member structure thereby reduces the risk of arbitrary decision-making and abuse of power, and helps protect individual liberty. In other words, the heads of *executive* agencies are accountable to and checked by the President; and the heads of *independent* agencies, although not accountable to or checked by the President, are at least accountable to and checked by their fellow commissioners or board members.”).

176. As Part III.A discussed, executive officials may be opposed to measures that would impose more stringent disclosure requirements on their own agencies.

177. At the federal level, independent agencies are often structured as multi-member commissions, insulated (to a degree) from political considerations as a result of bipartisan legislative appointment, staggered term limits, and for-cause removal protections. See Paul R. Verkuil, *The Purposes and Limits of Independent Agencies*, 1988 DUKE L.J. 257, 259 (1988) (discussing the distinctive features of independent agencies at the federal level).

use to administer its own laws.¹⁷⁸ And even if the federal government could, consistent with the Constitution, preempt local and state regulatory action in this emerging area, it would frustrate the ability of local and state governments to act as laboratories of innovation and to tailor regulations to the specific needs of their jurisdictions.¹⁷⁹ Thus, local and state entities — not the federal government — must regulate the automated decision systems deployed by their own agencies.

In accordance with the recommendations made above, an ATC would promulgate a series of *ex ante* rules imposing minimum disclosure and algorithmic design and fairness requirements, within which public agencies and vendors would retain broad discretion to construct and implement their automated decision systems.¹⁸⁰ Additionally, the ATC would serve as a resource for oth-

178. In *An FDA for Algorithms*, Andrew Tutt argues that the “case for regulation by a single expert [federal] agency outweighs the case for regulation by the states or jurisdiction distributed across multiple agencies because algorithms have qualities that make centralized federal regulation uniquely appealing.” Tutt, *supra* note 50, at 115–16. This may be true for algorithms used in interstate commerce by massive tech companies like Amazon, Google, and Facebook. But as applied to state or local agencies, Tutt’s proposal — requiring federal “pre-market approval” before certain algorithms could be deployed — would not pass constitutional muster. See, e.g., *New York v. United States*, 505 U.S. 144 (1992) (holding that Congress may not pass legislation that compels state legislatures to adopt a federal regulatory program); *Printz v. United States*, 521 U.S. 898 (1997) (holding that Congress may not compel state officials to participate in the administration of a federal program). Although Congress certainly has some power, under section five of the Fourteenth Amendment, to pass legislation that remedies constitutional violations, such legislation must possess “congruence and proportionality between the injury to be prevented or remedied and the means adopted to that end.” *City of Boerne v. Flores*, 521 U.S. 507, 520 (1997). There are undoubtedly Due Process and Equal Protection Clause concerns with some automated decision systems, but the Supreme Court would almost certainly strike down a federal algorithm law that placed fairness or disclosure requirements on all algorithms adopted by state agencies. The “congruence and proportionality” test in *Boerne* would require Congress to put forward significant evidence of unconstitutional algorithmic harms undertaken by the states — evidence that is currently, without the benefit of robust transparency laws, very difficult to demonstrate. Whether the advent of new, state-level algorithmic transparency laws around the country could alter this calculus remains to be seen.

179. As Tutt acknowledges, “state-level regulation might prove agile, responsive, and effective. . . . It might be argued that state level regulation could better grapple with [] sources of failure [of federal regulation] . . . because, for example, state legislatures are more attuned to competing priorities and stakeholders, and so will not as readily fall prey to tunnel vision and inconsistency.” Tutt, *supra* note 50 at 112–13.

180. See Sabel & Simon, *supra* note 170, at 79 (“First, framework goals (such as ‘adequate education’ or ‘good water status’) and provisional measures for gauging their achievement are established, whether by legislation, administrative action, or court order, through consultation among the center and local units and relevant outside stakeholders. Second, local units are explicitly given broad discretion to pursue these ends as they see fit. But third, as a condition of this autonomy, the local units must report regularly on their performance and participate in a peer review in which their results are compared

er agencies and for the public, and would continuously amend its rules in ways that are responsive to the needs of affected stakeholders. To effectuate these rules, the ATC should be armed with enforcement mechanisms to encourage compliance, including the legal authority to conduct audits and investigations, to hold hearings, and to issue subpoenas.¹⁸¹ Additionally, the legislation creating ATCs should give individuals a private right of action to challenge an agency's failure to meet any of the ATC's minimum disclosure or fairness requirements.¹⁸²

When a government agency deprives any person of "life, liberty, or property," the Fifth and Fourteenth Amendments require that the agency afford that person Due Process.¹⁸³ But for reasons discussed in Part II.C, claims that an individual's Due Process rights have been violated based on the decisions of a publicly-deployed algorithm do not fare well under a traditional *Mathews* analysis.¹⁸⁴ As Danielle Citron argues, automated deci-

with those units employing other means to the same general ends. These reviews require the local units to describe and explain their efforts to peers and superiors; to show that they have considered alternatives; and to demonstrate that they are making progress by some jointly acknowledged measure of success, or are making plausible adjustments if not. The center provides services and inducements that facilitate this disciplined comparison of local performances and mutual learning among local units. Finally, the framework goals, performance measures, and decision-making procedures themselves are periodically revised on the basis of alternatives reported and evaluated in peer reviews, and the cycle repeats.").

181. There are, of course, other enforcement possibilities. One approach would be for the legislature to encourage agency compliance by conditioning agency funding on meeting certain standards for disclosure, fairness, privacy, and bias. Additionally, the Supreme Court has held that federal courts may hear a lawsuit for prospective relief against state officials brought by another agency of the same state. *Va. Off. for Prot. and Advoc. v. Stewart*, 563 U.S. 247 (2011) (involving an independent state agency that sued state officials in their official capacities for refusing agency access to records to which it was entitled under federal law). Thus, an ATC would likely have standing to bring other agency officials to court.

182. See H.B. 1655, 66th Leg. § 6, Reg. Sess. (Wash. 2019).

183. U.S. CONST. amend. XIV, § 1.

184. Citron, *supra* note 31, at 1283 ("Under *Mathews*, courts weigh the value of the person's threatened interest, [the risk of erroneous deprivation,] the probable benefit of additional or substitute procedures, and the government's asserted interests, including the cost of additional safeguards."). On the one hand, the public interest is served by the availability of an opportunity to challenge inaccurate and unfair determinations made by automated decision systems, and the magnitude of the deprivation — causing someone to lose their public assistance benefits, for example — may not be insignificant. On the other hand, making an algorithm's source code public, examining algorithms for potential errors or disparate impact, or granting individuals the right to appeal algorithmic decisions all impose significant costs. Courts therefore have been reluctant to entertain such arguments. See *id.* at 1284 n.242 ("In the automated administrative state, the de facto rules [of an algorithm] are hidden from hearing officers who may be inclined to adopt a computer's finding without checking the accuracy of a computer-generated decision.").

sion-making systems jeopardize the norms of Due Process by “combin[ing] individual adjudications with rulemaking while adhering to the procedural safeguards of neither.”¹⁸⁵ When individuals lack the opportunity to challenge algorithmic determinations, injuries caused by discriminatory algorithms or those bearing a disparate impact go without remedy. Citron thus calls for courts to recognize “technological due process,” which would strike a better balance between automation and discretion, and offer the subjects of automated decisions meaningful notice and an opportunity to be heard.¹⁸⁶ But policymakers need not rest their hopes on the development of new common law doctrines. Regulatory adjustments to administrative adjudication — allowing a private right of action for individuals who have suffered from a flawed or biased algorithmic decision — can establish technological due process more quickly, comprehensively, and flexibly than a constitutional doctrine developed by courts.

B. REGULATING TRANSPARENCY

The ATC’s greatest challenge would be striking the appropriate balance between transparency and accountability, on the one hand, and commercial secrecy and security, on the other.¹⁸⁷ Without more transparency into automated decision systems, significant algorithmic harms can go undetected.¹⁸⁸ But as previously noted, local and state agencies often rely on private vendors to produce their automated decision systems, and without protections in place for proprietary software, companies may be less willing to contract with local governments and may seek to extract a much higher price upfront that a local or state agency may be unwilling to pay. In balancing these competing principles, an

185. *Id.* at 1249. “Automation jeopardizes the due process safeguards owed individuals and destroys the twentieth-century assumption that policymaking will be channeled through participatory procedures that significantly reduce the risk that an arbitrary rule will be adopted.” *Id.* at 1281.

186. *Id.*

187. *See* Levine, *supra* note 61.

188. *See* Tutt, *supra* note 50, at 109–10 (“There appears to be a growing consensus among scholars that the ability to require transparency should be one of the first tools used to regulate algorithmic safety.”).

agency must seek jurisdiction-specific reforms tailored to the needs of each state or local government.¹⁸⁹

Transparency regulations can fall along a spectrum from partial to full disclosure.¹⁹⁰ The ATC might begin, for example, by promulgating rules articulating a prioritization framework for algorithmic risk, with levels of risk determined by a series of criteria based on factors including: the complexity and explicability of the system, the decision-making purposes for which the system is used, the degree of human oversight in decisions based on the use of such systems, the nature and magnitude of such decisions' potential impacts on people's liberty and property, and the probable number of people affected.¹⁹¹ For high-risk algorithms, as determined by the factors above, the ATC could require the most complete disclosures, perhaps even requiring — as a condition precedent to procurement or implementation of the system — that the contractor (or agency, if the agency created its own algorithm) consent to full public disclosure of the source code and training data of these systems.¹⁹² For lower-risk algorithms, the ATC's rules might simply require other agencies to “provide qualitative disclosures (analogous to SEC disclosures) that do not reveal trade secrets or other technical details about how their algorithms work but nonetheless provide meaningful notice about how the algorithm functions, how effective it is, and what errors it is most likely to make.”¹⁹³ Rather than revealing the source code of an algorithm, such qualitative disclosures could explain the process by which an agency acquired its automated decision system, the policy considerations relied upon in this determination, and why they — or the private vendor — elected to use one set of programming criteria rather than any alternatives.

189. *See id.* at 110 (“An agency could strike that difficult balance in a granular way by drawing together many stakeholders and mandating only those disclosures that are most appropriate to certain kinds of algorithms used in specific contexts.”).

190. *See id.*

191. For suggestions on establishing a framework for automated decision system prioritization, *see* N.Y.C. AUTOMATED DECISION SYS. TASK FORCE, *supra* note 90, at 20.

192. The ATC would need to determine, pursuant to the definition of automated decision system supplied by the legislation, which algorithms would be subject to regulation. As part of this inquiry, the ATC would need to decide whether to apply the same rules to agency-created algorithms as to privately-created ones, and whether contracts with private vendors for *services* that happen to use an algorithm would also be subject to regulation.

193. Tutt, *supra* note 50, at 110.

In many cases, the ATC can likely serve the interests of transparency and accountability without making an algorithm's source code and training data public. Instead, the ATC could make public only supplemental information — such as the objectives and principles governing the algorithms design, the source of its training data, the factors and variables it considers, how those factors or variables are weighed, and its role in making agency decisions.¹⁹⁴ One advantage of this alternative is that companies can protect their proprietary interests by allowing only the ATC — and perhaps an outside auditing agency retained by the ATC — to access the source code.¹⁹⁵ The tradeoff of this approach is that it seriously limits public contestation and input. Some reformers envision a law that makes automated systems available for public design and testing, while limiting automation of decisions to areas that have undergone rulemaking procedures with opportunity for public response and feedback.¹⁹⁶ Some even want to prohibit agencies from contracting with companies who decline to produce open-source software¹⁹⁷ and require such companies to waive the right to defend any proprietary or trade secret claims in court.¹⁹⁸ This Note, by contrast, proposes channeling algorithmic regulation through an independent agency structure with robust disclosure requirements that vary according to the relative risk posed by an algorithm — a structure which remains, by design, unaccountable to the public.

Insofar as public contestation and input produce better regulatory results, they should be sought at every opportunity. Indeed, requiring agencies to use open-source software, in theory, could

194. See N.Y.C. AUTOMATED DECISION SYS. TASK FORCE, *supra* note 90, at 14 (“Agencies make countless decisions daily, from simple decisions about which supplies to purchase, to policy decisions with citywide impact. Many decisions they make are subject to various types of internal review. Before a decision is made, it may undergo multiple layers of approvals.”).

195. See Frank A. Pasquale, *Beyond Innovation and Competition: The Need for Qualified Transparency in Internet Intermediaries*, 104 NW. U. L. REV. 105, 110 (2010) (“Given legitimate needs for secrecy, this monitoring need not be transparent to all — just to the relevant regulators charged with maintaining the integrity of networks and search. Like the Foreign Intelligence Surveillance Court developed in the national security context, monitors at the FCC and the FTC would balance intermediaries’ need for confidentiality with a public need for accountability. Developing such monitoring is the first step toward assuring responsible Internet intermediaries.”).

196. See AI NOW INSTITUTE, *supra* note 108, at 14.

197. See Chessman, *supra* note 24, at 223 (“Open-source software is software whose source code is publicly available and open to scrutiny by the general public.”).

198. See, e.g., H.B. 1655, 66th Leg., Reg. Sess. (Wash. 2019).

catalyze meaningful reforms.¹⁹⁹ Open-source software generally reduces costs and has fewer errors.²⁰⁰ When an algorithm's source code is available for public testing and review, public citizens and groups can investigate the algorithm's objectives and the assumptions on which its construction was based.²⁰¹ As Pauline Kim argues, third-party auditing of algorithmic decision criteria enables governments to root out disparate treatment and disparate impact.²⁰² Such a practice — evaluating the ongoing accuracy, efficacy, and fairness of the systems in use — would also encourage participatory government and public faith in our institutions, as well as incentivize the design of fair and just automated decision systems.²⁰³ Thus, to the extent practicable, an ATC should make public the source code, input data, and system design of agency automated decision systems.

Nevertheless, for efficiency reasons alone, not every publicly-deployed algorithm needs to be subject to this level of public transparency. Moreover, the disclosure of source code and training data can generate security risks, violate privacy, and reveal proprietary information to an extent that might drive private vendors away from the bargaining table. By creating a prioritization framework for algorithmic risk, the ATC can allow policymakers to maintain fair oversight without making public, in every instance, the actual data or source code involved in automated decision-making systems.²⁰⁴ Producing supplemental information publicly, rather than the source code of an algorithm or the training data itself, achieves a middle-ground between transparency

199. See Chessman, *supra* note 24, at 223 (“Because of its transparency, open-source software empirically and categorically has fewer errors and security concerns than similarly situated programs that are privately developed.”); *id.* at 226–27 (“The use of open-source software, statewide software, or both has been linked to significant cost savings. . . . Governments that use open-source software also save money on litigation. Because open-source software contains fewer errors, it is less likely to form the basis for reversal or protracted litigation than computer code with significant flaws.” (citations omitted)).

200. *Id.*

201. See Kim, *supra* note 106, at 202.

202. *Id.* at 190–91.

203. See *id.* at 191 (“Technical tools alone cannot reliably prevent discriminatory outcomes because the causes of bias often lie not in the code, but in broader social processes.”).

204. See generally Joshua A. Kroll et. al, *Accountable Algorithms*, 165 U. PA. L. REV. 633 (2017).

and accountability interests on the one hand, and security and proprietary interests on the other.²⁰⁵

V. CONCLUSION

This Note has argued that state and local algorithmic harms can best be regulated at the state and local level through a particular regulatory structure: namely, a centralized, independent commission with the authority to issue and enforce robust disclosure and fairness requirements. Algorithmic regulation requires flexibility, agility, and expertise. Given the present lack of transparency and accountability in the public use of automated decision systems, an Algorithmic Transparency Commission offers the best hope for restraining the harms identified in this Note, and those yet to be discovered. As state and local governments increasingly turn to private vendors for automated solutions, such ATCs will need to adapt, in an ongoing way, to rapid changes in algorithmic technology, and to do so in a manner that both protects consumers and allows governments to continue optimizing the administration of public functions.

205. See Brauneis & Goodman, *supra* note 29, at 176 (“Public entity contracts should require vendors to create and deliver records that explain key policy decisions and validation efforts, without necessarily disclosing precise formulas or algorithms.”); Jody Freeman, *The Private Role In Public Governance*, 75 N.Y.U. L. REV. 543, 549 (2000) (calling for a mix of formal and informal accountability mechanisms — including “contract as a vehicle for the exercise of authority and as an instrument of regulation” — to restrain public/private regulatory regimes).