The Administrative State and Artificial Intelligence: Toward an Internal Law of Administrative Algorithms

Amit Haim*

The administrative state is gradually embracing artificial intelligence (AI) algorithms. The advent of the so-called automated state has raised concerns over accountability, transparency, and fairness and engendered proposals for legal regulation. Yet the notion that algorithms are not merely technical instruments but encode social behavior embedded in a bureaucratic context has largely been missing from the discourse. This Article identifies algorithms as sociotechnical systems embedded in an organizational context, which can function as bureaucratic governance instruments. It argues that external legal institutions, whether legislative endeavors or judicial review, lack the capacity, insight, and perspective to achieve meaningful accountability in reviewing the administrative use of AI algorithms.

The Article suggests moving beyond seeing algorithms as a distinct phenomenon to regulate, to a more holistic view of algorithms as a bureaucratic challenge, which entails confronting inconsistencies, inaccuracies, and administrative culture, while taking account of institutional design. By doing so, it follows in the footsteps of scholars of internal administrative law, comprising of the complex set of rules, guidelines, and procedures of the bureaucracy, and highlights internal governance as means of improving outcomes and ensuring accountability. It also discusses the points of contention and outlines the doctrinal questions of administrative law that are likely to occupy judges and lawyers when dealing with internal governance with AI in the government.

Concurrently, this Article uncovers the internal law of administrative algorithms, which is emerging from a set of informal documents developed in the federal government. The Article reviews this corpus and distills the main tenets of responsible and trustworthy AI that will guide how administrative agencies design and implement their AI systems in the foreseeable future and imbues general principles with actionable goals.

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* J.S.D Candidate, Stanford Law School. Many thanks to Anne Joseph O'Connell, David Freeman Engstrom, Katherine J. Strandburg, Itay Ravid, Aziz Z. Huq, and Rory Van Loo for helpful comments and input. All mistakes are mine.

INTRODUCTION

Artificial intelligence (AI) algorithms of various kinds are slowly but surely permeating the administrative state.[1] The advent of the so-called automated state raises important concerns, including over transparency, fairness, and accountability, of decision-making with AI.[2] This in turn has already generated various proposals for regulation and adaptation of legal frameworks to achieve accountability in the public use of algorithmic systems.[3]

The debate so far has been fruitful in identifying problems and harms and has generally oscillated between (1) ex ante procedures to ensure consideration and democratization of algorithmic implementation and (2) ex post mechanisms to allow subjects to contest and empower courts or other reviewing institutions to pass judgments on algorithmic outputs.[4] Proposals are seeking to either commit algorithms to ex post review in individual cases to correct errors,[5] or to impose ex ante mechanisms to prevent harms, such as impact assessments, public registries, and other transparency measures.[6]

Indeed, most proposed accountability frameworks have been *static* assessments of algorithmic systems.[7] These assessments have largely overlooked one important aspect, the fact that AI algorithms are sociotechnical systems embedded in an organizational context, which can function as bureaucratic

1. *See generally* DAVID FREEMAN ENGSTROM, DANIEL E. HOE, CATHERINE M. SHARKEY & MARIANO-FLORENTINO CUÉLLAR, GOVERNMENT BY ALGORITHM: ARTIFICIAL INTELLIGENCE IN Federal Administrative Agencies (2020), https://law.stanford.edu/wp-content/uploads/2020/02/ACUS-AI-Report.pdf [https://perma.cc/J2AZ-EWF3]; Cary Coglianese & Lavi M. Ben Dor, *AI in Adjudication and Administration*, 86 BROOK. L. REV. 791 (2021); Aziz Z. Huq, *Constitutional Rights in the Machine Learning State*, 105 CORNELL L. REV. 1875 (2020) [hereinafter Huq, *Constitutional Rights*]; Aziz Z. Huq, *A Right to a Human Decision*, 106 VA. L. REV. 611 (2020) [hereinafter Huq, *Right to a Human Decision*]; Karen Levy, Kyla E. Chasalow & Sarah Riley, *Algorithms and Decision-Making in the Public Sector*, 17 ANN. REV. L. SOC. SCI. 309 (2021); Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 GEO. L.J. 1147 (2017); Rory Van Loo, *Rise of the Digital Regulator*, 66 DUKE L.J. 1267 (2017) (providing an earlier account of agencies using algorithmic tools for digital regulatory purposes).

2. *See generally Ryan Calo & Danielle Keats Citron, The Automated Administrative State: A Crisis of Legitimacy*, 70 EMORY L.J. 797 (2021); Sofia Ranchordas, *Empathy in the Digital Administrative State*, 71 DUKE L.J. 1341 (2022). For a recent categorization of the critiques and concerns, see David Freeman Engstrom, *The Automated State: Realist's View,* 56 GEO. WASH. L. REV. (forthcoming 2024).

3. *See generally* Levy et al., *supra* note 1; Calo & Citron, *supra* note 2; Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249 (2008); ADA LOVELACE INSTITUTE, ALGORITHMIC ACCOUNTABILITY FOR THE PUBLIC SECTOR: LEARNING FROM THE FIRST WAVE OF POLICY IMPLEMENTATION (2021); https://www.opengovpartnership.org/documents/algorithmic-accountability-public-sector/ [https://perma.cc/DUR4-4WNC].

4. For a general overview of proposals, see ADA LOVELACE INSTITUTE, *supra* note 3. For a critique of the ex post and ex ante divide, see Huq, *Constitutional Rights*, *supra* note 1.

5. Citron, *supra* note 3.

6. ADA LOVELACE INSTITUTE, *supra* note 3.

7. Engstrom and Haim call this the "snapshot" and "bookend" problems. *See* David Freeman Engstrom & Amit Haim, *Regulating Government AI and the Challenge of Sociotechnical Design*, 19 ANN. REV. L. SOC. SCI. 277 (2023).

measures of control.[8] Consider, for example, an agency that handles unemployment benefits. It has several tasks to carry out, including to determine eligibility of large amounts of applicants, approve and disburse benefits, deny the ineligible, handle appeals and petitions, and prevent and prosecute fraudulent behavior. It will do so using a set of rules and guidelines through numerous discretionary actions by numerous line-levels workers.[9] This will result in inevitable mistakes and inconsistencies, leading to unjustly unpaid applicants on the one hand and excess public expenditure on the other. Should the agency seek to utilize AI to improve its operations—for instance, by assisting reviewing officers with recommendations, identifying potential wrongdoers for audits, or automating aspects of the application process—it will run into the intricate problems that AI for decision-making raises—for example, how to improve results using the algorithm, how to ensure frontline workers trust the system and use it, how might some aspects of work be fully automated and how might that violate due process rights, how to prevent unfair outcomes, and how to propagate trust and legitimacy from the public. Since algorithmic systems are embedded in a sociotechnical and organizational context, many of the institutional characteristics of the agency will come into play when designing a decision-making process with AI. Algorithmic systems in the administrative state can function as bureaucratic governance instruments: they facilitate information processing and sharing, they operate as part of managerial control schemes guiding frontline discretion, they can serve as "online" quality assurance and peer review mechanisms, and they have the potential to enhance bureaucratic capacity.[10]

How should the law tackle the internal governance structures of the administrative state? Past endeavors to rein in administrative action through legal accountability mechanisms have met the reality of bureaucracies, with unique internal structures, norms, and culture, and attempting to reshape them from the

8. Engstrom & Haim, *supra* note 7; Juho Pääkkönen, Matti Nelimarkka, Jesse Haapoja & Airi Lampinen, *Bureaucracy as a Lens for Analyzing and Designing Algorithmic Systems*, *in* PROCEEDINGS OF THE 2020 CHI CONFERENCE ON HUMAN FACTORS IN COMPUTING SYSTEMS 1 (2020), https://dl.acm.org/doi/10.1145/3313831.3376780 [https://perma.cc/G889-YLUJ]; Andrew D. Selbst, Danah Boyd, Sorelle A. Friedler, Suresh Venkatasubramanian & Janet Vertesi, *Fairness and Abstraction in Sociotechnical Systems*, *in* FAT* '19: PROCEEDINGS OF THE CONFERENCE ON FAIRNESS, ACCOUNTABILITY, AND TRANSPARENCY 59 (2019), http://dl.acm.org/citation.cfm?doid=3287560.3287598 [https://perma.cc/YNA9-VF7H]; Justin B. Bullock, Hsini Huang & Kyoung-Cheol (Casey) Kim, *Machine Intelligence, Bureaucracy, and Human Control*, 5 PERSPS. ON PUB. MGMT. & GOVERNANCE 187 (2022).

9. MICHAEL LIPSKY, STREET-LEVEL BUREAUCRACY: DILEMMAS OF THE INDIVIDUAL IN PUBLIC SERVICES 38 (2nd ed. 2010).

10. DANIEL E. HO, DAVID MARCUS & GERALD K. RAY, QUALITY ASSURANCE SYSTEMS IN AGENCY ADJUDICATION: EMERGING PRACTICES AND INSIGHTS 26–29 (2021); Kurt Glaze, Daniel E. Ho, Gerald K. Ray & Christine Tsang, *Artificial Intelligence for Adjudication: The Social Security Administration and AI Governance*, *in* THE OXFORD HANDBOOK ON AI GOVERNANCE 18 (Justin B. Bullock et al. eds., 2022).

outside is often difficult, has unexpected consequences, or is even bound to fail.[11] Take decisional accuracy, a central tenet of public law—that one is entitled to have their case adjudicated by the government in a correct manner according to their circumstances. Achieving accuracy in administrative action has been a central goal of many legislative reforms and litigation, yet most have not been satisfactory.[12] Internal endeavors, while they have their fair share of failures, have often been more successful.[13] Another issue is consistency, a basic pillar of the rule of law, that implies that similar cases should be adjudicated similarly and that outcomes should not depend on the assigned adjudicator. Many adjudicatory systems, especially those that handle vast number of cases, have fared poorly on consistency and created a roulette-like situation.[14] However, legal reform has not done much to improve this inconsistency, while internal measures have done better in some cases.[15] As a response to this tension, *internal administrative law* has emerged as a distinct field of study, undoing the complex set of rules, guidelines, and procedures that make up the internal governance of administrative agencies.[16] This scholarly focus reflects the understanding that external legal constraints are effective only at the margins of administrative behavior. Instead, the set of control measures and bureaucratic instruments are more influential in attaining improvement.[17]

The debate over governance and accountability of algorithms in administrative decision-making suffers from a similar disconnect between governance frameworks and organizational realities.[18] In fact, much of the previous discussion has treated

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11. The canonical example being the Social Security Administration's disability insurance program (SSDI), which repeated reforms and court proceedings failed to improve. *See generally* JERRY L. MASHAW, BUREAUCRATIC JUSTICE: MANAGING SOCIAL SECURITY DISABILITY CLAIMS (1983). *See also* JAMES Q. WILSON, BUREAUCRACY: WHAT GOVERNMENT AGENCIES DO AND WHY THEY DO IT (YALE U. PRESS eds., 1991); Lauren B. Edelman, Linda H. Krieger, Scott R. Eliason, Catherine R. Albiston & Virginia Mellema, *When Organizations Rule: Judicial Deference to Institutionalized Employment Structures*, 117 AM. J. SOCIO. 888 (2011); Paul J. DiMaggio & Walter W. Powell, *The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields*, 48 AM. J. SOCIO. REV. 147 (1983).

12. *See, e.g.*, JACK SMALLIGAN & CHANTEL BOYENS, URBAN INSTITUTE, IMPROVING THE SOCIAL SECURITY DISABILITY DETERMINATION PROCESS 13 (2019).

13. As Mashaw documented several decades ago, improving social security adjudications was done internally. MASHAW, *supra* note 11, at 194.

14. *See* David K. Hausman, *Reviewing Administrative Review*, 38 YALE J. REGUL. 1059 (2021); Jaya Ramji-Nogales, Andrew I. Schoenholtz & Philip G. Schrag, *Refugee Roulette: Disparities in Asylum Adjudication*, 60 STAN. L. REV. 295 (2007).

15. *See generally* Daniel E. Ho & Sam Sherman, *Managing Street-Level Arbitrariness: The Evidence Base for Public Sector Quality Improvement*, 13 ANN. REV. L. & SOC. SCI. 251 (2017); David Ames, Cassandra Handan-Nader, Daniel E. Ho & David Marcus, *Due Process and Mass Adjudication: Crisis and Reform*, 72 STAN. L. REV. 1 (2020).

16. Gillian E. Metzger & Kevin M. Stack, *Internal Administrative Law*, 115 MICH. L. REV. 1239 (2017); Christopher J. Walker & Rebecca Turnball, *Operationalizing Internal Administrative Law*, 71 HASTINGS L.J. 1225 (2020).

17. Ho & Sherman, *supra* note 15.

18. Engstrom & Haim, *supra* note 7.

algorithms either as part of the external-facing system of rules and adjudications,[19] or simply as benign computational tools.[20] But in many situations, algorithms will be situated somewhere in the middle and function more like internal governance systems. I argue, therefore, scholars and lawmakers should pay more attention to what the law governing such systems requires and what we can expect it to achieve.

Thinking about algorithms as bureaucratic instruments, it is clear they will meet similar obstacles to legal accountability. The limitations of judicial review will complicate the ability to achieve accountability, due to its sporadic nature and relative institutional disadvantage. Moreover, the focus on individual errors and harms will not capture the systemic nature of algorithms and may be ill-suited.[21] That is in addition to substantial portions of administrative behavior, like enforcement priorities, that are hived off and will create "algorithmic grey holes."[22] On the legislative side, the inability to predetermine effective safeguards and mechanisms through ex ante frameworks will render many legislative and other efforts futile, or at least marginally effective. In general, external legal governance guardrails are not well poised to consider institutional and systemic factors, which will drive much of the impact of algorithmic systems in the administrative state.[23]

This Article suggests a different course for the legal discourse around algorithmic accountability in public administration. The goals of this Article are twofold, intertwined, and somewhat complex: *First,* it argues algorithms should be seen, in some instances, as internal governance mechanisms, and discusses the legal implications of this recognition under several administrative law domains. *Second*, it expounds the *internal law of administrative algorithms,* explains what this body of law looks like as it emerges from a growing body of literature and informal government guidance documents,[24] and then discusses the advantages and pitfalls of governing via internal mechanisms.

While there has been tremendous progress in research over sociotechnical

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19. Calo & Citron*, supra* note 2.

20. Coglianese & Lehr, *supra* note 1.

21. Citron, *supra* note 3; David Freeman Engstrom & Daniel E. Ho, *Algorithmic Accountability in the Administrative State*, 37 YALE J. REGUL. 800 (2020) [hereinafter Engstrom & Ho, *Algorithmic Accountability*]; David Freeman Engstrom & Daniel E. Ho, *Artificially Intelligent Government: A Review and Agenda*, *in* RESEARCH HANDBOOK ON BIG DATA LAW 57 (2021) [hereinafter Engstrom & Ho, *Artificially Intelligent Government*], https://www.elgaronline.com/view/edcoll/9781788972819/9781788972819.00009.xml [https://perma.cc/TC33-JFQB].

22. Engstrom, *supra* note 2; Alicia Solow-Niederman, *Algorithmic Grey Holes*, 5 J.L. & INNOVATION 116, 117 (2023).

23. Gillian E. Metzger, *Embracing Administrative Common Law*, 80 GEO. WASH. L. REV. 1293, 1366–68 (2012). To find a similar argument in the context of content moderation on the internet, see generally Evelyn Douek, *Content Moderation as Systems Thinking,* 136 HARV. L. REV. 526 (2022).

24. *See infra* Section IV.A; *see, e.g.*, BLUEPRINT FOR AN AI BILL OF RIGHTS: MAKING AUTOMATED SYSTEMS WORK FOR THE AMERICAN PEOPLE, THE WHITE HOUSE 4 (2022); U.S. GOV'T ACCOUNTABILITY OFF., ARTIFICIAL INTELLIGENCE: AN ACCOUNTABILITY FRAMEWORK FOR FEDERAL AGENCIES AND OTHER ENTITIES (2021) [hereinafter GAO REPORT], https://www.gao.gov/assets/gao-21-519sp.pdf [https://perma.cc/FQ36-DU5G].

design, it has largely not percolated into the legal discourse. Therefore, this Article is the first to define the contours of this internal law. It identifies and portrays its main goals and tenets, among them the framework thinking of *Design, Integrate, Assess*; a focus on continuous and iterative evaluation and updating; component- and system-level emphasis; and capacity building and integrated expertise. In essence, this body of law begins to articulate that it is important to structure the ways in which human decision-makers interact with algorithmic outputs rather than simply specifying they will need to remain in the loop.

However, a fundamental problem of any internal legal structure is its boundaries vis-à-vis external legal norms, since exterior governance—through legislative action and judicial interpretation—"crowds out" internal law.[25] Viewed from this perspective, a main point of contention for administrative algorithmic applications will be grappling with the contours of external versus internal law. Consider again an unemployment agency adopting an AI algorithm for its eligibility determination process—will it have the power to bind adjudicators? If so, can it be defined as administrative *guidance,* or must it be considered a *legislative rule* that has to be promulgated through a notice-and-comment procedure under the Administrative Procedure Act?[26] This has important implications since guidance offers flexibility and does not require agencies to publicize any documentation or go through laborious procedures to amend it. The factors that will determine whether an algorithm is considered as *binding,* and *towards who,* are currently unclear and require thinking hard about both technology and doctrine. Courts will have to wrestle with the question of whether an algorithmic system, deemed merely supportive, has binding effects in practice due to its influence on decision-makers' judgment—thus crossing the line into substantive legal effects on rights and entitlements. Such determinations will define what remains under the dominance of internal governance and what is externalized.[27]

Despite its promise, internal law has significant limitations. Internal pressures agencies face risk distorting governance mechanisms. These include culture, personnel, and the political environment, which can all subvert internal governance mechanisms and lead them to fail adequate quality.[28] This dynamic is all too familiar with algorithmic systems. Resistance from frontline workers against algorithmic systems could prove pivotal in implementation.[29] Subversion and political pressures[30] can all alter algorithms and lead to very different outcomes than intended.[31] Where these dynamics are present, external law may have an important

25. Metzger & Stack, *supra* note 16.

26. *See* Section II.B *infra* for a discussion on these questions.

27. Engstrom & Ho, *Algorithmic Accountability*, *supra* note 21.

28. Ames et al., *supra* note 15.

29. Katherine C. Kellogg, Melissa A. Valentine & Angéle Christin, *Algorithms at Work: The New Contested Terrain of Control*, 14 ACAD. MGMT. ANNALS 366, 366–67 (2020).

30. Ames et al., *supra* note 15, at 61; Kellogg et al., *supra* note 29.

31. Kate Evans & Robert Koulish, *Manipulating Risk: Immigration Detention Through*

role in correcting flaws through setting methodology and process standards, defining oversight measures, and propagating best practices.

The Article proceeds as follows. Section I surveys and catalogues the use of AI algorithms in administrative decision-making and lays out the main concerns that arise from this utilization. It then shifts to portraying algorithms as sociotechnical systems within an organizational context and illustrates the bureaucratic environment in which algorithms are embedded. Section II moves forward to characterize the uses of algorithmic systems as bureaucratic instruments. It then examines how several central administrative doctrines interact with internal algorithmic governance. Section III tackles the problem of regulation and accountability directly. It discusses the landscape of regulation of public algorithms, shows the main drawbacks, and applies insights from the study of external governance of agency actions to the algorithmic context, explicating the limitations of legislative efforts and judicial review. Section IV expounds the internal law of administrative algorithms: it chronicles the emergence of a body of documents and reports that begin to outline the government's thought on accountability with AI algorithms and distills its main tenets as they emerge. The section then returns to external governance and explains why it might still need to play an important role in promoting accountability of algorithmic systems when several typical problems appear. A brief conclusion follows.

I. ALGORITHMS IN THE GOVERNMENT: SOCIOTECHNICAL SYSTEMS IN A BUREAUCRATIC CONTEXT

Efforts to automate government have a long history with bouts of renewal every several years as technology progresses.[32] In fact, many of the advancements in the field of AI, with its winter and spring cycles,[33] have been directly related to the government's work, which entails large swaths of data, big scale problems, and significant funds for research.[34] As Herbert Simon observed, administrative decision-making suffers from inherent limitations, and automation is an important component in overcoming those by improving transparency and evaluation.[35]

Automation, 24 LEWIS & CLARK L. REV. 789, 794–95 (2020); Jennifer Raso, *Displacement as Regulation: New Regulatory Technologies and Front-Line Decision-Making in Ontario Works*, 32 CAN. J.L. SOC. 75, 92 (2017).

32. L. Bainbridge, *Ironies of Automation*, *in* ANALYSIS, DESIGN AND EVALUATION OF MAN–MACHINE SYSTEMS 129 (1982), https://www.sciencedirect.com/science/article/pii/B9780080293486500269 [https://perma.cc/9CDV-AJVN].

33. *See generally* Luciano Floridi, *AI and Its New Winter: from Myths to Realities*, 33 PHIL. TECH. 1 (2020).

34. *See* Michael Haenlein & Andreas Kaplan, *A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence*, 61 CAL. MGMT. REV. 5, 8–9 (2019).

35. HERBERT A. SIMON, ADMINISTRATIVE BEHAVIOR: A STUDY OF DECISION-MAKING PROCESSES IN ADMINISTRATIVE ORGANIZATIONS 20–40 (4th ed. 1997). *See generally* Patrick S. Roberts & Kris Wernstedt, *Herbert Simon's Forgotten Legacy for Improving Decision Processes*, 22 INT'L PUB. MGMT J. 591 (2019).

If the administrative state is a vehicle for delivery of policy set forth by the legislative branch, then automating its execution and removing the fallibility of human input makes sense. This is, of course, easier said than done, but automation and algorithmization of decision-making have long been aspirational goals in the public sector.[36]

Skeptics may therefore be justified in questioning the recent hype around adoption of AI algorithms in general and particularly in government work.[37] Nevertheless, as David Engstrom argues, the change in quality and quantity of processing made possible by the remarkable technological advancements over the last decade, seems—though history will be the judge—to be leading to a new era of automation in government.[38] It is unsurprising that trends that appear in the private sector are not always quickly followed by the public sector, which is bound by complex constraints. Yet recent years have shown discernable advancements in the use of AI and algorithmic systems in government.

AI algorithms can—and are already—being implemented in various kinds and stages of administrative decision-making. They can be deployed at the front end for triage and case selection,[39] for entry point decisions,[40] for opinion writing support[41] and adjudication fact-finding,[42] for analysis of mass public comments,[43] and various other tasks.[44] Many potential applications revolve around internal information processing, as administrative agencies handle large amounts of data of different kinds. This may include search procedures as part of informal adjudications,[45] or clinical enhancements.[46] These applications involve a wide range of techniques

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36. *See generally* Patrick Dunleavy, Helen Margetts, Simon Bastow & Jane Tinkler, *New Public Management is Dead–Long Live Digital-Era Governance*, 16 J. PUB. ADMIN. RES. THEO. 467 (2005).

37. Calo & Citron, *supra* note 2; Levy et al., *supra* note 1.

38. Engstrom, *supra* note 2.

39. See, for example, the applications adopted at the Social Security Administration (SSA) under the Quick Disability Determination program, including using clustering of claims to foster micro-specialization of SSA personnel. ENGSTROM ET AL., *supra* note 1, at 39–40; Glaze et al., *supra* note 10.

40. For example, AI algorithms were used in assisting screening of hotline calls in Child Protection Services. *See* ALLEGHENY CNTY. ANALYTICS, ALLEGHENY METHODOLOGICAL REPORT 195 (2019), https://www.alleghenycountyanalytics.us/wp-content/uploads/2019/05/16-ACDHS-26_PredictiveRisk_Package_050119_FINAL-2.pdf [https://perma.cc/F3YZ-XDZV]; Stephanie Cuccaro-Alamin, Regan Foust, Rhema Vaithianathan & Emily Putnam-Hornstein, *Risk Assessment and Decision Making in Child Protective Services: Predictive Risk Modeling in Context*, 79 CHILD. & YOUTH SERVS. REV. 291 (2017).

41. GAIL S. ENNIS, THE SOCIAL SECURITY ADMINISTRATION'S USE OF INSIGHT SOFTWARE TO IDENTIFY POTENTIAL ANOMALIES IN HEARING DECISIONS 11 (2019); ENGSTROM ET AL., *supra* note 1, at 40.

42. ENGSTROM ET AL., *supra* note 1, at 48–49.

43. Steven J. Balla, Reeve Bull, Bridget C.E. Dooling, Emily Hammond, Michael Herz, Michael Livermore & Beth Simone Noveck, R*esponding to Mass, Computer-generated and Malatributed Comments,* 74 ADMIN. L. REV. 95, 96 (2022); ENGSTROM ET AL., *supra* note 1, at 59–61.

44. *See generally* ENGSTROM ET AL., *supra* note 1; Coglianese & Ben Dor, *supra* note 1.

45. Such as the prior art search at the USPTO. ENGSTROM ET AL., *supra* note 1, at 48–49.

46. For example, for medical analysis in the Department of Veteran Affairs. *See* U.S. DEP'T VETERANS AFFS., ARTIFICIAL INTELLIGENCE (AI) STRATEGY 12 (2021).

under the AI umbrella, including supervised machine learning for prediction, unsupervised machine learning for clustering, image recognition and analysis, text analysis and natural language processing, and more.[47]

Over the last decade, while many initiatives for algorithmization of governmental decision-making have emerged, there have also been notoriously less successful use-cases.[48] In some instances, these resulted in the impromptu and erroneous cutting of unemployment and other benefits to recipients, without thorough explanation. For example, in Michigan, a system called MiDAS (Michigan Integrated Data Automated System) was purported to automate identification of fraudulent employment filings to the State's Unemployment Insurance Agency.[49] MiDAS led to a fivefold increase in accusations of fraud, charging high penalties and seizing bank accounts and wages with inadequate notice.[50] Eventually, class action litigation resulted in scrapping the system, reversing 70% of fraud claims, and subsequent litigation between the federal government, the state, and the vendor.[51]

Such cases are exemplary of what is at stake in automation of government services and reflect violation of basic notions of public law that require the government to provide proper notice and reasoning for its actions. To be sure, some concerns are typical of any large-scale decision system, whether machine- or human-based, such as errors of different types, biases, compliance-driven behaviors like gaming, and more.[52] Other concerns, however, are specific to AI. In particular, these include opacity, inscrutability, unpredictability, and an inability to provide reasons for decisions.[53] Additionally, when algorithmic systems are procured, as is often the case,[54] another layer of complexity is added due to proprietary interests[55]

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47. ENGSTROM ET AL., *supra* note 1, at 19–20.

48. For a skeptical voice documenting some of these use-cases, see VIRGINIA EUBANKS, AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR (2018).

49. *See* Calo & Citron, *supra* note 2, at 827–831.

50. *Id.*

51. *See* Calo & Citron, *supra* note 2, at 827–831. In the Netherlands, a government was ousted due to a scandal that arose under similar circumstances where an automated system wrongly accused thousands of families of fraud in child support benefits. *See* Jon Henley & Robert Booth, *Welfare Surveillance System Violates Human Rights, Dutch Court Rules*, GUARDIAN (Feb. 5, 2020, 8:18 AM) https://www.theguardian.com/technology/2020/feb/05/welfare-surveillance-system-violates-human-rights-dutch-court-rules [https://perma.cc/PE4V-6XE4].

52. Engstrom & Ho, *Artificially Intelligent Government*, *supra* note 21.

53. Mike Ananny & Kate Crawford, *Seeing Without Knowing: Limitations of the Transparency Ideal and Its Application to Algorithmic Accountability*, 20 NEW MEDIA & SOC'Y 973, 982-3 (2018); Jenna Burrell, *How the Machine 'Thinks': Understanding Opacity in Machine Learning Algorithms*, 3 BIG DATA & SOC'Y 1, 9 (2016); Calo & Citron, *supra* note 2; FRANK PASQUALE, THE BLACK BOX SOCIETY 8 (2015); Andrew D. Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085 (2018); Rebecca Wexler, *Life, Liberty, and Trade Secrets: Intellectual Property in the Criminal Justice System*, 70 STAN. L. REV. 1343 (2018).

54. *See* Deirdre K. Mulligan & Kenneth A. Bamberger, *Procurement as Policy: Administrative Process for Machine Learning*, 34 BERKELEY TECH. L. J. 781 (2019).

55. Cary Coglianese & David Lehr, *Transparency and Algorithmic Governance*, 71 ADMIN. L.

and the oversight challenges that come with increased reliance on private contracting.[56] At the risk of overgeneralizing, these matters mostly boil down to a concern about accountability—the ability to attribute actions to an agent, demand explanations about the action from that agent, and have recourse where it is due.[57]

A starting point for the debate over accountability for algorithmic systems is the insight that algorithms are sociotechnical systems embedded in human organizational contexts.

A. Algorithms are Sociotechnical Systems

Algorithms are sociotechnical systems.[58] Machines, humans, and institutions are all involved in making technology work, and all these components need to be accounted for in thinking about governance. Beyond technical design, the effects of algorithmic systems depend also on the social and organizational environment in which they are implemented.[59]

This is manifested in the fact that policy preferences and value-laden judgments are embedded in every aspect of algorithmic systems. Unrepresentative or biased data for model training and validation can lead to biased predictions;[60] variable selection and categorization, and chosen targets variables, can lead to very different outcomes;[61] model architecture and type signifies strong assumptions about the world;[62] the optimization procedure includes policy trade-offs between different goals and error types,[63] and more. The initial decision to develop an

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REV. 1 (2018).

56. Kate Crawford & Jason Schultz, *AI Systems as State Actors*, 119 COLUM. L. REV. 1941 (2019); EUBANKS, *supra* note 48; Marion Fourcade & Jeffrey Gordon, *Learning Like a State: Statecraft in the Digital Age*, 1 J.L. POL. ECON. 78 (2020), https://escholarship.org/uc/item/3k16c24g [https://perma.cc/36LJ-AGVB]; Mulligan & Bamberger, *supra* note 54. For more regarding the effects of privatization on the public sector bureaucracy, see Jon D. Michaels, *Privatization's Progeny*, 101 GEO. L.J. 1023 (2013).

57. *See generally* JERRY L. MASHAW, REASONED ADMINISTRATION AND DEMOCRATIC LEGITIMACY: HOW ADMINISTRATIVE LAW SUPPORTS DEMOCRATIC GOVERNMENT (2018); Jerry L. Mashaw, *Accountability and Institutional Design: Some Thoughts on the Grammar of Governance*, *in* PUBLIC ACCOUNTABILITY, DESIGNS, DILEMMAS AND EXPERIENCES 115 (Michael W. Dowdle ed., 2006).

58. Albert Meijer & Stephan Grimmelikhuijsen, *Responsible and Accountable Algorithmization: How to Generate Citizen Trust in Governmental Usage of Algorithms*, *in* THE ALGORITHMIC SOCIETY (2021); Selbst et al., *supra* note 8; Ali Alkhatib & Michael Bernstein, *Street-Level Algorithms: A Theory at the Gaps Between Policy and Decisions*, *in* PROC. 2019 CHI. CONF. HUM. FACTORS IN COMP. SYS. 1 (2019), https://dl.acm.org/doi/10.1145/3290605.3300760 [https://perma.cc/VYG2-J7S3].

59. Selbst et al., *supra* note 8.

60. Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CALIF. L. REV. 671 (2016); Sandra G. Mayson, *Bias In, Bias Out,* 128 YALE L. J. 2218 (2019).

61. John Monahan & Jennifer L. Skeem, *Risk Assessment in Criminal Sentencing*, 12 ANN. REV. CLIN. PSYCH. 489 (2016); Rashida Richardson, Jason M Schultz & Kate Crawford, *Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice,* 94 N.Y.U. L. REV. 192 (2019).

62. Mulligan & Bamberger, *supra* note 54, at 781.

63. Emily Black, Hadi Elzayn, Alexandra Chouldechova, Jacob Goldin & Daniel E. Ho, *Algorithmic Fairness and Vertical Equity: Income Fairness with IRS Tax Audit Models, in* FACCT '22:

algorithmic system, and the definition of its purpose, arise in a certain context comprised of norms, power allocation, and more.[64] All stages in the development process, including choosing the type of model, training data, optimization goals, outcome variables, and user interface design, are infused with policy choices and value preferences. Assuming algorithms are exogenous technological phenomena that are slotted into a human environment is understating how they really work.[65]

The implementation of algorithmic systems in an organizational context shapes their potential outcomes. The design of hybrid human-machine decision-making, and the organizational structures that embody it, is notably difficult and important.[66] Designing a hybrid process requires an understanding of the distribution of potential (and certain to occur) errors and their relative weights, and an appreciation of what disagreements between humans and machine reflect and teach us.[67]

Take for example a child protection services (CPS) agency attempting to improve its hotline screening apparatus.[68] This is the first entry point to CPS's domain, where serious allegations about abuse and neglect are made. An agency opting to design an algorithm to assist in screening calls based on risk assessment will have to consider the probability of false negative errors (cases predicted as low risk, while being in fact high risk) against the probability of false positives (low risk cases predicted as high risk). The consequences of a false negative could be failing to act on an allegation of abuse, leading to eventual real harm to a child (and inviting public and political scrutiny), while the ramifications of false positives are unwarranted investigations which are both costly and generate an emotional burden for families, especially in lower socioeconomic strata. Not all errors can be avoided, and so the agency must decide how many errors can be tolerated, and of which kind.

2022 ACM CONF. FAIRNESS, ACCOUNTABILITY & TRANSPARENCY (2022).

64. Fourcade & Gordon, *supra* note 56.

65. The field of science and technology studies (STS) has long advocated the notion that technology is not a foreign object but rather part of a wider social and political context. *See, e.g.*, Bruno Latour, *Technology is Society Made Durable*, 38 SOCIO. REV. 103 (1990).

66. Rebecca Crootof, Margot E. Kaminski & W. Nicholson Price, *Humans in the Loop*, 76 VAND. L. REV. 429 (2023); Christian Leibig, Moritz Brehmer, Stefan Bunk, Danalyn Byng, Katja Pinkert & Lale Umutlu, *Combining the Strengths of Radiologists and AI for Breast Cancer Screening: A Retrospective Analysis*, 4 LANCET DIGIT. HEALTH e507 (2022); Sebastian Raisch & Sebastian Krakowski, *Artificial Intelligence and Management: The Automation–Augmentation Paradox*, 46 ACAD. MGMT. REV. 192 (2021); MAITHRA RAGHU, KATY BLUMER, GREG CORRADO, JON KLEINBERG, ZIAD OBERMEYER & SENDHIL MULLAINATHAN, THE ALGORITHMIC AUTOMATION PROBLEM: PREDICTION, TRIAGE, AND HUMAN EFFORT (2019), http://arxiv.org/abs/1903.12220 [https://perma.cc/LB9U-GD5K].

67. Avi Gesser, Anna Gressel, Mengyi Xu & Samuel J. Allaman, *When Humans and Machines Disagree – The Myth of "AI Errors" and Unlocking the Promise of AI Through Optimal Decision Making,* DEBEVOISE DATA BLOG (Nov. 14, 2022), https://www.debevoisedatablog.com/2022/11/14/when-humans-and-machines-disagree-the-myth-of-ai-errors-and-unlocking-the-promise-of-ai-through-optimal-decision-making-adm-algorithm/ [https://perma.cc/B8BT-GRNL].

68. Cuccaro-Alamin et al., *supra* note 40.

While an algorithmic system may reduce overall error rates, it still requires decisions about the metrics of error that are deemed most important by the agency. This complex balance also includes questions of costs, resources, and efficiency:[69] the agency cannot afford to send out caseworkers to meet children in all reported cases. On the other hand, investigating too widely may also impede public trust and make the community less willing to cooperate with CPS. Moreover, the agency will also have to consider that while the algorithm may be less likely to make some errors that humans are prone to making,[70] it may be prone to other errors. Algorithmic systems may fail to detect situations that are less common in the training data, for instance predicting a low risk when a family has no prior CPS history due to a move from out-of-state—a mistake a human decision-maker is not likely to make.[71]

All these organizational aspects will affect what algorithm is developed, what outcomes it will lead to, and how it will be implemented in the agency.

B. The Bureaucratic Context

Organizational design and implementation, apart from the algorithmic model itself, shape outcomes, in what Engstrom and Haim call second-level design choices.[72] Many algorithmic systems operate at the street- or front-line level. Some conjecture that algorithmic systems will transform public bureaucracies from the street- to the screen-level and ultimately system-level.[73] A common description in the emerging literature of *automated discretion* is that algorithms routinize the ways discretion is manifested and remove some of the power that frontline agents have

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69. *See* Brett Drake, Melissa Jonson-Reid, María Gandarilla Ocampo, Maria Morrison & Darejan Daji Dvalishvili, *A Practical Framework for Considering the Use of Predictive Risk Modeling in Child Welfare*, 692 ANNALS AM. ACAD. POL. & SOC. SCI. 162 (2020); Emily Bosk & Megan Feely, *The Goldilocks Problem: Tensions Between Actuarially Based and Clinical Judgment in Child Welfare Decision Making*, 94 SOC. SERV. REV. 659 (2020).

70. Such as relying on representative heuristics from personal experience rather than statistical tendencies. *See generally* DANIEL KAHNEMAN, THINKING, FAST AND SLOW (2011); Robyn M.Dawes, David Faust & Paul E. Meehl, *Clinical Versus Actuarial Judgment,* 243 SCIENCE 1668 (1989).

71. This is often referred to as the Broken Leg Problem. *See* William M. Grove & Paul E. Meehl, *Comparative Efficiency of Informal (Subjective, Impressionistic) and Formal (Mechanical, Algorithmic) Prediction Procedures: The Clinical–Statistical Controversy*, 2 PSYCH. PUB. POL'Y. & L. 293, 307–09 (1996); Kurt Salzinger, *Clinical, Statistical, and Broken-Leg Predictions*, 33 BEHAV. & PHIL. 91 (2005).

72. Engstrom & Haim, *supra* note 7.

73. Mark Bovens & Stavros Zouridis, *From Street-Level to System-Level Bureaucracies: How Information and Communication Technology is Transforming Administrative Discretion and Constitutional Control*, 62 PUB. ADMIN. REV. 174 (2002); Stavros Zouridis, Marlies van Eck & Mark Bovens, *Automated Discretion*, *in* DISCRETION AND THE QUEST FOR CONTROLLED FREEDOM 313 (2020). Several authors characterize the blending of algorithmic systems and human decision-making in government by calling the new phenomenon artificial, digital, or automated. *See* Matthew M. Young, Justin B. Bullock & Jesse D. Lecy, *Artificial Discretion as a Tool of Governance: A Framework for Understanding the Impact of Artificial Intelligence on Public Administration*, 2 PERSPS. PUB. MGMT. & GOVERNANCE 301 (2019); Peter André Busch & Helle Zinner Henriksen, *Digital Discretion: A Systematic Literature Review of ICT and Street-level Discretion*, 23 INFO. POLITY: INT'L J. GOV'T & DEMOCRACY INFO. AGE 3 (2018).

traditionally employed in public administration.[74] Instead, they render administrative decision-making more rule-oriented, gravitating away from the agent's judgment at a decision point to pre-defined systematic rules.[75]

Nevertheless, currently, most administrative discretion is still dispersed across the frontlines. In these situations, algorithmic systems need to be situated within an organizational context. Some have surmised that power and discretion are likely to flow along three axes: *Up*, *Over*, and *Out*.[76] But this will not necessarily be a smooth, one-directional change but rather a dialectic ebb and flow. Rather than turning agencies into ideal Weberian types, algorithmic systems will shift discretion to other points of entry. Rules tend to redistribute discretion, and power accumulates at junctions of uncertainty or indeterminacy.[77] Oftentimes this is not by design but a reality which agencies face when aspiring to high automation but failing to control how discretion is manifested.[78]

Administrative agencies are diverse, and their structure and culture are a determinative aspect in how decisions are made and outcomes are reached.[79] Agencies, even those similarly positioned, function differently, for various reasons including observable factors, such as statutory requirements or subject-matter expertise, and less readily discernable traits, such as political influence or internal status hierarchies. For one thing, internal culture and structure are more likely to influence the policy outcomes of agencies that are more reliant on a frontline workforce for fact-finding and judgment.[80] Administrative agencies with more centralized operations, such as some federal agencies, are still influenced by internal culture and dynamics between scientists, economists, lawyers, and other professionals. Inconsistencies across decision-makers remain one of the most difficult problems in government decision-making.[81]

74. Noortje de Boer & Nadine Raaphorst, *Automation and Discretion: Explaining the Effect of Automation on How Street-level Bureaucrats Enforce*, 25 PUB. MGMT REV. 42 (2021); Peter André Busch, Helle Zinner Henriksen & Øystein Sæbø, *Opportunities and Challenges of Digitized Discretionary Practices: A Public Service Worker Perspective*, 35 GOV'T INFO. Q. 547 (2018); Aurélien Buffat, *Street-Level Bureaucracy and E-Government*, 17 PUB. MGMT. REV. 149 (2015).

75. De Boer & Raaphorst, *supra* note 74.

76. Engstrom, *supra* note 2.

77. Pääkkönen et al., *supra* note 8.

78. *Id.*

79. WILSON, *supra* note 11.

80. LIPSKY, *supra* note 9; Ho & Sherman, *supra* note 15. For example, a study of child welfare agencies in two adjacent counties, where frontline decision-making is key, found substantially different implementations of an identical risk assessment protocol due to differences in power hierarchies and status based on gender, race, and experience. *See* Emily Bosk & Megan Feely, *The Goldilocks Problem: Tensions Between Actuarially Based and Clinical Judgment in Child Welfare Decision Making*, 94 SOC. SERV. REV. 659 (2020).

81. DANIEL KAHNEMAN, OLIVIER SIBONY & CASS R. SUNSTEIN, NOISE (2020); Ramji-Nogales et al., *supra* note 14.

1. Hybrid Human-Algorithm Decision-making

Algorithmic systems are entwined within underlying organizational conditions. Designing a hybrid (human-machine-organization) process involves many decisions about implementing algorithms into a process involving human personnel in an organizational context. Particularly, consider the level of discretion a human decision-maker retains. A CPS agency could institute a mandatory protocol predicated on a likelihood threshold, such as screening out all cases predicted as low risk unless a screener overrides.[82] Overrides can be affixed to costs, such as seeking supervisory approval to do so or providing a written explanation that can later be reviewed.[83] In other scenarios, the whole procedure may change, and agencies could route certain cases (for instance, high probability of eligibility for an application) to a reviewing team staffed by lower-level officials with less capacity to assess cases, serving in a corrective role rather than performing holistic determination.[84]

However, frontline staff cajoled to use algorithmic systems will often exhibit "strategies of resistance" and render the implementation a "contested terrain."[85] Staff may be afraid of de-skilling and loss of professional autonomy,[86] which often translates into a tug-of-war over discretion between line-level staff and management echelons.[87] Frontline staff that feel discretionary authority is being curtailed will seek ways to resist,[88] and workers will find ways to subvert systems and game them to match their preferred outcomes, especially if they feel tension between professional judgment and the algorithm.[89]

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82. Allegheny County instituted similar mandatory protocols to its child-protection screening tool after learning that screeners tended to ignore the algorithm's recommendations in previous iterations. *See* RHEMA VAITHIANATHAN, NAN JIANG, TIM MALONEY, PARMA NAND & EMILY PUTNAM-HORNSTEIN, DEVELOPING PREDICTIVE RISK MODELS TO SUPPORT CHILD MALTREATMENT HOTLINE SCREENING DECISIONS, *in* ALLEGHENY METHODOLOGICAL REPORT 5 (2017).

83. For example, see Alex Chohlas-Wood, Joe Nudell, Keniel Yao, Zhiyuan (Jerry) Lin, Julian Nyarko & Sharad Goel , *Blind Justice: Algorithmically Masking Race in Charging Decisions*, *in* PROCEEDINGS OF THE 2021 AAAI/ACM CONFERENCE ON AI, ETHICS, AND SOCIETY 35, 36 (2021), https://dl.acm.org/doi/10.1145/3461702.3462524 [https://perma.cc/T4AG-H4GS]. For a further development of this idea in the administrative context, see Katherine J Strandburg, *Rulemaking and Inscrutable Automated Decision Tools*, 119 COLUM. L. REV. 1851 (2019) [hereinafter Strandburg, *Rulemaking and Automated Tools*]; Katherine J. Strandburg, *Adjudicating with Inscrutable Decision Rules*, *in* MACHINES WE TRUST: PERSPECTIVES ON DEPENDABLE AI (Marcello Pelillo & Teresa Scantamburlo eds., 2020) [hereinafter Strandburg, *Adjudicating with Inscrutable Rules*].

84. The QDD algorithm deployed by the Social Security Administration, for example, routes cases predicted as very likely to be eligible to a lower-level and speedier review. *See* ENGSTROM ET AL., *supra* note 1, at 40, 82–85.

85. Kellogg et al., *supra* note 29.

86. Sarah Brayne & Angèle Christin, *Technologies of Crime Prediction: The Reception of Algorithms in Policing and Criminal Courts*, 68 SOC. PROBS. 608, 615–18 (2021).

87. Raso, *supra* note 31; Jennifer Raso, *Implementing Digitalization in an Administrative Justice Context*, *in* THE OXFORD HANDBOOK OF ADMINISTRATIVE JUSTICE 521, 526 (2021).

88. Kellogg et al., *supra* note 29.

89. *Id.*; Devansh Saxena, Karla Badillo-Urquiola, Pamela J. Wisniewski & Shion Guha, *A Human-Centered Review of the Algorithms Used Within the U.S. Child Welfare System*, *in* CHI '20:

In some cases, internal culture that empowers line-level decision-making can yield perverse results.[90] For example, in the immigration context, a risk assessment algorithm that was adopted to *reduce* detainment in removal proceedings ended up with the reverse consequences. The tool was initially meant to direct officers' decisions and better align them with actuarial measures of risk.[91] But internal power struggles and pressure from line-level ICE officers led to updates to how the risk is calculated and what the threshold is, leading it to be more likely to recommend detention.[92] In fact, the agency sought to minimize override rates of the algorithm but ended up doing so not by changing the agents' behavior, but by transforming the algorithm to be harsher.[93]

However, a contrary dynamic could also unfold. Organizational culture and norms could yield stronger effects of algorithmic systems than intended by agencies. Algorithmic systems that are only meant to add supplemental tools could be seen by workers to establish rigid rules, or workers may over-rely due to misplaced trust and lack of capacity and resources to critically reflect on algorithmic predictions or suggestions. The issues of attention and cognitive resources of human users are pertinent. Empirical findings suggest that humans may have a basic aversion towards algorithms and tend to mistrust them.[94] This would suggest agencies may have to seek ways to engender trust in systems to ensure their usefulness, and in some cases mandate or encourage their use. The results are mixed, however, with other findings suggesting aversion is not permanent, and in fact, when humans become familiar with algorithms, they may end up over-relying on them.[95] The phenomenon of automation bias, widely documented in different fields, is an instance of over-reliance.[96] This instead suggests agencies will have to find ways to guard against over-reliance and perfunctory human oversight of algorithmic tools.

PROCEEDINGS OF THE 2020 CHI CONFERENCE ON HUMAN FACTORS IN COMPUTING SYSTEMS (2020), https://dl.acm.org/doi/pdf/10.1145/3313831.3376229 [https://perma.cc/A2PE-ES4F].

90. Robert Koulish, *Immigration Detention in the Risk Classification Assessment Era*, 16 CONN. PUB. INT. L.J. 3 (2017); Mark Noferi & Robert Koulish, *The Immigration Detention Risk Assessment,* 29 GEO. IMMIGR. L.J. 45 (2014); Evans & Koulish, *supra* note 31.

91. Noferi & Koulish, *supra* note 90.

92. Evans & Koulish, *supra* note 31, at 795–96.

93. *Id.* at 804–33.

94. Berkeley J. Dietvorst, Joseph P. Simmons & Cade Massey, *Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err*, 144 J. EXPERIMENTAL PSYCH.: GEN. 114 (2015); Berkeley J. Dietvorst, Joseph P. Simmons & Cade Massey, *Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms if They Can (Even Slightly) Modify Them*, 64 MGMT. SCI. 1155 (2018).

95. SAMIR PASSI & MIHAELA VORVOREANU, OVERRELIANCE ON AI: LITERATURE REVIEW 24 (2022).

96. Linda J. Skitka, Kathleen Mosier & Mark D. Burdick, *Accountability and Automation Bias*, 52 INT'L J. HUM.-COMPUT. STUD. 701, 716 (2000); Linda J. Skitka, Kathleen Mosier & Mark Burdick, *Does Automation Bias Decision-Making?*, 51 INT'L J. HUM.-COMPUT. STUD. 991, 991–92 (1999).

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What is becoming increasingly clear is that organizational context matters substantially to how algorithms are perceived and implemented. While algorithm aversion and automation bias are both potential—though opposite—concerns, they are greatly influenced by the culture, norms, and structures in which algorithms are embedded. This is true for any sector, but it is even more apparent in the public sector, where bureaucracies handle large portions of everyday decision-making. Organizational structure, culture, and norms will have an important role in shaping how administrative agencies develop and implement algorithmic systems and what outcomes they yield. These are, in essence, a component of bureaucratic systems rather than an independent, exogenous, artifact. The legal frameworks that will regulate and handle how agencies use algorithmic systems are only starting to grapple with this understanding.[97]

Up to this point, this article portrayed the bureaucratic context in which administrative algorithms are situated and their sociotechnical characteristics which complicate regulatory approaches to ensuring accountability. The following section furthers this endeavor by situating algorithmic systems within this setting. It argues that since algorithms can function as internal governance mechanisms, we should be paying more attention to what the law governing such internal systems requires, which differs from administrative law concerning administrative actions.

II. ADMINISTRATIVE LAW AND INTERNAL ALGORITHMIC GOVERNANCE

Much of the previous literature has treated algorithms either as part of the external-facing system of rules and adjudications,[98] or as simply computational tools.[99] Yet in many situations, algorithms are functioning more like internal governance systems.

Algorithmic systems are information processing apparatuses, utilizing computational power and various processing techniques to yield a prediction or another outcome according to specified goals and tasks.[100] Bureaucracies are also information-processing apparatuses, collecting data about phenomena (e.g., health statistics), processing them according to an overarching objective set by the law (e.g., public health), and making decisions about executable actions to best achieve these goals (e.g., an inoculation campaign).[101] In reality, of course, bureaucracies are constrained by imperfect information and the bounded rationality of administrative

97. *See generally* Engstrom & Haim, *supra* note 7.

98. Ryan Calo & Danielle Keats Citron, *The Automated Administrative State: A Crisis of Legitimacy*, 70 EMORY L.J. 797, 800–01 (2021).

99. Coglianese & Lehr, *supra* note 1, at 1167.

100. Peter Duchessi, Robert O'Keefe & Daniel O'Leary, *A Research Perspective: Artificial Intelligence, Management and Organizations*, 2 INTELLIGENT SYS. ACCT., FIN. & MGMT. 151 (1993); Thomas J. Barth & Eddy Arnold, *Artificial Intelligence and Administrative Discretion: Implications for Public Administration*, 29 AM. REV. PUB. ADMIN. 332, 334–35 (1999).

101. *See* Duchessi et al., *supra* note 100.

behavior.[102] Moreover, relying on a cadre of line-level employees for information collection and executing policy introduces noise and inconsistencies across decisions.[103] Besides inconsistencies, ample discretionary powers can impede the effective implementation of policy goals in an instantiation of the principal-agent problem.[104] Bureaucracies thus deploy different methods to control and standardize the discretion of their employees. Beginning with rules that set out the contours of a decision and moving towards managerial tools of control and incentivization, direction of docket, direct supervisory review, quality assurance procedures, and more.[105] Experimentalist approaches also include peer review programs and other innovative programs.[106] Recently, AI algorithms have begun being noticed as potential governance mechanisms as well.[107]

A. Algorithms as Instruments of Internal Governance

1. Information Processing

The simplest purpose algorithmic systems can serve is information processing. While this may appear obvious, it is a fundamental idea of modern organizational and public management theory that information flow and processing are central problems, and their improvement can yield significant gains for any organization.[108] Humans make decisions under bounded rationality[109] and suffer from crucial and well-documented flaws in information capturing, retrieval, and application.[110] This leads the human-based bureaucracy to suffer from apparent flaws in predictions, preparation, applying expertise, or mere lackadaisical attitudes, all of which can undermine public trust and legitimacy. Unsurprisingly, then, scholars and administrators have sought numerous ways to improve information flows and remove blockages, moving from early standardization efforts to computerization of public services, to investing in information technology and infrastructure.[111] AI

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102. SIMON, *supra* note 35.

103. This is prevalent in street-level bureaucracies that carry out policy in the field. *See* LIPSKY, *supra* note 9; Ho & Sherman, *supra* note 15. But it is also widespread in more formal adjudicatory settings. *See* Hausman, *supra* note 14; Ramji-Nogales et al., *supra* note 14. It is well-known in the criminal justice context as well. *See* Itay Ravid & Amit Haim, *Progressive Algorithms*, 12 U.C. IRVINE L. REV. 527 (2021); Jeffrey J. Rachlinski, Sheri Lynn Johnson, Andrew J. Wistrich, & Chris Guthrie, *Does Unconscious Racial Bias Affect Trial Judges,* 84 NOTRE DAME L. REV. 1195 (2008).

104. LIPSKY, *supra* note 9.

105. Ho & Sherman, *supra* note 15.

106. *See generally* Daniel E. Ho, *Does Peer Review Work: An Experiment of Experimentalism*, 69 STAN. L. REV. 1 (2017); Charles F. Sabel & William H. Simon, *Minimalism and Experimentalism in the Administrative State,* 100 GEO. L.J. 53 (2011).

107. HO ET AL., *supra* note 10.

108. SIMON, *supra* note 35.

109. *Id.*

110. KAHNEMAN ET AL., *supra* note 81.

111. For an overview and a discussion of these issues, see David Landsbergen Jr. & George Wolken Jr., *Realizing the Promise: Government Information Systems and the Fourth Generation of*

algorithms are a continuation of this trend, as they maximize utilization of data and available information and allow agencies to take better advantage of the vast amounts of administrative data they generate.[112]

2. Managerial Tools

Informational barriers between high-level officials and delegatees are one of the main impetuses for internal control mechanisms.[113] Algorithmic systems can bridge some of these gaps, lessening the need for blunter instruments.[114]

Public bureaucracies are largely constrained in their managerial flexibility: public servants are insulated from employment termination, and pay is unpegged from performance in most public services.[115] Moreover, in many cases, the law restricts interference from actors other than a designated decision-maker, lest there be risk of political or other illegitimate influence.[116] Agencies are thus left with a limited toolbox to control and direct discretion at the line-level. As managerial tools, algorithmic systems allow agencies to centrally guide the discretion of every line-level employee or official, without having to review each decision ex post. For instance, a risk-assessment instrument that automatically generates a prediction for each case on the docket reduces the need to formalize risk definition through guidelines or manuals and can reduce inconsistencies across decision-makers by anchoring them around the same risk levels with subjective assessments.

They may also allow agencies to increase specific domains of expertise, thus improving overall performance and reducing noise. For example, a system that clusters similar cases together will allow adjudicators to develop micro-specialization in certain types of claims without the need to learn a wide variety of

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Information Technology, 61 PUB. ADMIN. REV. 206 (2001).

112. Most AI applications listed in the federal AI inventory fall under this category. *See Agency Inventories of AI Use Cases*, NAT'L A.I. INITIATIVE OFF., https://www.ai.gov/ai-use-case-inventories/ [https://perma.cc/YEF7-4W78] (last visited Jan 24, 2023).

113. Elizabeth Magill, *Agency Self-Regulation*, 77 GEO. WASH. L. REV. 859, 886 (2009). ("Effectively controlling those who exercise delegated authority is a hard problem for any organization, and there are trade-offs associated with each mechanism of control. That complexity aside, the point for present purposes is that many self-regulatory measures will be best explained as efforts by the top-level agency decisionmakers to control authority delegated to others within the agency."); *see also* Jennifer Nou, *Intra-Agency Coordination*, 129 HARV. L. REV. 421 (2015); Strandburg, *supra* note 83; David K. Hausman, Daniel E. Ho, Mark S. Krass & Anne McDonough, *Executive Control of Agency Adjudication: Capacity, Selection and Precedential Rulemaking*, 40 J.L. ECON. & ORG. (forthcoming 2024).

114. Strandburg develops this idea by conceptualizing how reason-giving and explanations of decisions flow in the bureaucratic structures. *See* Strandburg *Rulemaking and Automated Tools*, *supra* note 83.

115. Sean Gailmard & John W. Patty, *Slackers and Zealots: Civil Service, Policy Discretion, and Bureaucratic Expertise*, 51 AM. J. POL. SCI. 873, 873 (2007); Susan Rose-Ackerman, *Reforming Public Bureaucracy through Economic Incentives*, 2 J.L. ECON. & ORG. 131 (1986).

116. For example, in the context of decisional independence in APA adjudications. *See infra* Section II.B.3.

topics.[117] Likewise, by removing high probability cases from the main docket and routing them to lower-level officials, the efforts and expertise of higher-level and experienced personnel can be better utilized. Algorithmic systems can also provide high-level data on individual performance and productivity. Importantly, if used inappropriately, these can turn into intrusive surveillance measures on workers,[118] but proper use to aid managerial control can facilitate a better-performing bureaucracy.

3. Quality Assurance

As quality assurance measures, algorithms can allow agencies to detect recurrent and similar errors across employees or detect specific workers that substantially deviate from the main tendencies of the agency. They can allow agencies to better tailor quality review teams by allowing them to focus on specific cases algorithmically flagged as high priority by some measure, such as risk or predisposition for error.

Moreover, algorithms can facilitate peer review, a highly promising technique that is rarely adopted.[119] The advantages of peer review are apparent: it works bottom-up from the frontline level, it is individualized and based on replication of work processes, and it can be evaluative (in both quantity and quality) and publicly disclosed.[120] Agencies can have a team of experienced adjudicators to regularly review predictions (sampled on some guiding policy principle), discuss in depth the case and the right disposition, highlight any policy ambiguities that arise and that the algorithm may or may not be capturing, and raise recommendations both for policy amendments and updating of the algorithm.[121] This idea echoes the insight of law and technology studies that technology exposes latent ambiguities in the law;[122] algorithms expose ambiguities in legal standards, which the peer-review process can expose and expound before directly and substantially influencing public parties, and foster continuous development of the law in a better-structured way. That can be fed back into the algorithm through a reinforcement learning procedure. If done systematically, this could allow agencies to flag two types of problems: systemic errors of decision-making and design issues of algorithmic systems.

Feedback is especially important and scarce in most decision-making contexts. Adjudicators can improve with time and experience, but direct feedback is often

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117. ENGSTROM ET AL., *supra* note 1, at 39–40; Glaze et al., *supra* note 10.

118. Kellogg et al., *supra* note 29.

119. Ho & Sherman, *supra* note 15; Ho, *supra* note 106; HO ET AL., *supra* note 10.

120. Ho & Sherman, *supra* note 15, at 254–55.

121. *See* HO ET AL., *supra* note 10, at 27 ("AI can help agencies shift from a purely ex-post model of quality review and toward continuous assessment. Relatedly, insight reflects the potential for AI to promote continuous learning for actors across the system.").

122. LAWRENCE LESSIG, CODE AND OTHER LAWS OF CYBERSPACE 25 (2nd ed. 2006).

not possible. In domains where decisions can be appealed, adjudicators theoretically could learn about their errors—yet the skewed nature of review, along with the time lapse between an initial administrative decision and appellate review, makes this barely beneficial.[123] Some agencies have moved towards publishing opinions or finding other ways to generate feedback for adjudicators.[124] Algorithmic systems can support this effort by generating ways to measure one's work against others and flagging specific cases which warrant special attention and a learning opportunity.

4. *Capacity Enhancing Tools*

As capacity enhancing instruments, algorithmic systems can function to improve quality of written opinions by detecting errors, correct precedent, and statute citation mistakes[125] and augment information quality by improving search capabilities and similar methods.[126]

A paradigmatic problem of administrative decision-making, especially in the mass adjudicatory context,[127] is the lack of sufficient capacity to support accurate decisions. Agencies that lack ample resources, including material infrastructure, expert adjudicators, and support staff, resort to relying on coping mechanisms to manage workloads.[128] These include shortening hearings, making assumptions based on appearance and additional preliminary factors, and other cognitive shortcuts to reduce burdens. These mechanisms undoubtedly lead to errors, which are not random, thus affecting not only the levels of inconsistencies and inaccuracies but creating disparate impacts against certain classes.[129] Algorithmic systems can serve as cognitive counterweights to some of these problems by countering assumptions and heuristics with data-based predictions and suggestions.[130]

Likewise, algorithmic tools can be used to effectively provide workers with appropriate information in real time. Policy and regulatory guidelines are often convoluted and difficult for workers to internalize, and their inaccessibility during decision-making instances may often be the impetus for inconsistencies (rather than more novel problem such as ambiguity in the legal standard). Experienced adjudicators are more likely to retrieve guidelines easily, but experience and training

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123. HO ET AL., *supra* note 10, at 18.

124. *Id.* at 23.

125. *Id.*; ENNIS, *supra* note 41.

126. For instance, in prior art search in patent and trademark adjudications at the USPTO. ENGSTROM ET AL., *supra* note 1, at 48–49.

127. Ames et al., *supra* note 15.

128. Nicholas Bednar, *The Public Administration of Justice*, CARDOZO L. REV. (forthcoming 2023).

129. *See* David Hausman, *The Failure of Immigration Appeals*, 164 U. PA. L. REV. 1177 (2015); Hausman, *supra* note 14; HAUSMAN ET AL., *supra* note 113; Ames et al., *supra* note 15.

130. William D. Eggers, David Schatsky & Peter Viechnicki, *AI-augmented Government: Using Cognitive Technologies to Redesign Public Sector Work*, DELOITTE UNIV. PRESS (Apr. 26 2017), https://www2.deloitte.com/xe/en/insights/focus/cognitive-technologies/artificial-intelligence-government.html [https://perma.cc/YE47-ULWD].

are costly and, obviously, take time to accumulate. Using nimble, user-oriented design, algorithmic tools can automatically highlight relevant policy considerations or legal standards when an issue arises and streamline workers' ability to hold complex concepts.

In most decision-making apparatuses, cases vary in their complexity. The majority of common cases are relatively easy to resolve as they do not raise novel issues. Algorithmic systems can be designed to handle common cases and redirect human attention and judgment where it is most needed—the unique, complicated, unforeseen cases.[131] The average case does not require the most qualified administrative officers, and algorithms can approximate the average handling rather than the best or worst.[132]

B. Application and Adaptation

The integration of algorithms in administrative processes is likely to raise various doctrinal dilemmas, and courts will have to determine if certain APA provisions or a governing statute applies, and what are the remedial consequences. In that manner, courts will shape the contours of internal administrative law. Scholars have termed this dynamic "crowding out" of internal law[133] as its domain is residual to the demarcation of external law. The rest of this section delves into some of implicated doctrines of administrative law as applied to algorithmic systems, to explicate how internal law may be displaced or preserved.

1. Guidance and Legislative Rules

When engaged in rulemaking, agencies have several procedures to follow. At a minimum, any proposed agency action that amounts to a legislative rule must be promulgated through a notice-and-comment procedure that seeks public input and addresses concerns and information raised in the process.[134] There are exceptions to this principle: *First*, notice-and-comment requirements only apply to *legislative rules*, and not to *statements of policy* or *interpretative rules* (collectively referred to as *guidance*).[135] The problem, of course, is to determine what counts as a legislative rule. The doctrine on this point is decidedly murky, as it strives and struggles to differentiate between legislative rules and the residual category of guidance

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131. For a formal discussion of the advantages of algorithms in case triage, *see* Raghu et al., *supra* note 66, at 9–11.

132. Of course, defining what the common cases are—whether by learning from data (machine-learning approach), by expert coding (rule/expert-based systems), or some mix of the two—is not easily achieved and requires substantial expert input, but algorithms can allow bureaucracies to divide their workload into separate tiers which will have different combinations of human and algorithmic handling.

133. Metzger & Stack, *supra* note 16.

134. Administrative Procedure Act, § 5 U.S.C. 553(b) (2006).

135. *See* Ronald M. Levin, *Rulemaking and the Guidance Exemption*, 70 ADMIN. L. REV. 264 (2018).

documents.[136] In essence, courts examine whether the rule in question has a binding effect on the agency, whether it affects public rights or interests, and how it relates to previous promulgated rules or the governing statute.[137] *Second*, the APA exempts *"rules of agency organization, procedure, or practice*."[138] I review the exceptions in order.

a. Policy Statements

When a said document is held by the agency to be a policy statement rather than a rule, courts examine whether it appears to be facially binding or binding-in-effect by agency practice.[139] A rule that has a binding effect on the rights or interests of regulated parties or the public at large will be deemed *legislative*.[140] An algorithmic system that alters a right, such as liberty interests in detention proceedings in the immigration system, will undoubtedly be seen as legislative and thus requiring notice-and-comment prior to taking effect. However, the caselaw differs on the question of the object of bindingness. When rules are binding only on the agency there is some disagreement on what the standard should be.[141] One approach is that a binding effect on line-level decision-makers is enough to trigger notice-and-comment.[142] Another approach suggests that line-level discretion can be curtailed by guidance documents, insofar as the agency as a whole retains the ability to change the outcome, meaning that the guidance entails a primary and not a final position of the agency.[143] This could include the possibility that higher-level officials can authorize deviation from policy,[144] or allow affected persons a fair opportunity to contest the policy at a later stage in the process.[145] The advantages of the latter approach are that regularity, centralized control of personnel, and imposition of public policy is desirable, and structuring discretion is a positive outlook for administrative law. Algorithmic systems can serve a similar purpose by creating preliminary presumptions that may be later altered by the agency. Consider the flagging of cases for review, auditing, or screening in for investigation. Even if initial presumptions are produced algorithmically, downstream inquiries by investigators may decide that there was no reason to take action, or conversely proceed with enforcement action. Either way, higher-level officials or a different unit retains the possibility to change course.

136. *See, e.g.*, *id.* at 265.

137. Pac. Gas & Elec. Co. v. Fed. Power Comm'n, 506 F.2d 33 (D.C. Cir. 1974).

138. *See* 5 U.S.C. § 553(b)(A).

139. Gen. Elec. Co. v. EPA, 290 F.3d 377 (D.C. Cir. 2002); *see* Levin, *supra* note 135, at 292 (providing elaboration on the specific formulation of the test).

140. Levin, *supra* note 135, at 302.

141. Alexander Nabavi-Noori, *Agency Control and Internally Binding Norms*, 131 YALE L.J. 1278 (2022).

142. See for example *Texas v. U.S.*, 809 F.3d 134, 188 (2015).

143. Levin, *supra* note 135, at 305.

144. ADMINISTRATIVE CONFERENCE OF THE U.S, ADMINISTRATIVE CONFERENCE RECOMMENDATION 2017-5: AGENCY GUIDANCE THROUGH POLICY STATEMENT (2017).

145. Levin, *supra* note 135, at 309.

The main concern of the binding norm test is not the degree of freedom that bureaucrats enjoy, but rather preventing harms and coercive effects to external parties. Therefore, an internally robust process that seeks to ameliorate the risks algorithmic systems pose can mitigate concerns. Take for example the MiDAS conundrum in Michigan reviewed earlier.[146] In essence, the problem did not arise from the use of an algorithm to flag fraud but rather that enforcement actions were automatically sent out without a robust review process and notice, leading to coercive enforcement actions.

b. Interpretive Rules

Interpretive rules are rules that interpret and clarify previous statutes or regulations.[147] Courts generally apply the legal effect test to examine whether the rule in question actually makes new law or merely interprets existing law.[148] The test asks whether the rule can credibly be seen as construing an interpretation and not creating a new substantive position that would amount to a legislative rule.[149] There is no obvious way to draw lines: courts sometime ask whether there would be an adequate basis for an agency action, such as enforcement or conferral of benefits, had the rule in question not been in place, or whether it effectively amends a previous rule.[150]

Can algorithmic systems be interpretive? There is no evident reason why they could not be. The text of the APA or administrative law doctrine and precedent do not restrict rules to certain textual formulations, and courts have been very flexible in capturing what could constitute a rule.[151] Besides, the document in question will not only be the code and technical infrastructure of the algorithm, but any protocols constructed in policy documents. Insofar as an algorithmic system encodes previous agency standards and practice, it could be regarded as translating policy into another form, not drawing a distinctly new body of law. Regarding the question of prior basis for action, in most cases it is unlikely algorithmic systems will function as the sole and newfound basis for agency action. This is true for the type of systems used for quality review and assurance and will probably hold for situations where the algorithm is involved in upstream tasks (such as triage, docket clustering, and the

146. Calo & Citron, *supra* note 2, at 827–31; *see* Part I.

147. Levin, *supra* note 135, at 315.

148. Michael Asimow, *Nonlegislative Rulemaking and Regulatory Reform*, 1985 DUKE L.J. 381 (1985). A different approach equates both the policy and interpretive rule exceptions, but at least in some cases, courts have used a somewhat different standard. *See* Levin, *supra* note 135.

149. *Id.* at 394.

150. Am. Mining Con. v. Mine Safety & Health Admin., 995 F.2d 1106, 1111 (D.C. Cir. 1993).

151. CropLife Am. v. Env't Prot. Agency, 329 F.3d 876, 881 (D.C. Cir. 2003) (invalidating, albeit in the policy-statement context, an agency guidance document in the form of a press release for using "clear and unequivocal language, which reflect[ed] an obvious change in established agency practice, [and] create[d] a binding norm that is finally determinative of the issues or rights to which it is addressed").

like) after further downstream efforts are carried out.

The most contentious application will probably be where an algorithm is involved in more substantive decision-making points, but it will mostly be in a supportive capacity. It will generally be hard to argue algorithmic systems in these situations have created an altogether new standard to be applied, and design specifications such as the outcome to be optimized will probably be within the bounds of preexisting legislative rules.

An interesting question is what happens when a machine learning algorithm learns a new pattern in the data to suggest that a certain action should be taken (e.g., auditing).[152] While it may seem desirable to conclude that this is a new substantive standard, it ignores the intricacies of human discretion and agency practice that previously determined the basis for action. Legislative rules rarely mark a bright line but rather define the goals and factors to be considered and later applied by agency officers.

c. Agency Procedures

Probably the most underdeveloped exception to the notice-and-comment requirement excepts internal organizational and procedural rules. A procedural rule does not impose new substantive burdens, though it may alter how parties present themselves or their viewpoints to an agency.[153] This exception may be applicable to many of the applications of algorithmic systems as bureaucratic measures, at least where they are not involved in a decision-making point per se but influence the overall flow of information and workload in the agency. Where an automated process is public facing—for instance, in digitization of certain services—the main question is whether the change is in how the public presents its case to the agency, or whether it has altered rights substantially—for instance, by limiting acceptable evidentiary inputs. But for most internal applications, this exception could very well apply.

d. Can Algorithms Serve as Guidance?

Several commentators have considered the question of applying notice-and-comment to algorithmic systems. Engstrom and Ho suggest that whether an algorithm will be considered a legislative rule or fall within an exception will depend on the degree to which there is a human involved in the decision-making loop.[154] Elsewhere, Engstrom et al. argue that the binding effect of algorithms depends on the "level of adherence" to them and "the extent to which models prospectively

152. Black et al., *supra* note 63.

153. Batterton v. Marshall, 648 F.2d 694, 707 (D.C. Cir. 1980); Aulenback, Inc. v. Fed. Highway Admin., 103 F.3d 156, 169 (D.C. Cir. 1997).

154. Engstrom & Ho, *Algorithmic Accountability*, *supra* note 21, at 836–39.

adapt."[155] Similarly, Coglianese and Lehr argue the main inquiry is whether the algorithm is supportive or determinative of outcomes.[156] Cuellar and Huq take a somewhat different approach and argue the main question is whether the algorithm creates substantive policy.[157]

These are all important inquiries, and the doctrine and caselaw on these issues will evolve in the coming decades. Yet the main problem that already emerges is that courts will find it hard to assess these questions, and their resolution may not be optimal. First, human involvement is not a guarantee of good results, as it may in fact skew outcomes.[158] Second, adherence to an algorithm—for instance, in the form of override rates—may be an indication of its practically binding effect, but it will be hard to ascertain ex ante. The complexity of human-machine interaction and the calibration of trust may change and shift over time and according to a whole set of organizational factors.[159] Relatedly, the stated label of determinative or supportive may not correspond to how things play out in practice. An algorithm that is proclaimed to be supportive may change to become essentially determinative, and even algorithms that are meant to be determinative—provided a human decision-maker is still involved—may lose their prominence over time. In essence, notice-and-comment procedures are not likely to capture these complexities. Moreover, as mentioned earlier, if the binding norm test is to allow agencies flexibility while not relinquishing accountability, constraining line-level discretion should not be precluded. Insofar as the public's rights are not directly affected, agencies should have more freedom to use algorithmic systems to direct the discretion of their officers.

Prospective adaptation poses a harder problem. While some models can be described in a fairly comprehensible way,[160] for most machine learning and deep

155. ENGSTROM ET AL., *supra* note 1, at 84.

156. Coglianese & Lehr, *supra* note 1; *see also Francesca Bignami, Artificial Intelligence Accountability of Public Administration*, 70 AM. J. COMP. L. 312 (2022); Melissa D Mortazavi, *Rulemaking Ex Machina*, 117 COLUM. L. REV. ONLINE 202 (2017).

157. Mariano-Florentino Cuéllar & Aziz Z. Huq, *Artificially Intelligent Regulation*, 151 DAEDALUS 335 (2022).

158. Alex Albright, If You Give a Judge a Risk Score: Evidence from Kentucky Bail Decisions, (Sept. 3, 2019) (unpublished manuscript) (available at https://thelittledataset.com/about_files/albright_judge_score.pdf [https://perma.cc/PF2F-KMRW]) (finding that judges override recommendations differently for black and white defendants); Mitchell Hoffman, Lisa B. Kahn & Danielle Li, *Discretion in Hiring**, 133 Q.J. ECONS. 765 (2018) (finding that managers that override hiring algorithms fare worse than the algorithm); Ben Green, *The Flaws of Policies Requiring Human Oversight of Government Algorithms,* COMPUT. L. & SEC. REV. 45 (arguing generally that ensuring a human in the loop is not a guarantee of good results).

159. *See* Part I; *see also* Peter Henderson & Mark Krass, *Algorithmic Rulemaking v. Algorithmic Guidance*, 37 HARV. J.L. & TEC. (forthcoming 2024) (manuscript at 19-34) (on file with the author).

160. For example, Naïve Bayes and Decision Trees for classification tasks. For an approach that promotes simpler, more explainable, models for high-stakes decisions see Cynthia Rudin, *Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead,* 1 NAT. MACH. INTEL. 206 (2019).

learning applications, it will be essentially impossible to delineate how predictions are made. Agencies could provide global explanations and details over methodology, including data description and model choice, but the model architecture and weights are not suitable for notice-and-comment. This is especially true when such details may adapt over time and releasing them for public comment in every iteration will essentially be a death sentence.

Furthermore, notice-and-comment procedures are costly and protracted. They require agencies to give ample time for comments which may be prolonged by a court, especially on technical matters that require more attention, analysis, and response.[161] Not responding properly to arguments raised in comments may hinder agencies and move courts to require them to do so down the line. Applying these procedures to all algorithmic systems seems, to say the least, suboptimal.[162] Moreover, public notice-and-comment procedures are useful especially in cases where there are substantial gaps of information between regulated parties or regulatory beneficiaries, where agencies can learn from practice and expertise in the field. When algorithms are designed to structure agencies' internal practice, the justification is not as forceful.

Another aspect that highlights the futility of applying the binding norm test is manifested in the expected remedies. A successful challenger to a rule will enjoy one main remedy: a pronouncement that a rule is not binding and remand to the agency to promulgate the rule again if it so chooses. What effect will this have on agency practice? It is hard to speculate, but insofar as an algorithmic system is embedded within a decision-making structure, declaring it non-binding as a matter of law may not have substantial impact. If agency employees are receptive to the algorithm and rely on it for their decisions, proclaiming it supportive rather than determinative may not change their practice. It may require more input and reasoning rather than signing-off a recommendation, but most administrative decisions do not require a written and expansive opinion as a matter of law. Moreover, experimental evidence suggests that reminding decision-makers that an algorithm is merely a source of information does not change their tendency to rely on it.[163] As we have seen, algorithms are embedded in bureaucratic structures that function in practice very differently than what courts may believe or hope. Furthermore, an algorithm may be binding in the sense that it *must* be considered when making a decision, not that the prediction outcome of the algorithm is itself *binding in effect*.

Furthermore, challenging guidance documents in court is difficult, and most

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161. U.S. v. Nova Scotia Food Prods. Corp., 568 F.2d 240 (1977) (finding that the FDA notice-and-comment procedures for a proposed rule were not sufficient when failing to disclose scientific research as a basis for action and to respond to comments that posed alternative hypotheses).

162. Engstrom & Ho, *Algorithmic Accountability*, *supra* note 21, at 839.

163. Christoph Engel & Nina Grgić-Hlača, *Machine Advice with a Warning about Machine Limitations: Experimentally Testing the Solution Mandated by the Wisconsin Supreme Court*, 13 J. LEGAL ANALYSIS 284 (2021).

will not be reviewed.[164] Algorithmic systems as bureaucratic measures will often be embedded within guidance, whether strategically or not, and could fall under the different exceptions to the legislative rule doctrine. Therefore, even if one does not believe algorithms *should* be considered guidance, they should still seek to ensure accountability in their use.

Guidance documents are important in an age of uncertainty, allowing administrative agencies to advance the public interest with frequent correction and improvement.[165] Formally, they are only recognized by the doctrine as a suggestive instrument.[166] They demand flexibility from the agency, as a regulated party may ask the agency to reconsider another approach and the agency must give a fair consideration. Choosing to depart from the course set in guidance will require a reasoned explanation.[167] If agencies can adhere to this model, algorithmic systems could be seen as guidance instruments, in the sense that they depict a course of action which may ultimately be changed by the agency. According to this approach, in relevant settings, an outward facing interface of the algorithmic system can give an applicant a preliminary pre-ruling. If they are discontented or have reservations, the applicant can then file a request with the agency to reconsider and have an adjudicator decide the case. The adjudicator can give fair consideration and give a reasoned explanation for deciding one way or the other.

An apparent issue in this scenario is if the applicant assumes the predetermination is binding upon them, which as outlined above runs against the doctrine. Agencies could take actions to clarify the non-binding nature of the pre-determination, and they may also ameliorate some of the tension and receive public input by going through notice-and-comment, if they so choose. Additionally, in most applications, algorithmic predictions will not be available for outside actors for reasons of privacy, proprietary interests, or fear of strategic gaming and procedure.[168] Therefore, they cannot provide the public information about what the agency is thinking. Allowing agencies to publicly present their intentions and

164. Connor N. Raso, *Strategic or Sincere? Analyzing Agency Use of Guidance Documents* (2010), https://www.yalelawjournal.org/pdf/855_phetapk6.pdf [https://perma.cc/MP3E-GTVF]; Nicolas R. Parrillo, *Federal Agency Guidance and the Power to Bind: An Empirical Study of Agencies and Industries*, 36 YALE J. ON REG. 165; NICHOLAS R. PARRILLO, FEDERAL AGENCY GUIDANCE: AN INSTITUTIONAL PERSPECTIVE 5 (2017), https://www.acus.gov/sites/default/files/documents/parrillo-agency-guidance-final-report.pdf [https://perma.cc/9ZF7-46K2] ("[The current literature] misses much about the everyday workings of guidance that pervade the administrative state, for it focuses on the tiny fraction of guidance documents that get challenged in litigation, and only on the kinds of facts about guidance that reach the courts").

165. Jeremy Kessler & Charles Sabel, *The Uncertain Future of Administrative Law*, 150 DAEDALUS 188, 190–91 (2021).

166. Parrillo, *supra* note 164, at 168–69 ("[Guidance is] a mere tentative announcement of the agency's current thinking about what to do . . ., not something the agency will follow in an automatic, ironclad manner as it would a legislative rule.").

167. Kessler & Sabel, *supra* note 165, at 194.

168. Engstrom & Ho, *Algorithmic Accountability*, *supra* note 21, at 822.

thoughts on complex matters is an important advantage of guidance documents, for which they are touted.[169] In such cases, they are only directed inwards, as bureaucratic measures of standardizing discretion. Their overall design can perhaps be publicized and inform the public how *in general* predictions are made and contribute to decisions.

Guidance has the advantage of offering regulated parties predictability while not ruling out flexibility on the side of the agency—what Nick Parrillo calls "principled flexibility."[170] Agencies have some incentive to develop reasoned departures because of regulated parties demanding consistency and producing litigation risk when guidance is used in adjudications,[171] but this is likely underenforced because of litigation considerations on the part of the regulated parties or because the guidance pertains to enforcement action which is unreviewable. Therefore, it is to a large extent, according to Parrillo, organizational and political factors that encourage principled flexibility.[172] The issue is that principled flexibility is "an expensive, logistically challenging process to carry out and manage."[173] Parrillo documents the challenges in practice to principled flexibility, stemming from agency capacity, logistics, and incentives.[174]

When algorithmic systems are involved in the guidance process, there is the potential for a kind of common law of algorithmic departures to develop. Algorithms can be involved in the principled flexibility endeavor by lowering coordination and dissemination costs inside the agency and supporting deliberation on specific applications for departure. For example, another issue Parrillo highlights is the challenge, especially for non-lawyer officials, in constantly recalling the distinction between guidance and binding rules.[175] In this case, for instance, a well-tailored, text-based algorithm could aid officials in being *more* flexible by flagging questions about reasons an applicant gave for departure and an official did not consider in their opinion.

169. Christopher J. Walker, *Administrative Law Without Courts*, 65 UCLA L. REV. 1620, 1624–26 (2018).

170. Parrillo, *supra* note 164, at 241 ("[A]gency officials make departures from guidance, but for each departure, they give a written explanation that is accessible to other agency officials and to regulated parties, with the understanding that the exception thereby becomes generally applicable to like facts going forward. The departure explanations form a body of rationally evolving precedent that informs future decisions about departure requests.").

171. Or even if it isn't, though this position is contested. *Id.* at 242–43.

172. *Id.* at 243 ("[I]nsofar as agencies adopt principled flexibility, it will, to a great degree, be organizational and political factors that drive them to it, not just legal ones.").

173. *Id.* at 244.

174. The ratio of resources to volume of work (or in other words, capacity) determines the ability to deliberate on individualized requests for departures, especially when high-level officials must be involved in the process and departures need to be recorded and disseminated. *Id.* at 247–61.

175. *Id.* at 258–59.

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After all, which role *should* notice-and-comment play? *First*, pronouncing the use of an algorithmic system and outlining its general structure could promote public legitimacy and help agencies avoid unforeseen harms and challenges.[176] This should include the intention and general goals, as well as potential applications, but does not necessarily need to cover the technical aspects and specific institutional design. These require greater flexibility and are not within the ambit of the legislative rule doctrine. Requiring agencies to air out every aspect just because there is an algorithm involved will undoubtedly stymie much of their innovative efforts. *Second*, if substantive decision-making points that directly affect parties are expected to be automated such that human discretion is not involved in executing a major decision, there is greater justification for notice-and-comment to ensure agencies take heed of potential design flaws and promote legitimacy through accountability. When an algorithm decides outright or *strongly* dictates frontline action, it functions as a binding rule and, as such, must go through full notice-and-comment.[177] When, however, an algorithmic system contains a robust and well-constructed override scheme, its outputs are not binding and it need not go through notice-and-comment.[178] *Third*, agencies will have a greater incentive to go through notice-and-comment for an algorithmic system application if they could know that doing so will shield them from engaging in burdensome litigation down the line, in a "pay now or pay later" incentive structure.[179] If being upfront about their intended actions mean that they will not be easily revoked later on, they are more likely to invest in expansive public consultation.

2. The Accardi *Principle*

An important principle of administrative law, formulated in *Accardi v. Shaughnessy*, holds that agencies are bound by their own rules.[180] Following the basic logic of rule of law, agencies are held accountable to the procedures and standards they put forth, and must abide by them.

Accardi applies to agency rules promulgated through rulemaking. Yet when agencies rely on internal law, such as guidance documents and manuals, they may

176. For the importance of transparency with algorithms for the purposes of public legitimacy, see Amit Haim & Dvir Yogev, *Perceived Algorithmic Legitimacy in the Administrative State* (on file with Author); Ari Waldman & Kirsten Martin, *Governing Algorithmic Decisions: The Role of Decision Importance and Governance on Perceived Legitimacy of Algorithmic Decisions*, 9 BIG DATA & SOC'Y, Jan.–June 2022; Ryan P. Kennedy, Philip D. Waggoner & Matthew M. Ward, *Trust in Public Policy Algorithms*, 84 J. POL. 1132 (2022).

177. Engstrom & Ho, *Algorithmic Accountability, supra* note 21, at 846.

178. Engstrom & Haim, *supra* note 7. See also Henderson & Krass, *supra* note 159, at 42.

179. Levin, *supra* note 135, at 292 n.142 and accompanying text.

180. U.S. *ex rel.* Accardi v. Shaughnessy, 347 U.S. 260 (1954); *see* Magill, *supra* note 113, at 873–82; Thomas W. Merrill, *The Accardi Principle,* 74 GEO. WASH. L. REV. 569 (2005).

be subjected to the same logic and compelled by a reviewing court to follow them.[181] This interpretation runs against the ideas of internal law, suggesting that *Accardi* should not apply to non-legislative guidance. A nuanced *Accardi* principle will hold that the agency faces a choice of policymaking forum: substantive rules with binding effect on the public but with external judicial oversight, or rules without external bindingness and without external enforcement.[182] Accordingly, internal guidance that structures and constrains agency decisions, especially line-level discretion, should not be seen by courts as triggering review under the APA as it does not establish "law to apply." This gives agencies greater leeway and flexibility to design their decision-making structures, as they can more easily cabin their own discretion and decide to change course down the line, without judges insisting they adhere to a constraint that agencies initially put forward—much in line with the notion that guidance is appropriate so long as there is an opportunity to change a decision at a later point in time.[183]

In the algorithmic context, embedding algorithmic systems in cabining discretion should not *ipso facto* trigger external review. Compelling agencies to abide by algorithmic outputs can lead to perverse outcomes and unintentionally elevate and give more weight than intended for the algorithm in question. Agencies should have flexibility in deciding how to design their override structures and safety nets, even if in some individual cases it turns out that the agency decided to override a correct prediction by the algorithm. For instance, if frontline staff decided not to abide by a low-risk prediction and move forward with an investigation of some sort, the agency will have to justify its reasons for action—for example, if seeking legal action in court—but will not be obliged to determine the case to be low risk.[184]

3. Adjudications

The APA distinguishes between formal adjudications, which are quasi-trial settings led by Administrative Law Judges (ALJ) or similar functions, and informal adjudications, which are loosely structured determinations that make up the bulk of administrative decisions.[185] While these fora are sanctioned by law,[186] internal administrative law still plays a significant role. In the context of formal adjudications, only a fraction of adjudications will result in judicial review. Internal mechanisms such as internal appellate review, peer review, and quality assurance

181. Marc B. Wilenzick, *Guidelines and the Rule of Law: Claims under the Accardi Doctrine for Violations of Internal Rules*, 18 AM. J. CRIM. L. 357 (1990).

182. Metzger & Stack, *supra* note 16; Metzger, *supra* note 23.

183. *See* RECOMMENDATION 2017-5: AGENCY GUIDANCE THROUGH POLICY STATEMENTS, *supra* note 144.

184. In fact, granting *Accardi* status to algorithmic systems may induce strategic behavior: people will demand agencies to abide by the algorithm when a prediction was in their favor and conversely demand agencies to deviate from the algorithm when it is unfavorable.

185. Asimow, *supra* note 148.

186. In substantive statutory provisions and the APA alike.

programs are important to reduce errors and improve quality, as discussed above.[187] Informal adjudications are even less likely to be reviewed externally.

4. Individualized Assessments

When applying an algorithmic system to adjudications across the board, an issue arises regarding individualized determinations, which are required by some statutory provisions such as the Social Security Act (SSA), which obligates "individualized determinations based on evidence adduced at a hearing."[188] In *Heckler v. Campbell*, the Supreme Court considered whether the SSA had the authority to decide classes of issues in common.[189] The SSA had developed a scheme (referred to as "the grid") that directed hearing officers in their decision-making. It created vocational-medical guidelines (promulgated through notice-and-comment rulemaking) to expound the statutory definition of eligibility for disability insurance. In other words, the SSA had created a rudimentary algorithm or flowchart that adjudicators had to follow when deciding a case, resolving some factors uniformly and not on a case-by-case basis at each separate adjudication. The Court found no foul in the SSA's conduct, finding that "the agency may rely on its rulemaking authority to determine issues that do not require case-by-case consideration."[190] Otherwise, the agency will have to "continually to relitigate issues that may be established fairly and efficiently in a single rulemaking proceeding," providing "uniformity that previously had been perceived as lacking."[191] The Court found that determinations that have to rely on facts collected at hearings can be made generally, provided that claimants have a sufficient opportunity to present evidence on their own situation and argue why the guidelines do not apply to them.[192] The Court also held that the agency did not have to give every claimant notice about the guidelines since the notice-and-comment promulgation provided a procedural safeguard to ensure accuracy.[193]

A precedent then seems to exist of an agency excluding case-by-case determination for each claimant, which could apply to algorithmic systems.[194] However, a few problems arise. *First*, the holding rests on rulemaking promulgation as a procedural safeguard to ensure accuracy. Even if an algorithmic system is promulgated via notice-and-comment, its high level of abstraction such as the Quick

187. For instance, in the Veteran Administration. *See* Ames et al., *supra* note 15.

188. Social Security Act, 42 U.S.C. § 423(d)(2)(A).

189. Heckler v. Campbell, 461 U.S. 458 (1983).

190. *Id.* at 467.

191. *Id.* at 468.

192. *Id.* at 469.

193. *Id.* at 470.

194. Engstrom & Ho, *Algorithmic Accountability supra* note 21; Mariano-Florentino Cuéllar, *Cyberdelegation and the Administrative State*, *in* ADMINISTRATIVE LAW FROM THE INSIDE OUT 134 (Nicholas R. Parrillo ed., 1st ed. 2017), https://www.cambridge.org/core/product/identifier/9781316671641%23CT-bp-6/type/book_part [https://perma.cc/7PVA-2ABP].

Disability Determination program of the SSA,[195] providing only general information about the design of the algorithm, may not be enough to cross the hurdle of fair notice. It is unclear whether an algorithmic system devised only as guidance could pass muster, as it does not generally permit public input as rulemaking procedures do. Public consultation, however informal, may improve this to some extent.[196] Moreover, it is unlikely agencies will be able to provide the level of detail the SSA had in publishing its grid, due to the fact the underlying algorithmic architecture may be much more complex and nonlinear.

Second, in *Campbell* a hearing was not altogether precluded, and claimants had an opportunity to be heard and convince the adjudicator to deviate from the grid.[197] This issue should not categorically prevent agencies from using algorithmic systems, insofar as when there is a statutory requirement for a hearing, they provide one and allow override or deviation. In this case, agencies may restrict access to a prediction until the hearing is performed, so as not prejudice the hearing officers or share the information generated by the algorithm with the claimant. As the Administrative Conference of the United States recommended, agencies should help applicants understand how the algorithmic system works and how it relates to other aspects of the decisions, to dispel misunderstanding and misconceptions and better challenge presumptions and algorithmic predictions.[198]

a. Adjudicatory Independence

In formal adjudications, hearing officers are protected by the APA from interference with their work.[199] Independence is important for procedural regularity and perceptions of fairness.[200] The APA grants several independence protections to adjudicatory functions conducting hearings[201] and requires maintaining a distance from policymakers, prohibits ex parte communications, mandates the development of a formal record, and requires being fair and impartial.[202] Essentially, decisional

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195. *See* Engstrom & Ho, Algorithmic Accountability, *supra* note 21; ENGSTROM ET AL., *supra* note 1.

196. For example, through good guidance practices. *See* Final Bulletin for Agency Good Guidance Practices, 72 Fed. Reg. 3432 (Off. of Mgmt. & Budget Jan. 25, 2007), https://www.govinfo.gov/content/pkg/FR-2007-01-25/pdf/E7-1066.pdf [https://perma.cc/4S9V-8732].

197. Heckler v. Campbell, 461 U.S. 458 (1983).

198. HO ET AL, *supra* note 10.

199. *See* Nash v. Califano*,* 613 F.2d 10, 16 (2nd Cir. 1980) (SSA ALJ alleged invasion of statutory right to decisional independence upon receipt of "mandatory, unlawful instructions regarding every detail of their judicial role"); Verkuil, Paul Verkuil, *Meeting the Mashaw Test for Consistency in Administrative Decision-Making*, *in* ADMINISTRATIVE LAW FROM THE INSIDE OUT 239 (Nicholas R. Parrillo ed., 2017), https://www.cambridge.org/core/product/identifier/9781316671641%23CT-bp-10/type/book_part [https://perma.cc/P9TQ-RFUR]; *see also* Ass'n of ALJs v. Colvin, 777 F.3d 402 (7th Cir. 2015).

200. Martin H. Redish & Lawrence C. Marshall, *Adjudicatory Independence and the Values of Procedural Due Process*, 95 YALE L.J. 455 (1985).

201. Ramspeck v. Fed. Trial Examiners Conf., 345 U.S. 128, 132 (1953).

202. 5 U.S.C. §§ 554, 556, 557.

independence is the extent to which an adjudicator may "exercise his independent judgment on the evidence before him, free from pressures by . . . officials within the agency."[203] Reducing ALJs' discretion impairs their independence.[204] Decisional independence is not unlimited. ALJ decisions are subjected to de novo review by agency heads, on factual and legal bases,[205] setting them apart from Article III judges.[206]

An ALJ may not be subjected to *direction* or *supervision* by other employees of the agency.[207] The use of algorithmic systems may challenge this definition, as adjudicators are compelled to compare their own inclinations to those of others or subjected to supervisory input when conducting a hearing. Nevertheless, internal law will have significant impact because challenges to independence are hard to win; the interests of adjudicators and claimants do not always align; and even if algorithms are seen to be infringing on decisional independence in some cases, this will not affect the majority of applications.

III. LAW ON THE MARGINS

Algorithmic systems as internal governance mechanisms may prove beneficial for the administrative state. Nevertheless, they may also raise issues that policymakers will seek to address. The issue is that external legal intervention could prove to be both ineffective and counterproductive. When the law attempts to regulate the insides of the bureaucracy, it often results in what dynamic scholars have termed "crowding out" of internal law,[208] whereby the internal governance mechanisms agencies develop are displaced by external mechanisms, which are sub-optimal.

If algorithmic systems provide any beneficial prospects for the administrative state, then crowding out by imposing legal constraints is objectionable. Judicial intervention in agency structure—for example, by mandating human review, subjecting every algorithmic system to notice-and-comment rulemaking, or seeing them as interfering with independence in adjudications—could undermine administrative efforts while not achieving sought-after accountability.[209]

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203. Butz v. Economou, 438 U.S. 478 (1978).

204. D'Amico v. Schweiker, 698 F.2d 903, 905 (7th Cir. 1983) ("Reduction in discretion is a reduction in an important though nonpecuniary form of compensation for a judge.").

205. 5 U.S.C. § 557; *See also* James E. Moliterno, *The Administrative Judiciary's Independence Myth*, 41 WAKE FOREST L. REV. 1191, 1211 (2006); Jennifer Nou, *Dismissing Decisional Independence Suits*, 86 U. CHI. L. REV. 1187, 1190 (2019).

206. Moliterno, *supra* note 205.

207. 5 U.S.C. §§ 554(d)(2); Ass'n of Admin. L. Judges v. Colvin, No. 13-cv-2925 (N.D. Ill. Feb. 26, 2014).

208. Metzger & Stack, *supra* note 16.

209. Conversely, algorithmic systems may lead to some easing of the dilemma, as they allow a reduction of arbitrariness while permitting more individualized assessment. For instance, if agencies can improve the accuracy of their decisions systematically through algorithmic tools, a main impetus for due process hearings will have to be re-evaluated, and courts may find that this new decision-making

On the other hand, there are instances where internal law fails.[210] The previous sections have shown how algorithmic systems fit within the internal governance structures of public bureaucracies. Internal administrative law is an effective approach to promote consistency, quality, and predictability.[211] However, internal law must be consistent with governing statutes and nonarbitrary.[212] Judicial review is important where legal quandaries that involve the interpretation of law arise.[213]

In many legal and policy circles discussing the problems and prospects of AI writ large, public uses of AI algorithms are bundled as part of a wider discussion of risks and concerns. [214] In lieu of this approach, I argue that the regulation of public algorithms should be seen as a distinct endeavor with unique challenges. It is first crucial to understand how that regulation might look like and then understand why external legal interventions are unlikely to achieve satisfactory results. In this Section, I first review the extant legal frameworks for the regulation of public algorithms and then move on to show the limits of external legal interventions. This is followed by a critical evaluation of internal legal mechanisms, and a proposal for a compromise on the role of external law.

A. Regulating Public Algorithms

Legal frameworks can be categorized along various axes including, inter alia, source, type, timing, and scope.

The first axis is the *source* of law. Prevailing constitutional law offers a first line of defense but will probably prove too thin, as most algorithmic systems will easily pass muster.[215] An alternative approach is to propagate accountability through

process meets the *Mathews* test for additional procedure. *See* ENGSTROM ET AL., *supra* note 1, at 82–85; Huq, *Constitutional Rights*, *supra* note 1, at 1915–17.

210. A note regarding doctrinal soundness is in order. This Section has mostly focused on current administrative law or, at most, on those areas where the law is unclear and will need to adapt. Yet, there may be circumstances where current doctrine will stop short and retrofitting of the law will be needed. *See* Engstrom & Ho, Algorithmic Accountability*, supra* note 21. For example, generative AI algorithms, which have caught the public's attention in the last several years, may pose higher level quandaries that go beyond mere support of administrative discretion, should agencies seek to incorporate them. However, this Article leaves these questions for future and further work, as it goes beyond its domain.

211. Metzger & Stack, *supra* note 16; Parrillo, *supra* note 164.

212. Metzger & Stack, *supra* note 16.

213. This is important to ensure that administrative agencies do not exceed their democratic and constitutional affordances. *See id.* The legitimacy of administrative agencies and their control by the political branches is a continuously heated topic in American administrative law. *See* Gillian E Metzger, *Foreword: 1930S Redux: The Administrative State Under Siege*, 131 HARV. L. REV. 1 (2017).

214. A preliminary observation is that some legal frameworks are directly applicable and specifically address public sector use-cases, but most current efforts are directed towards a larger purview of regulation of AI, mainly in the private sector. These efforts do not always differentiate between the unique circumstances of public versus private use. For example, Article 22 of the GDPR. *See* note 144 *infra* and accompanying text.

215. Huq, *Constitutional Rights*, *supra* note 1; Coglianese & Lehr, *supra* note 1; Engstrom & Ho, *Algorithmic Accountability, supra* note 21. Furthermore, there are challenges with legal doctrines that are

legislative constructions that force public agencies to offer some procedure, such as requiring a human decision-maker to be involved in every decision.[216] This approach, heralded by the European Union,[217] is likely to fall short because algorithmic systems are embedded within organizational settings as sociotechnical apparatuses, as the following section argues. A third approach aims to retrofit existing legal frameworks to handle algorithmic systems. The bulwark of this endeavor will be administrative law, that is the body of law that governs how agencies operate.[218]

A second dimension is the *type* of law. Engstrom and Haim offer a helpful typology of regulatory approaches.[219] One category are mandates on particular contexts, such as certification requirements of medical-AI applications[220] or facial-recognition bans in law enforcement.[221] Another category comprises of rules pertaining to transparency, aimed at "ventilating" important information through disclosure, such as aspects of data or design or prospective harms included in "algorithmic impact assessments."[222] A separate effort addresses democratization efforts through demanding participatory design and including community stakeholders throughout the process.[223]

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not well-suited to handle questions of algorithmic decisions. For instance, notions of classification in constitutional and anti-discrimination law do not comport with research on bias in machine learning, which highlights awareness to characteristics such as race. *See* Daniel E. Ho & Alice Xiang, *Affirmative Algorithms: The Legal Grounds for Fairness as Awareness*, 2020 U. CHI. L. REV. ONLINE 134 (2020). Another example is the inability to optimize all notions of fairness in a given algorithm: calibration, false negative equity, and false positive equity. This means there cannot be a fully fair algorithm according to mathematically definable notions of fairness. *See* Jon Kleinberg, Sendhil Mullainathan & Manish Raghavan, *Inherent Trade-Offs in the Fair Determination of Risk Scores*, ARXIV:1609.05807 [CS, STAT] (2016), http://arxiv.org/abs/1609.05807 [https://perma.cc/B3K8-SVA7].

216. *See* Green, *supra* note 158.

217. LILIAN EDWARDS, REGULATING AI IN EUROPE: FOUR PROBLEMS AND FOUR SOLUTIONS (2022), https://www.adalovelaceinstitute.org/wp-content/uploads/2022/03/Expert-opinion-Lilian-Edwards-Regulating-AI-in-Europe.pdf [https://perma.cc/X9DY-KBJB].

218. Engstrom and Ho started laying out the foundations of administrative law for algorithms. *See* Engstrom & Ho, *Algorithmic Accountability, supra* note 21.

219. *Id.*; *see also* EXAMINING THE BLACK BOX (2020), https://www.adalovelaceinstitute.org/wp-content/uploads/2020/04/Ada-Lovelace-Institute-DataKind-UK-Examining-the-Black-Box-Report-2020.pdf [https://perma.cc/M2XU-RT5B]; ADA LOVELACE INSTITUTE, *supra* note 3, at 20.

220. Andrew Tutt, *An FDA for Algorithms*, 69 ADMIN. L. REV. 83 (2017).

221. Ravid & Haim, *supra* note 103.

222. Jacob Metcalf, Emanuel Moss, Elizabeth A. Watkins, Ranjit Singh & Madeleine C. Elish, *Algorithmic Impact Assessments and Accountability: The Co-construction of Impacts*, *in* PROCEEDINGS OF THE 2021 ACM CONFERENCE ON FAIRNESS, ACCOUNTABILITY, AND TRANSPARENCY 735 (2021), https://dl.acm.org/doi/10.1145/3442188.3445935 [https://perma.cc/ZH6Q-S3F7]; DILLON REISMAN, JASON SCHULTZ, KATE CRAWFORD & MEREDITH WHITTAKER, ALGORITHMIC IMPACT ASSESSMENTS: A PRACTICAL FRAMEWORK FOR PUBLIC AGENCY ACCOUNTABILITY (2018); Andrew D. Selbst, *An Institutional View of Algorithmic Impact Assessments*, 35 HARV. J.L. & TECH. 79 (2021).

223. Kate Crawford & Ryan Calo, *There is a Blind Spot in AI Research*, 538 NATURE 311 (2016); Min Kyung Lee, Daniel Kusbit, Anson Kahng, Ji Tae Kim, Xinran Yuan, Allissa Chan, Daniel See, Ritesh Noothigattu, Siheon Lee, Alexandros Psomas & Ariel D. Procaccia, *WeBuildAI: Participatory*

Third is the *timing* and *scope* of legal intervention. Some proposals suggest ex ante measures, such as impact assessments, public consultation, or advisory boards.[224] Other proposals are ex post measures, focused on audits, error correction, or institutional review.[225] Regarding scope, interventions can spotlight an affected individual and seek to redress harms while establishing procedural safeguards for similar cases in the future,[226] while others concentrate on systemic review and error detection.[227]

Naïve approaches to regulation purport to ensure accountability, prevent harm, and address concerns through the creation of legal rights and liability mechanisms.[228] Indeed, most proposed accountability frameworks have been *static* assessments of algorithmic systems. They are oriented, inflexibly, towards either ex ante procedures to ensure consideration and democratization of algorithmic implementation, or on ex post mechanisms to allow subjects to contest and empower courts or other reviewing institutions to pass judgments on algorithmic outputs.[229] For example, on the front-end side there are calls for written justifications prior to the adoption of an algorithmic system[230] or focus on the procurement process.[231] Conversely, there are ex post remedies for individual wrongs through private rights of action or appeals, and other liability and rights-based approaches,[232] or third-party audits which are time-bound rather than continuous.[233]

The challenge that public law has often neglected—and that the current landscape of algorithmic governance seems to continue to miss—is that inducing public bureaucracies to think critically about institutional and systemic design and oversight is very difficult. A long line of research shows that regulation that does

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Framework for Algorithmic Governance, 3 PROC. ACM HUM.-COMPUT. INTERACT. 1 (2019); Matthew M. Young, Justin B. Bullock & Jesse D. Lecy, *Artificial Discretion as a Tool of Governance: A Framework for Understanding the Impact of Artificial Intelligence on Public Administration*, 2 PERSPS. ON PUBLIC MGMT. & GOVERNANCE 301 (2019). For a skeptical view, see Johannes Himmelreich, *Against "Democratizing AI*,*"* A.I. & SOC. (2022), https://link.springer.com/10.1007/s00146-021-01357-z [https://perma.cc/QV9Z-MQRB].

224. REISMAN ET AL., *supra* note 223; ADA LOVELACE INSTITUTE, *supra* note 3, at 21–24.

225. ADA LOVELACE INSTITUTE, *supra* note 3, at 24–33.

226. *Id.* at 31–33.

227. *Id.* at 28–31.

228. Inioluwa Deborah Raji, Peggy Xu, Colleen Honigsberg & Daniel E. Ho, *Outsider Oversight: Designing a Third Party Audit Ecosystem for AI Governance*, *in* PROCEEDINGS OF THE 2022 AAAI/ACM CONFERENCE ON AI, ETHICS, AND SOCIETY 557 (2022), https://dl.acm.org/doi/10.1145/3514094.3534181 [https://perma.cc/G3AZ-LSWC].

229. Engstrom and Haim call this the "snapshot" and "bookend" problems. *See* Engstrom & Haim, *supra* note 7, at 17; *see also* Huq, *Constitutional Rights*, *supra* note 1.

230. Green, *supra* note 158.

231. Mulligan & Bamberger, *supra* note 54.

232. ADA LOVELACE INSTITUTE, *supra* note 3, at 31–33; Citron, *supra* note 3.

233. Inioluwa Deborah Raji, Andrew Smart, Rebecca N. White, Margaret Mitchell, Timnit Gebru, Ben Hutchinson, Jamila Smith-Loud, Daniel Theron & Parker Barnes, *Closing the AI Accountability Gap: Defining an End-to-End Framework for Internal Algorithmic Auditing* (2020).

not consider internal organizational reality is bound to fail and that oblivious external governance becomes ineffectual or even counterproductive, as agencies react to imposed mandates in unexpected ways.[234] This is a pertinent issue in algorithmic governance, since achieving accountability requires thinking hard about design and oversight on a continuous basis throughout the algorithmic lifecycle and creating institutional responses to problems as they emerge and before they cause harm.[235]

Scholarly and public debate over proper regulatory reactions has been heated. However, it has largely overlooked one major issue: the fact that AI algorithms are sociotechnical systems embedded in an organizational context, which can function as bureaucratic measures of control. The rest of this Section expounds this observation and begins to unravel the bureaucratic context of algorithms in the administrative state.

B. Shortcomings of External Governance

Scholars of public administration have extensively documented how organizational structure, culture, and norms influence administrative decisions and have also shed light on the limited ability of external regulation in shaping administrative behavior.[236] Understanding the boundaries of external governance of bureaucracies has led to a prominent view in administrative legal scholarship in recent decades, arguing that external legal constraints are, by and large, effective only at the *margins* of administrative behavior.[237] Instead, *internal administrative law* is a distinct set of internal rules and procedures, bureaucratic systems, and internal

234. DiMaggio & Powell, *supra* note 11; Edelman et al., *supra* note 11.

235. Glaze et al., *supra* note 10; Douek, *supra* note 23.

236. WILSON, *supra* note 11; MASHAW, *supra* note 11; Robert A. Kagan, *Varieties of Bureaucratic Justice: Building on Mashaw's Typology*, *in* ADMINISTRATIVE LAW FROM THE INSIDE OUT 247 (Nicholas R. Parrillo ed., 2017), https://www.cambridge.org/core/services/aop-cambridge-core/content/view/BAF899643A7C1ABA4016A00128C09982/9781316671641c10_p247-270_CBO.pdf/varieties_of_bureaucratic_justice.pdf [https://perma.cc/B5C7-VDDG]; Charles F. Sabel & William H. Simon, *The Management Side of Due Process in the Service-Based Welfare State*, *in* ADMINISTRATIVE LAW FROM THE INSIDE OUT, *supra*, at 63, https://www.cambridge.org/core/product/identifier/9781316671641%23CT-bp-3/type/book_part [https://perma.cc/FLK4-8LKA]; Paul Verkuil, *Meeting the Mashaw Test for Consistency in Administrative Decision-Making*, *in* ADMINISTRATIVE LAW FROM THE INSIDE OUT, *supra*, at 239, https://www.cambridge.org/core/product/identifier/9781316671641%23CT-bp-10/type/book_part [https://perma.cc/4GJC-ZMDF]; Edelman et al., *supra* note 11; DiMaggio & Powell, *supra* note 11.

237. For an early antecedent, see R. Shep Melnick, *Administrative Law and Bureaucratic Reality*, 44 ADMIN. L. REV. 245 (1992). ("So much of administrative law happens without courts. Put differently, federal agencies regulate us in many meaningful, and sometimes frightening, ways that either evade judicial review entirely or are at least substantially insulated from such review."); Christopher J. Walker, *Administrative Law without Courts*, 65 UCLA L. REV. 1620, 1624–26 (2018) ("Regardless of whether agency guidance can be formally binding yet escape judicial review, it often functionally binds regulated parties in a way that is insulated from judicial review."); Nicholas R. Parrillo, *Federal Agency Guidance and the Power to Bind: An Empirical Study of Agencies and Industries*, 36 YALE J. ON REG. 107 (2019).

techniques of instruction, oversight, and control of agency personnel, as Metzger and Stack notably argued.[238] As such, internal law is much more influential for the operation of administrative bodies and their staff. Jerry Mashaw had famously shown how the internal procedures to standardize, direct, constrain, and improve mass adjudications have had a significant impact even on behemoth operations such as the Social Security Disability Insurance (SSDI) program,[239] and others have continued to detail this pattern in other contexts as well.[240]

Proponents of internal administrative law suggest it is a promising avenue to "encourage consistency, predictability, and reasoned argument."[241] The inverse of this observation is that judicial review lacks the competence, level of detail, and frequency to ensure agency practice comports with legal requirements, balances competing goals, and yields high quality outcomes. Agencies have the practical expertise and profound awareness of resource, budgetary, political, and other constraints, and possess better tools to decipher the interests of diffuse regulatory beneficiaries and regulated parties and the means to achieve their goals.[242]

Many of the problems of legal accountability that have been identified in the setting of internal administrative law transfer to the algorithmic context. The limitations of judicial review and legislative frameworks are apparent when considering administrative applications of algorithmic systems.

1. *Legislative Frameworks*

Legislative frameworks purported to govern administrative algorithms are in the works, with more or less realistic prospects of becoming good law.[243] Besides future frameworks, preexisting provisions, such as aspects of the European General Data Protection Regulation (GDPR), are directly applicable to algorithmic systems.[244] However, legislative mandates will meet significant challenges. For one thing, AI and algorithmic systems do not (and cannot) have well-bounded definitions, and their ambiguity will always haunt regulations that seek to constrain them, aside perhaps from specific and concrete use-cases such as facial recognition

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238. Metzger & Stack, *supra* note 16, at 1244–45.

239. MASHAW, *supra* note 57.

240. Ames et al., *supra* note 15.

241. Metzger & Stack, *supra* note 16, at 1244.

242. Hausman et al., *supra* note 113.

243. The European Commission published a proposal for the Artificial Intelligence Act on April 2021, which includes a comprehensive regulatory, risk-based plan to regulate AI systems, with realistic prospects of materializing. *See* EDWARDS, *supra* note 217. Legislative efforts in the United States, conversely, are less promising. *See* Daniel J. Felz, Alysa Austin & Kimberly Kiefer Peretti, *AI Regulation in the U.S.: What's Coming, and What Companies Need to Do in 2023*, ALSTON & BIRD (Dec. 9, 2022), https://www.alston.com/en/insights/publications/2022/12/ai-regulation-in-the-us [https://perma.cc/4DA9-3UWE].

244. Article 22 of the GDPR restricts fully automated decisions on data subjects. For exploration of this and other aspects see Margot E Kaminski, *The Right to Explanation, Explained*, 34 BERKELEY TECH. L.J. 189 (2019).

technology in law enforcement.[245]

Moreover, much will depend on how agencies implement governance structures, and the devil tends to be in the details. Take for example a mandate requiring some form of human input, such as Article 22 of the GDPR, which requires decisions not to be fully automated.[246] There is a wide variety of options agencies will have to implement such a requirement, some of which will be counterproductive and some of which will have human input on paper but will not ensure meaningful oversight.[247] In fact, such requirements can significantly distort agency incentives and drive them to focus on compliance with salient aspects like human involvement, which may not be the most important and systemic issues that an algorithmic system faces. For instance, the type of errors that a decision-making structure handles and their relative weight is very important for how agencies should design a decision schema. Yet instructing agencies to instill a human review may intensify a type of error humans are more prone to rather than ameliorate it, culminating in an overall detrimental outcome.

Furthermore, most legislative frameworks suffer from a static and undynamic nature, which is not easily adaptable and updated, and are at risk of quickly becoming "totemic" for agency compliance, producing a checklist to tick rather than meaningful accountability.[248]

2. Judicial Review

Given the limited prospects and narrow scope of legislative action, it is likely that most efforts will be concentrated in judicial avenues. Most legal accountability mechanisms aim to bring the agency in front of reviewing judges in some capacity, whether through pre-enforcement review, violations of procedural guarantees, or individual claims of harm.[249] Nevertheless, administrative actions in general are reviewed only rarely due to standing and other procedural constraints.[250] Algorithmic systems add another layer of complexity.

The subtle issue is that while internal law should be externally reviewed for its

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245. For example, the New York City special task force on automated decision-making spent arduous efforts in coming up with a definition that will include all relevant automated and algorithmic systems but will preclude banal instances such as use of spreadsheets like Excel. JEFF THAMKITTIKASEM, NEW YORK CITY AUTOMATED DECISION SYSTEMS TASK FORCE REPORT 26 (2019), https://www1.nyc.gov/assets/adstaskforce/downloads/pdf/ADS-Report-11192019.pdf [https://perma.cc/4DCW-2QWG]. For further discussion about the problem of ambiguity of AI, see Engstrom, *supra* note 2; Engstrom & Haim, *supra* note 7.

246. Kaminski, *supra* note 244, at 196–200.

247. *See* Ben Green, *The Flaws of Policies Requiring Human Oversight of Government Algorithms*, 45 COMPUT. L. & SEC. REV. 105681 (2022).

248. Engstrom & Haim, *supra* note 7.

249. Engstrom & Ho *Algorithmic Accountability, supra* note 21, at 836.

250. Adrian Vermeule, *Our Schmittian Administrative Law*, 122 HARV. L. REV. 1095 (2009). Plaintiffs' material interests will usually not be at direct peril, especially in the context of pre-enforcement review. *See* Engstrom & Ho, *Algorithmic Accountability, supra* note 21, at 839.

validity, holding it as triggering external enforcement *in and of itself* undercuts its advantages.[251] If courts maintain that confining or constraining administrative discretion prompts judicial review, agencies will find it hard to institute robust internal procedures.[252] The tension between internal governance and external legal oversight is paradigmatic to administrative law.[253] On their part, courts have repeatedly compelled administrative forums to afford subjects quasi-formal procedural rights, which mold them in the image of courts, under the assumption that strong due process safeguards legitimize the execution of law.[254]

As a preliminary matter, constitutional review of administrative action requires a high bar, which most suits against algorithmic systems are likely to fail.[255] Claims of procedural due process violations, even though they have gained some

251. *See* Metzger & Stack, *supra* note 16, at 1283 ("In short, to the extent an agency's internal pronouncements appear to do the work of internal law—to establish norms that bind agency actors, or confine, structure, and constrain the agency's discretion—they risk creating grounds for external judicial review of the agency's compliance. This is not to say that there are no valid grounds for judicial review of agency internal law. Agency internal law must be consistent with the governing statutory scheme and nonarbitrary—and, assuming the internal law at issue satisfies finality and other jurisdictional prerequisites, those requirements can and are enforced through judicial review. There is a difference, however, between allowing that internal law may be reviewed for its validity and viewing internal law as authorizing its own external enforcement against the agency.").

252. ADMIN. CONF. OF THE U.S., ADMINISTRATIVE CONFERENCE RECOMMENDATION 2017-5: AGENCY GUIDANCE THROUGH POLICY STATEMENTS (2017), https://www.acus.gov/sites/default/files/documents/Recommendation%202017-5%20%28Agency%20Guidance%20Through%20Policy%20Statements%29_2.pdf [https://perma.cc/N77F-UD7Q] ("Agencies may use policy statements to bind some agency employees to the approach of the policy statement, so long as such employees are not bound in a manner that forecloses a fair opportunity for the public or employee to argue for approaches different from those in the policy statement or seek modification of the policy statement."); *see also* Final Bulletin for Agency Good Guidance Practices, 72 Fed. Reg. 3432 (Off. of Mgmt. & Budget Jan. 25, 2007), https://www.govinfo.gov/content/pkg/FR-2007-01-25/pdf/E7-1066.pdf [https://perma.cc/42RX-5W85].

253. Agencies are often caught in the dilemma between constraining inconsistency and arbitrariness and formalizing their procedures in a way that better aligns with judicial notions of rule of law and individualized determination. *See* MASHAW, *supra* note 11; Jerry L. Mashaw, *Models of Administrative Justice*, *in* THE OXFORD HANDBOOK OF ADMINISTRATIVE JUSTICE (Marc Hertogh et al. eds., 2021), https://oxfordhandbooks.com/view/10.1093/oxfordhb/9780190903084.001.0001/oxfordhb-9780190903084-e-18 [https://perma.cc/CQS4-XXFL]; Kagan, *supra* note 236.

254. Mashaw, *supra* note 11; Scott Limbocker, William G. Resh & Jennifer L. Selin, *Anticipated Adjudication: An Analysis of the Judicialization of the US Administrative State*, 32 J. PUB. ADMIN. RSCH. & THEORY 610 (2022).

255. Huq, *Right to a Human Decision*, *supra* note 1; Engstrom & Ho *Algorithmic Accountability, supra* note 21; Coglianese & Lehr, *supra* note 1.

traction,[256] are not likely to have a significant impact on most agency actions.[257] Likewise, claims of equal protection based on algorithmic discrimination will also face significant challenges and will probably have marginal effects, if any.[258] Moreover, algorithmic systems used in an enforcement context are even less likely to be reviewed, since long-standing doctrine holds agency enforcement priorities as unreviewable and hived off from judicial scrutiny,[259] making them a "gray hole."[260]

Even those cases that make it to the merits stage will meet significant challenges. Deciphering and understanding algorithmic systems requires high levels of expertise and methods that lawyers and judges generally lack in full measure. Even systems that do not rely on deep learning can be challenging to understand and will require considerable expert testimony, and challenges with trade secrets and other proprietary mechanisms may make litigation even more complex.[261]

Moreover, since algorithmic systems should be considered within their institutional and organizational context, typical problems of judicial review of internal procedures will apply. Courts will find it hard to untangle the complex and multi-level structure of agencies and the constraints within which they operate. They are also not well-suited to anticipate how agencies' operations will respond and adapt to judicial pronouncements.[262] For example, a common option for judges will likely be to instruct agencies to use an algorithmic system merely as an advisory or supportive tool and inform agency employees about this status, as was done in the case of *Loomis v. Wisconsin* in the context of criminal risk assessment.[263] Nevertheless, this may not have much effect in practice, as the behavioral mechanism of decision-making with algorithms could make warnings superfluous.[264] Moreover, we may find that judicial remedies, such as requiring

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256. Several such efforts have been documented. To mention a few, in Houston, Texas, a teachers union challenged the use of proprietary algorithms for school employment practices. In Arkansas, an algorithmic decision system allocating home health care to Medicaid patients was challenged for failing to accurately determine the needs of several classes of patients. *See generally* RASHIDA RICHARDSON, JASON M. SCHULTZ & VINCENT M. SOUTHERLAND, LITIGATING ALGORITHMS 2019 US REPORT: NEW CHALLENGES TO GOVERNMENT USE OF ALGORITHMIC DECISION SYSTEMS (2019), https://ainowinstitute.org/publication/litigating-algorithms-2019-u-s-report-2 [https://perma.cc/BUY7-MCJY]; Calo & Citron, *supra* note 2.

257. Huq, *Constitutional Rights*, *supra* note 1, at 1905–17.

258. *Id.* at 1917–27; Ho & Xiang, *supra* note 215.

259. *See generally* Heckler v. Chaney, 470 U.S. 821 (1985).

260. Engstrom, *supra* note 2; Solow-Niederman, *supra* note 22.

261. KATE CRAWFORD ROEL DOBBE, THEODORA DRYER, GENEVIEVE FRIED, BEN GREEN, ELIZABETH KAZIUNAS, AMBA KAK, VAROON MATHUR, ERIN MCELROY, ANDREA NILL SÁNCHEZ, JOY LISI RANKIN, RASHIDA RICHARDSON, JASON SCHULTZ, MYERS WEST & MEREDITH WITTAKER, AI NOW 2019 REPORT (2019); Crawford & Schultz, *supra* note 56.

262. Edelman et al., *supra* note 11; DiMaggio & Powell, *supra* note 11.

263. *See* Loomis v. Wisconsin, 881 N.W.2d 749 (Wis. 2016), *cert. denied*, 137 S. Ct. 2290 (2017).

264. Experimental research based on the *Loomis* decision found that warnings did not induce an effect in how subjects used machine advice. *See* Christoph Engel & Nina Grgić-Hlača, *Machine Advice with a Warning about Machine Limitations: Experimentally Testing the Solution Mandated by the Wisconsin Supreme Court*, 13 J. LEGAL ANALYSIS 284 (2021).

human override, bring about perverse results that undermine the very impetus for agencies' adoption of algorithmic tools: retaining strong discretionary override can result in biased outcomes, often on the basis of race, since humans tend to override predictions differently based on racial attributes.[265] Humans suffer from a variety of well-documented biases, and agency staff, or even judges, are no exception.[266]

As Aziz Huq has forcefully argued, the effects of judicial review in individual cases are problematic for the systemic nature of algorithmic tools.[267] Judicial review is sporadic and depends on plaintiffs having strong interests in challenging agency action. Algorithms exacerbate this trait, as there are significant informational barriers to even knowing whether an algorithm is used.[268] Even if claimants are aware of an algorithm, they will find it hard to produce the information to allow them to meaningfully challenge its operation.[269] Furthermore, only claimants that have been rejected in some capacity or otherwise disfavored by an agency (e.g., detained, audited, etc.) will have an interest in bringing forth claims, meaning that courts will only have purview over one side of the distribution of errors. While appeals procedures are predicated on error correction, they are problematic for fixing systemic errors.[270] As Danielle Citron pointed out long ago, the calculus that courts employ in determining procedural rights is ill-suited for the systemic nature of algorithms.[271] Even more troubling is that reviewing individual erroneously decided cases does not necessarily mean that an overall bias or equality problem occurred.[272] Fixating on individual errors makes procedures to redress them seem attractive, but this is likely to result in overall costlier, slower, and more error-prone systems.[273] Thus additional procedure, the likely outcome of most judicial review,

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265. There is evidence to show that in pre-trial detention, judges may release predicted low-risk *white* detainees in higher numbers than low-risk *black* detainees. Meaning that when defendants are white, the predicted risk score allows judges to be more lenient, while at the same time similar levels of risk (calibrated such that a score means the same for white and black defendants) for black defendants are met with a prior proclivity to detain. *See* Albright, *supra* note 156.

266. KAHNEMAN ET AL., *supra* note 81; Rachlinski et al., *supra* note 103.

267. Huq, *Constitutional Rights*, *supra* note 1.

268. Many applications are on the backend of agency work, and agencies may not give notice or publicize their use. *See* RICHARDSON ET AL., *supra* note 256.

269. Litigants will often have to rely on the imperfect measures of Freedom of Information Act requests. For an example in the immigration context, see Evans & Koulish, *supra* note 31.

270. Ames et al., *supra* note 15.

271. Citron, *supra* note 3; Engstrom & Ho, *Algorithmic Accountability, supra* note 21.

272. Huq, *Constitutional Rights*, *supra* note 1, at 1937–38.

273. *See* Bednar, *supra* note 128, manuscript at 59–60 ("Nor is it clear that we should want courts to impose managerial remedies for maladministration. Most federal judges have little training or experience in public administration. Courts do not know where adjudicatory agencies should build their next courtroom, which adjudicators should receive law clerks, or how many law clerks the agency needs to hire to prevent adjudicators from resorting to coping mechanisms. Whatever remedy courts may impose could prove ineffective or, worse, may require the agency to take actions that further exacerbate ongoing issues. Courts have traditionally viewed 'more procedure' as the solution to mismanagement in contexts implicating the Due Process Clause. There are good reasons to believe that more procedure would only increase agency workloads and further strain capacity.").

may increase trust in particular cases but undermine trust overall.[274]

Administrative capacity is another important factor to consider when contemplating judicial review of agency actions. Courts and judges do not have a good vantage point into public administration and the inner structures and constraints of agency decisions-making, and the remedies they may impose can aggravate existing problems.[275] Courts typically see additional procedure as a solution to mismanagement and due process concerns, yet "there are good reasons to believe that more procedure would only increase agency workloads and further strain capacity."[276] Additional procedure, as well as focusing on performance metrics (such as reversal rates), increases the likelihood that adjudicators rely on coping mechanisms.[277] Internal law, on the other hand, can alleviate burdensome workloads and thus improve the overall administration of justice.[278]

Finally, while many instances of review will occur in federal courts over federal agencies' conduct, which gain the most attention, much of the activity will transpire at the state level with state- and even local-level agencies.[279] Such courts may be even less well equipped to handle the type of problems that ensue from the use of algorithmic systems.[280]

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Internal administrative law offers a different approach to governance and accountability. While informational gaps exist within agencies, including between hierarchical levels,[281] agencies possess better tools to overcome them. They are better poised to draw on the experience of line-level employees and understand the intricacies of a specific decision-making structure and environment. This is important for a user-oriented design which improves usability and engenders trust. Effective adoption of algorithmic systems in bureaucracies requires the institutional ability to move between phases of design, implementation, and evaluation.[282] The brittleness of algorithmic systems, combined with the idiosyncrasies of administrative structures and the quirks of human behavior, make adoption challenging. Iteration over the process, often non-linearly moving back and forth between stages, can ameliorate problems and improve results. Internal administrative law, by virtue of its relative informality, is distinctively more flexible

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274. Nicholas Bagley, *The Procedure Fetish*, 118 MICH. L. REV. 345, 381 (2019).

275. Bednar, *supra* note 128.

276. *Id.* at 60.

277. *Id.* at 35.

278. Bednar highlights two policies that may be effective in doing just that: priority-setting and jurisdiction-shifting. He suggests that administrative law should recognize "the administrative state uses internal administrative law to manage capacity and to reduce the harms that may otherwise impact respondents in agency adjudication" by categorizing such policies as sub-legislative rules to allow agencies greater flexibility and nimbleness. *See id.* at 64.

279. RICHARDSON ET AL., *supra* note 256.

280. Nestor M. Davidson, *Localist Administrative Law*, 126 YALE L.J. 564 (2017).

281. Nou, *supra* note 113.

282. Engstrom & Haim, *supra* note 7; Glaze et al., *supra* note 10.

than other forms of law. It allows agencies to rethink and revise their guidelines, a necessary quality when refining and reforming algorithmic systems. The following section delves deeper into internal law and algorithms in the government.

IV. THE INTERNAL LAW OF ADMINISTRATIVE ALGORITHMS

As AI algorithms have become more ubiquitous in government, and with legislative action lagging, a body of scholarly research and informal government exploration has begun to emerge, focusing on internal governance approaches to automated algorithmic systems. This Section is a first attempt to chronicle these developments, which I call the *internal law of administrative algorithms*, reflecting the notion that legal frameworks could eventually emerge from the language of public administration and organizational processes.[283]

A. The Emergence of Internal Law

In December 2020, a presidential Executive Order 13960 named *Promoting the Use of Trustworthy Artificial Intelligence in the Federal Government* (E.O. 13960) began to set forth high-level principles for federal use of AI.[284] It emphasized that AI use must be lawful and respectful of American values; purposeful and performance-driven; accurate, reliable, and effective; safe, secure, and resilient; understandable; responsible and traceable; regularly monitored; transparent; and accountable.[285] It also directed agencies to create public registries to catalogue their AI use cases[286] and sought to enhance AI implementation expertise at the agency level via the General Services Administration and the Office of Personnel Management.[287] This order prompted the Office of Management and Budget (OMB) to issue a memorandum further elaborating high-level principles for promoting trust in AI and instructing agencies to publicize their plans, use cases, and prospective regulatory actions.[288]

Building on EO 13960 and the OMB memo, in June 2021 following a series of consultation meetings, the U.S. Government Accountability Office (GAO) published an accountability framework for artificial intelligence use by federal agencies and other government entities.[289] The report builds on previous GAO

283. Engstrom & Haim, *supra* note 7.

284. Exec. Order No. 13960, Promoting the Use of Trustworthy Artificial Intelligence in the Federal Government, 85 Fed. Reg. 78939 (DEC. 8, 2020), https://www.govinfo.gov/content/pkg/FR-2020-12-08/pdf/2020-27065.pdf [https://perma.cc/U4MJ-2U6V].

285. *Id.*

286. *Agency Inventories of AI Use Cases, supra* note 112.

287. Exec. Order No. 13960, 85 Fed. Reg. 78939 (DEC. 8, 2020).

288. Memorandum from Director Russel T. Vought, Guidance for Regulation of Artificial Intelligence Applications, Exec. Off. of the President: Office of Mgmt. & Budget (Nov. 17, 2020) (on file with the White House).

289. GAO REPORT, *supra* note 24.

publications laying groundwork for AI in government[290] and identifies principles, practices, and questions to consider at the organizational, system-, and component-level. It highlights internal control as part of a wider approach to government accountability, focusing on achieving objectives effectively, efficiently, ethically, and equitably.

In October 2022, the White House Office of Science and Technology (OST) published a white paper named a *Blueprint for an AI Bill of Rights* (AI Blueprint), defining the main principles to guide the "design, development, and deployment of artificial intelligence and other automated systems so that they protect the rights of the American public."[291] The AI Blueprint defines any relevant system as (1) an automated system that (2) has potential to meaningfully impact the public rights, opportunities, or access to critical resources or services, and focuses on ensuring safe and effective systems, protections from discrimination, data privacy, notice and explanations, and providing human alternatives and fallbacks.[292]

The most significant development to date occurred in late 2023, as President Biden released Executive Order 14110 *On the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence* (EO 14110).[293] The Order began moving beyond setting high-level principles outlined in EO 13960 and the AI Blueprint into creating the organizational infrastructure for the integration of AI. EO 14110 contained many facets relating to AI policy and regulation, for instance, developing initial transparency and reporting requirements and defining thresholds for "dual-use foundation models" (very large, general-purpose AI models that power a wide range of downstream applications).[294] One of its stated purposes is to advance the use of AI in the federal government.[295] It contained the first steps in creating a coordination apparatus within the federal government to facilitate inter-agency collaboration and initiative, for example, by designating chief AI officers at each agency, and convening an interagency council, a White House AI council comprised of cabinet members, and internal AI governance boards within several agencies, all to strengthen effective and appropriate use of AI and manage risks. The Order highlighted the need to develop standards for government use of AI, including practices such as red-teaming, external testing, and safeguards against unsafe or misleading outputs, documentation of procurement, public reporting, and more. It also discussed, for the first time, generative AI and adopted a middle-ground approach that disfavors general bans, and instead promoted limiting access to

290. U.S. GOV'T ACCOUNTABILITY OFF., ARTIFICIAL INTELLIGENCE: EMERGING OPPORTUNITIES, CHALLENGES, AND IMPLICATIONS (2018), https://www.gao.gov/assets/700/690910.pdf [https://perma.cc/6XMN-KHEC].

291. BLUEPRINT FOR AN AI BILL OF RIGHTS: MAKING AUTOMATED SYSTEMS WORK FOR THE AMERICAN PEOPLE, *supra* note 24.

292. *Id.* at 8.

293. Exec. Order No. 14110, 88 Fed. Reg. 75191 (Oct. 30, 2023).

294. *Id.* at § 4.

295. *Id.* at § 10.

generative AI in agencies based on risk assessments and appropriate safeguards.[296]

Another important component of EO 14110 is investment in the federal AI workforce, including specialized programs to hire and retain talent, as well as providing training for federal employees. The Order puts special weight on implementation, by designating specific functions within the government and their responsibilities, marking remarkably specific and ambitious deadlines for many of its goals, and designating internal leadership roles to lead the efforts. It assigns many of the coordination roles to OMB, which has already acted to publish for public comments implementation guidance meant to further translate the Order into actionable items.[297]

Concurrent with these centralized efforts, individual agencies and executive departments have also begun devising AI-implementation frameworks focusing on governance and accountability, with domain-specific modifications.[298] One prominent example is the Department of Health and Human Services (HHS), which compiled the *Trustworthy AI Playbook*, consolidating presidential guidance and applying the Department's perspectives.[299] The document is meant to provide practical and executable frameworks for "applying Trustworthy AI principles throughout the AI lifecycle" and to serve as a basis for "future HHS policies on Trustworthy AI acquisition, development, and use."[300]

Similarly, the National Institute of Standards and Technology (NIST) in the Department of Commerce began a series of expert and public consultations to develop a risk management framework, followed by a playbook, meant as a "voluntary framework seeking to provide a flexible, structured, and measurable process to address AI risks prospectively and continuously throughout the AI lifecycle."[301] NIST has a long history of taking a leading role in standardizing

296. *Id.* at § 4.

297. Memorandum from Director Shalanda D. Young, Advancing Governance, Innovation, and Risk Management for Agency Use of Artificial Intelligence, Exec. Off. of the President: Office of Mgmt. & Budget (Nov. 1, 2023) https://www.whitehouse.gov/wp-content/uploads/2023/11/AI-in-Government-Memo-draft-for-public-review.pdf.

298. *E.g.*, Department of Veteran Affairs, *supra* note 46; *DOE AI Risk Management Playbook (AIRMP)*, DEP'T OF ENERGY, https://www.energy.gov/ai/doe-ai-risk-management-playbook-airmp [https://perma.cc/F4SF-H7CZ] (last visited Nov. 2, 2023). The Department of Education has begun a process of developing policies focused on effective, safe, and fair AI applications for education. *See Office of Educational Technology*: *Artificial Intelligence*, DEP'T OF EDUCATION, https://tech.ed.gov/ai/ [https://perma.cc/9NRT-8F43] (last visited Nov. 2, 2023). The Equal Employment Opportunity Commission has similar initiatives in the employment and hiring sectors. *See Artificial Intelligence and Algorithmic Fairness Initiative*, U.S. EQUAL EEMP. OPPORTUNITY COMM'N., https://www.eeoc.gov/ai [https://perma.cc/RJF6-LJRW] (last visited Nov. 2, 2023).

299. TRUSTWORTHY AI (TAI) PLAYBOOK, U.S. DEP'T OF HEALTH & HUMAN SERVS. (2021), https://www.hhs.gov/sites/default/files/hhs-trustworthy-ai-playbook.pdf [https://perma.cc/RYE2-WE8U]. The Playbook specifically incorporates principles from EO 13960 and the OMB Memo.

300. *Id.* at 7.

301. Elham (Fed) Tabassi, AI RISK MANAGEMENT FRAMEWORK: SECOND DRAFT 2 (2022). https://www.nist.gov/system/files/documents/2022/08/18/AI_RMF_2nd_draft.pdf [https://perma.cc/XQ3M-TPEH].

technological applications and coordinating industry-wide safety efforts.[302] Some departments, such the Department of Energy, have already started implementing similar frameworks for sector-specific domains.[303]

Table 1: Principles of AI Algorithms in Administrative Guidance

Guidance Source	Principles
Presidential EOs	1. Lawful and Respectful of Our Nation's Values 2. Understandable 3. Transparent 4. Responsible and Traceable 5. Safe, Secure, and Resilient 6. Purposeful and Performance-Driven 7. Accurate, Reliable, and Effective
Blueprint for AI Bill of Rights	1. Safe And Effective Systems 2. Algorithmic Discrimination Protections 3. Data Privacy 4. Notice And Explanation 5. Human Alternatives, Consideration, And Fallback
OMB Memo	1. Public Trust 2. Public Participation 3. Scientific Integrity and Information Quality 4. Risk Assessment and Management 5. Benefits and Costs 6. Flexibility 7. Fairness and Nondiscrimination 8. Disclosure and Transparency 9. Safety and Security 10. Interagency Coordination
GAO Framework	1. *Governance*: Promote accountability by establishing processes to manage, operate, and oversee implementation 2. *Data*: ensure quality, reliability, and representativeness of data sources, origins, and processing. 3. *Performance*: Produce results that are consistent with program objectives 4. *Monitoring*: Ensure reliability and relevance over time

302. David R. Lide, *A Century of Excellence in Measurements, Standards, and Technology*, 13 MEAS. SCI. TECHNOL. 1653 (2002).

303. *DOE AI Risk Management Playbook (AIRMP)*, *supra* note 298.

HHS Playbook	1. Fair/Impartial 2. Transparent / Explainable 3. Responsible / Accountable 4. Robust / Reliable 5. Privacy 6. Safe / Secure

All these are decidedly non-binding guidance documents, which do not hold authoritative power or judicially enforceable obligations over government action.[304] Administrative guidance is important to stimulate conceptual work that will serve as the backbone of any regulatory or governance approach.[305] This includes even the most fundamental questions agencies need to grapple with, such as what *is* an AI system for their purposes and what systems fall under the scope of their guidance. The Blueprint, for instance, takes an expansive approach on the one hand, applying to any automated system with relevant impacts, without attempting the difficult task of defining AI.[306] It also takes a rights-based rather than a risk-based approach, effectively subjecting all systems to the same procedure.[307] On the other hand, it takes a limited approach by excluding some domains such as law enforcement. Conversely, the HHS Playbook draws from legislative sources and adopts a series of questions and considerations to determine whether a system is considered an AI, including whether it solves "tasks that require human-like perception," "approximates a cognitive task," or "can learn from experience and improve performance."[308]

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While the corpus of internal law for administrative algorithms is burgeoning, it is also decidedly vague. Most importantly, they mainly provide a higher-order set of values and considerations to administrative AI and lack the required strategies

304. As the Blueprint's legal disclaimer points out, it is "non-binding and does not constitute U.S. government policy. It does not supersede, modify, or direct an interpretation of any existing statute, regulation, policy, or international instrument. It does not constitute binding guidance for the public or Federal agencies and therefore does not require compliance with the principles described." BLUEPRINT FOR AN AI BILL OF RIGHTS: MAKING AUTOMATED SYSTEMS WORK FOR THE AMERICAN PEOPLE, *supra* note 24, at 2. HHS clarifies in its Trustworthy AI framework that "[t]he Playbook is not a formal policy or standard." *See* TRUSTWORTHY AI (TAI) PLAYBOOK, *supra* note 299. Similar caveats appear in all other documents.

305. Jeremy Kessler & Charles Sabel, *The Uncertain Future of Administrative Law*, 150 DAEDALUS: J. AM. ACAD. ARTS & SCI. 188 (2021).

306. Engstrom, *supra* note 2; THAMKITTIKASEM, *supra* note 245.

307. Engstrom, *supra* note 2.

308. TRUSTWORTHY AI (TAI) PLAYBOOK, *supra* note 299, at 10. The definition is based on national defense statutory authority. *See* John S. McCain National Defense Authorization Act for Fiscal Year 2019, H.R. 5515, 115th Cong. § 238(g) (2018). Utilized in Executive Order 13960, Promoting the Use of Trustworthy Artificial Intelligence in the Federal Government. Exec. Order No. 13960, 85 Fed. Reg. 78939 (DEC. 8, 2020).

for implementation in complex institutions. EO 14110 has begun moving in this direction but is still an overarching framework and requires further specification and translation into specific contexts. Individual agencies and government-wide bodies[309] are beginning to weave together conceptual and organizational frameworks for governance of AI. Importantly, arising from this body of documents is the beginning of a common vocabulary across the government that can facilitate dialogue[310] and induce agencies to invest in institutional infrastructure to do so.[311] NAIAC, for example, which is an advisory committee convened expressly to promote trustworthy AI in the federal government, has stated that efforts are needed to foster strategic planning in individual agencies along with public confidence in the commitment to trustworthy AI.[312]

The following section seeks to aid this effort by distilling some of the principles of this corpus and translating it into actionable goals.

B. Main Tenets

Several main tenets arise from the nascent internal law of administrative algorithms, building on academic research at the intersection of organizational studies, computer science, and law.[313]

A first principle addresses the lifecycle of AI applications, which follows the rhythm of Design, Integrate, Assess.[314] First, an agency will have to consider

309. *See* MIRIAM VOGEL & JAMES MANYIKA, NATIONAL ARTIFICIAL INTELLIGENCE ADVISORY COMMITTEE (NAIAC) YEAR ONE REPORT (2023) [hereinafter NAIAC REPORT], https://www.ai.gov/wp-content/uploads/2023/05/NAIAC-Report-Year1.pdf [https://perma.cc/8HHF-Y7CY].

310. Avi Gesser, Jehan A. Patterson, Anna Gressel & Scott M. Caravello, *The White House's Blueprint for an AI Bill of Rights: What It Gets Right and What It Gets Wrong About Artificial Intelligence Regulation*, DEBEVOISE DATA BLOG (Oct. 26, 2022), https://www.debevoisedatablog.com/2022/10/26/the-white-houses-blueprint-for-an-ai-bill-of-rights-what-it-gets-right-and-what-it-gets-wrong-about-artificial-intelligence-regulation/ [https://perma.cc/QE3K-F3CZ].

311. For instance, by instituting chief AI officers and advisory bodies. The Social Security Administration, for example, appointed a Chief Artificial Intelligence Officer tasked to "[d]rive implementation of the HHS AI strategy, [s]tand up the HHS AI governance structure, [c]oordinate the HHS response to AI-related federal mandates, and [f]oster collaboration across HHS agencies and offices." *See About the HHS Office of the Chief Artificial Intelligence Officer (OCAIO)*, U.S. DEP'T OF HEALTH & HUMAN SERVS. (Mar. 4, 2022), https://www.hhs.gov/about/agencies/asa/ocio/ai/ocaio/index.html [https://perma.cc/6T74-QUQQ].

312. NAIAC REPORT, *supra* note 309, at 22.

313. *See* Engstrom & Haim, *supra* note 7.

314. Different agencies adopt different segmentation, but the principles are very similar. *See e.g.*, TRUSTWORTHY AI (TAI) PLAYBOOK, *supra* note 299; MICHAEL L. LITTMAN, IFEOMA AJUNWA, GUY BERGER, CRAIG BOUTILIER, MORGAN CURRIE, FINALE DOSHI-VELEZ, GILLIAN HADFIELD, MICHAEL C. HOROWITZ, CHARLES ISBELL, HIROAKI KITANO, KAREN LEVY, TERAH LYONS, MELANIE MITCHELL, JULIE SHAH, STEVEN SLOMAN, SHANNON VALLOR & TOBY WALSH, GATHERING STRENGTH, GATHERING STORMS: THE ONE HUNDRED YEAR STUDY ON ARTIFICIAL INTELLIGENCE (AI100) 2021 STUDY PANEL REPORT 65 (2021), https://ai100.stanford.edu/sites/g/files/sbiybj18871/files/media/file/AI100Report_MT_10.pdf [https://perma.cc/MJ7A-PVXT] ("[D]eployment carries the connotation of implementing a more or less ready-made technical system,

whether an AI tool is appropriate to adopt in the first place.[315] Assuming an AI solution is relevant, it is still important to acknowledge that an AI algorithm is not a product, but a process,[316] which require continuous attention and updating throughout the lifecycle. Not heeding to this insight may lead to dysfunctional systems that prove to be useless for agency personnel on the ground, especially where systems are developed via procurement.

Furthermore, agencies need to think at three levels of functionality: organization, system, and component. Each level requires different inputs and processes, through a lens of ongoing processes.[317]

A second tenet is that AI embedding requires continuous and iterative rounds of evaluation and updating. This implies that design has to be dynamic and allow insights from practice to inform how systems function. One important aspect is recalibration of predictions according to errors or disagreements that transpire in practice. An evaluation mindset also requires that agencies develop consistent and precise metrics that take into account operational context.[318] NAIAC has suggested that "an evaluation process should include testing of AI systems for safety and functionality, assessment of impact on stakeholder groups, and processes for reporting, mitigation, and redress of harms should harms occur."[319] This highlights that evolution is not only important to ensure attainment of policy goals but also to detect harms and risks early on, and not upon release.

A third tenet is concerned with data. Data abundance is the basis of the current surge in AI, yet problematic data practices are often the cause of problematic outcomes.[320] Therefore, data hygiene is important to mitigate concerns over bias and other problems. Data should come from reliable sources that are well-

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without regard for specific local needs or conditions. Researchers have described this approach as 'context-less dropping in.' The most successful predictive systems are not dropped in but are thoughtfully integrated into existing social and organizational environments and practices. From the outset, AI practitioners and decision-makers must consider the existing organizational dynamics, occupational incentives, behavioral norms, economic motivations, and institutional processes that will determine how a system is used and responded to. These considerations become even more important when we attempt to make predictive models function equally well across different jurisdictions and contexts that may have different policy objectives and implementation challenges.").

315. NAIAC REPORT, *supra* note 309, at 22.

316. GAO REPORT, *supra* note 24.

317. This framework fits within the larger context of administrative procedures: "Internal control is not one event, but a series of actions that occur throughout an entity's operations. Internal control is recognized as an integral part of the operational processes management uses to guide its operations rather than as a separate system within an entity. In this sense, internal control is built into the entity as a part of the organizational structure to help managers achieve the entity's objectives on an ongoing basis." *See* COMPTROLLER GENERAL OF THE UNITED STATES, STANDARDS FOR INTERNAL CONTROL IN THE FEDERAL GOVERNMENT 6 (2014), https://www.gao.gov/assets/gao-14-704g.pdf [https://perma.cc/6XPL-XC43].

318. Mark Krass, Peter Henderson, Michelle M. Mello, David M. Studdert & Daniel E. Ho, *How US Law Will Evaluate Artificial Intelligence for Covid-19*, BMJ, 2021, at 1.

319. NAIAC REPORT, *supra* note 309, at 26.

320. Mayson, *supra* note 60.

documented, be of high quality, be representative of the affected population,[321] and not compromise privacy interests.[322] Like other aspects of the AI lifecycle, data is also a dynamic aspect that changes over time and requires continuous attention.

A fourth principle is that governance requires defining clear goals, roles, responsibilities, and delegations in the bureaucratic structure. This also requires robust documentation of both technical specifications and organizational structures. Moreover, human supervision structures are especially important to define and document.[323] The documentation and specification of responsible officers lays the foundation for an accountability structure that allows the public at large or institutional observers to trace AI systems and follow a supervision path to avoid the problem of a faceless, nameless AI decision-making practice.[324] This principle may also include internal separation of powers—for example, dividing development and evaluation functions.[325]

Fifth, the type and cost (or weight) of potential errors are important for building failsafe mechanisms and designing optimal review procedures. This is true for every decision-making schema, but even more so for hybrid human-algorithmic teams and processes since humans and machines exhibit different types of errors.[326] Humans, for instance, may be prone to inconsistency across people and even within the same person over time, while algorithms are consistent but may produce unexpected and wrong outputs that are obvious to humans with experience or common sense.[327] Optimal procedures take into account these differences and seek to complement relative weaknesses with relative advantages.[328]

A final idea is the focus on capacity building and integrated expertise, including hiring of multidisciplinary workforce and cross-team work.[329] Integrative teams foster better design, as they wield technical expertise as well as subject-matter knowledge and familiarity with internal processes.[330] This is especially important in

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321. Another approach is to rely on augmented and synthetic data practices for correction. For a critical analysis of synthetic data for variability enhancement, see Benjamin N. Jacobsen*, Machine Learning and the Politics of Synthetic Data*, 10 BIG DATA & SOC'Y., Jan.–June 2023.

322. GAO REPORT, *supra* note 24, at 6.

323. TRUSTWORTHY AI (TAI) PLAYBOOK, *supra* note 299.

324. *Id.*

325. Engstrom & Haim, *supra* note 7.

326. Gesser et al., *supra* note 67.

327. This phenomenon is known as the Broken Leg Problem. *See* Grove & Meehl, *supra* note 71, at 93. In fact, the consistency of algorithms is also problematized with more advanced methods, where algorithmic outputs are sampled from a large probability distribution and may differ from query to query (known as the "temperature" of the model). *See* Andrew Johnson, *The Role of Temperature in Large Language Model Response Generation*, MEDIUM (Jul. 16, 2023), https://medium.com/@andrew_johnson_4/the-role-of-temperature-in-large-language-model-response-generation-c592c961ca9d [https://perma.cc/MC8D-PZ4S].

328. Leibig et al., *supra* note 66; Raisch & Krakowski, *supra* note 66; Raghu et al., *supra* note 66.

329. GAO REPORT, *supra* note 24; VA ARTIFICIAL INTELLIGENCE (AI) STRATEGY, *supra* note 46; NAIAC REPORT, *supra* note 309, at 48.

330. Gerald K Ray & Jeffrey S Lubbers, *A Government Success Story: How Data Analysis by the*

an ecosystem where most AI innovation at the frontier is achieved in the private sector and where agencies are at a disadvantage in procuring technology solutions.[331] Enhancing capacity and literacy, even if it does not completely solve the capability gap, can prevent the procurement of systems without proper customization and mitigate some of the concerns relating to outsourcing key government responsibility unintentionally.[332]

Table 2: Principles and Best Practices of Internal Law of Algorithms

Principle[333]	**Best Practices**
Design, Integrate, Assess	Consider different levels: organization, system, component; focus on designing for real needs, integrating and not deploying.
Continuous Evaluation and Iterative Updating	Not product, but process; prepare evaluation infrastructure
Data	Well-documented, high-quality sources; Representative of affected population; consider privacy interests
Clear Goals and Roles	Defining clear goals, roles, responsibilities, and delegations; robust documentation of technical specifications and organizational structures; internal separation of functions between development and evaluation
Tradeoffs and Balance of Potential Errors	Asserting the type of errors algorithms are prone to, and where humans are likely to fail; estimating the importance of errors and assigning weights; designing failsafe workflows based on these characteristics.
Integrated Expertise and Capacity	Focus on integrative teams for technical and subject-matter expertise and familiarity with internal processes; hiring multidisciplinary workforce.

Social Security Appeals Council (with a Push from the Administrative Conference of the United States) Is Transforming Social Security Disability Adjudication, 83 GEO. WASH. L. REV. 34 (2015); Glaze et al., *supra* note 10; HO ET AL., *supra* note 10; NAIAC REPORT, *supra* note 309, at 26.

331. *See* Mulligan & Bamberger, *supra* note 54.

332. Crawford & Schultz, *supra* note 56.

333. Based in part on Engstrom & Haim, *supra* note 7.

C. Impediments of Internal Governance

The previous section considered the emerging landscape of internal law for AI governance in the administrative state and discussed the predicaments of administrative law in defining the contours of internal law. Yet, despite the prominence of internal law in administrative work, there are conditions where internal law fails and cannot resolve problems that arise in public administration. This is true regardless of algorithmic systems,[334] but it is manifested in the context of decision-making with algorithms as well. There are beneficial interventions external legal frameworks could and should propagate, which I describe in the following section.

There is some evidence that the optimism over internal administrative law is too rosy. Ames et al. show that internal pressures in agencies can distort internal governance mechanisms and transform them into altogether different standards.[335] Aspects of institutional context that are hard to observe, such as culture, personnel, and political environment, can drive implementation, creating a gap between internal law *on the books* and internal law *in action*.[336] Indeed, a main problem of internal law is not what it purports to do but what actually happens. For instance, a stated standard of review of a quality review program may be altered into a lesser standard, even within the same agency across different units.[337] Effective internal mechanisms *can* be instigated and implemented from within by local initiative even without external mandate;[338] but, a notable problem is their fragility since they are vulnerable to changes by superiors—for example if a salient error occurs that shifts reputational incentives.[339] I identify three main factors that can thwart internal legal apparatuses—resistance from the frontlines, misaligned incentives between hierarchical levels, and conflicting goals—and discuss their application to the algorithmic context.

1. Resistance

Resistance is one of the main factors that can work against internal law, as line-level workers defy managerial control and weaken mechanisms. Ames et al. portray how adjudicators that possess legal protections can respond with legal challenges seeking to compel the agency to change design or relax its rules to comport with frontline demands.[340] Others may carry out successful resistance, even without

334. Ames et al., *supra* note 15.
335. *Id.*
336. *Id.* at 59.
337. *Id.*
338. *Id.* at 67–68.
339. *Id.* at 68.
340. *Id.* at 61. This is reminiscent of protracted battles between the Social Security Administration and the ALJ union over decisional independence. *See* Nou, *supra* note 205.

formal protection, by subverting and mounting internal tensions.[341] This can result in agencies designing mechanisms in anticipation of resistance and accounting for it, potentially undermining the sound administration it was meant to achieve. Resistance from line-level workers is evident in many algorithmic implementation case studies[342] and can be especially debilitating where there are strong norms of distributed discretion and power and an internal culture that does not favor centralized institutional review.

We have already seen how an algorithmic system accompanied by guidance can play out differently when applied. The example of a risk assessment tool in DHS exemplifies this dynamic.[343] Ongoing pressure from ICE officers in charge of detention decisions during removal proceedings made the agency cave and tweak its model such that it would fit line-level preferences towards detention.[344]

Likewise, frontline practice can disregard algorithmic systems and undermine them, even if instructed to rely on them. Agencies may find it necessary in these situations to move further in their attempt to control discretion by instituting a mandatory policy—for example, creating a presumption in favor of an applicant if they score high on the algorithmic prediction and are granted benefits unless overridden.[345] Nevertheless, even then, workers can exercise their override power and other mechanisms to resist and undermine the algorithm.[346]

2. Misaligned Incentives

Another factor that may undermine internal law is misaligned incentives between levels in the agency. If workers have an incentive to function in a certain way—for example, pass lenient judgment in a quality review procedure—in order to be promoted or achieve some other goal, they may undermine an internal governance regime.[347] Similarly, agencies may have incentives to err in a certain way that favors some policy preference (e.g., pro-veteran or anti-immigration),

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341. Raso, *supra* note 31; Raso, *supra* note 87; Rik Peeters, *The Agency of Algorithms: Understanding Human-Algorithm Interaction in Administrative Decision-Making*, 25 INFO. POLITY 507 (2020); Justin Bullock, Matthew M. Young & Yi Fan Wang, *Artificial Intelligence, Bureaucratic Form, and Discretion in Public Service*, 25 INFO. POLITY 491 (2020).

342. Kellogg et al., *supra* note 29.

343. Evans & Koulish, *supra* note 31; *see supra* section I.B.

344. Evans & Koulish, *supra* note 31.

345. ALLEGHENY METHODOLOGICAL REPORT, *supra* note 40.

346. Conversely, an algorithm that captures only one aspect of a decision (for example, risk of flight of a defendant) and is meant to be an additional informational input, can turn into a central factor if workers develop over-reliance and it displaces other less measurable factors (for example, good standing). *See* Ben Green & Yiling Chen, *Algorithmic Risk Assessments Can Alter Human Decision-Making Processes in High-Stakes Government Contexts*, 5 PROC. ACM HUM.-COMPUT. INTERACT. 1 (2021).

347. Ames et al., *supra* note 15, at 61–62. This is common in situations where subordinates evaluate their superiors. *See* MASHAW, *supra* note 11, at 17.

undermining governance regimes that do not have the same proclivities.[348] Regardless of how effective their mechanisms really are, agencies have incentives to show they excel at their own metrics, such as internal reversal rates, and due to complexity, external oversight bodies are unlikely to conduct searching review.[349]

In the algorithmic context, systems that are meant to detect errors may run up against the institutional incentives of an agency. Take, for example, the work of CPS hotline call-screeners.[350] Risk assessment models may predict a certain child to have a low risk of abuse or neglect. But a screener is more sensitive to *false negative* errors (i.e., screening out a call about a child in real danger) than to *false positive* errors (i.e., screening in a call about a child that is not in danger). An abused child makes frontpage news and invites scrutiny, political oversight, and pressure, including misconduct investigations. An investigated family, ending with an unsubstantiated allegation, suffers real costs and angst due to intrusive surveillance actions, but that does not necessarily translate into significant direct pressure on the agency. Screeners are thus more averse to risk of false negative errors ("err on the side of caution") and may tend to disregard more predictions of low risk. When the predicted risk is high, however, they would question the algorithm less often, therefore undermining its effects as a check on their discretion.

3. Conflicting Goals

Administrative agencies typically pursue more than one policy goal, and those tend to conflict.[351] This could result in prioritizing goals that serve institutional interests rather than the public, prioritizing measurable metrics over others,[352] and devising metrics that fit short-term interests and are not necessarily the most accurate.[353] For example, when their backlogs build up, agencies tend to reduce quality improvement regimes in favor of quantity and reroute resources to speed up dispensation of cases.[354]

It is evident how an algorithmic system embodies this problem. Generating more measurable metrics through algorithmization may encourage agencies to rely on those metrics rather than other less quantifiable aspects that could be equally important for quality of services. Overriding algorithmic recommendations is expensive. Minimizing override rates, for instance, could cut both ways: agencies can try to affect their workers' discretion such that they disagree less, or they can retrain the algorithm to fit workers' proclivities. Regardless of which outcome is

348. Hausman, *supra* note 129; Hausman, *supra* note 14.

349. Ames et al., *supra* note 15, at 63–64.

350. Cuccaro-Alamin et al., *supra* note 40.

351. Eric Biber, *Too Many Things to Do: How to Deal with the Dysfunctions of Multiple-Goal Agencies*, 33 HARV. ENV'T. L. REV. 1 (2009).

352. John Bohte & Kenneth J. Meier, *Goal Displacement: Assessing the Motivation for Organizational Cheating*, 60 PUB. ADMIN. REV. 173 (2002).

353. Ames et al., *supra* note 15, at 64.

354. *Id.* at 65; Bednar, *supra* note 128.

more desirable, this shows that internally determining goal prioritization may complicate how agencies use algorithms as bureaucratic governance measures. Other examples of this tension include which types of errors to focus on (e.g., false negatives or positives), which notions of fairness to apply, and which interventions to use.

D. What Role Should External Law Play?

Given that internal dynamics can undermine internal governance, some have advocated a role for external law to support internal reform.[355] Scholars of administrative reform have suggested fostering innovation and improvement through experimentalist legal frameworks that promote accountability and quality by focusing on testing and evaluation rather than ossifying administrative procedures.[356] In the AI algorithmic context, especially, focusing on creating robust experimentation frameworks and documentation, instead of prescribing concrete requirements, can yield a more accountable and trustworthy algorithm implementation without stymieing salutary forms of innovation.[357] In this Section, I discuss briefly several important roles that external legal mechanisms are able to play.

1. Methodological and Informational Transparency

Administrative law stops short of requiring full transparency from agencies regarding their internal processes, even through freedom of information procedures.[358] Nevertheless, legal frameworks are important for creating public information that can foster discussion and debate, invite academic and public scrutiny, and allow stakeholders to engage with agencies' processes. A first step is to require agencies to publicize their use of algorithmic systems in an accessible manner, similar to suggestions to make public and list guidance documents and other internal legal mechanisms.[359] Special attention should be given to documentation of internal procedures of embedding algorithmic systems and methodological clarity as to the deployment and assessment of systems. Not unlike exceptions to FOIA rights, agencies should be able to weigh counter-interests, such as risk of gaming and strategic behavior in relevant fields, since actors may seek to take advantage of increased transparency to overcome regulatory burdens. But as a starting point, informing the public at large on how algorithmic systems are purported to be used is important in cultivating legitimacy.[360]

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355. Ames et al., *supra* note 15, at 68.

356. Sabel & Simon, *supra* note 106; MASHAW, *supra* note 11.

357. Engstrom, *supra* note 2; Engstrom & Haim, *supra* note 7.

358. Coglianese & Lehr, *supra* note 55; Engstrom, *supra* note 2.

359. CARY COGLIANESE, PUBLIC AVAILABILITY OF AGENCY GUIDANCE DOCUMENT (2019).

360. A recent white paper from researchers at Stanford University found the level of transparency of federal agencies regarding AI to be partial and lacking. *See* CHRISTIE LAWRENCE, ISAAC

2. Best Design Practices

As discussed in Section IV.A, best practices regarding design, integration, and assessment of algorithmic systems are slowly emerging.[361] Yet translating practices into legal mandates probably requires much stronger consolidation and consensus in the scientific community. Thus, legal frameworks would be wise to begin by laying out broad contours, focusing on more established practices, and moving towards updating down the line. For example, in the matter of training data for algorithmic systems, agencies could be required to conduct reasonable efforts to ensure representativeness and down the line, if such a consensus emerges, move to concentrate on internally developed datasets or synthetic data solutions.[362]

3. Intra-agency Institutional Oversight

Expert agency bodies, especially when including stakeholders and academic partners, are better poised and able to understand the intricate substantive issues in a complicated technical and bureaucratic structure. They can also have access to internal data and firsthand impressions that judges in litigation are not privy to. Such bodies can be induced by legislative action, for instance by appropriating funds for public councils for artificial intelligence, and grant agencies stronger deference in judicial review.[363]

4. Inter-agency Oversight and Competencies

Inter-agency cooperation and oversight is an understudied area of administrative law and governmental work[364] but can be an important source of cross-pollination. In the algorithmic context, it has the potential to create overarching standards and best practices, such as the NIST Framework,[365] and help other agencies to implement them; to harness loci of knowledge and expertise by funding relevant research through NSF and similar programs;[366] and to conduct oversight and review through preexisting watchdogs, such as the GAO, Inspector

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CUI & DANIEL E. HO, IMPLEMENTATION CHALLENGES TO THREE PILLARS OF AMERICA'S AI STRATEGY (2022), https://hai.stanford.edu/sites/default/files/2022-12/HAIRegLab%20White%20Paper%20-%20Implementation%20Challenges%20to%20Three%20Pillars%20of%20America%E2%80%99s%20AI%20Strategy.pdf [https://perma.cc/Q4RQ-QA5B].

361. Engstrom & Haim, *supra* note 7.

362. Jacobsen, *supra* note 321.

363. Metzger made a similar argument regarding agency decision-making more generally. *See* Metzger, *supra* note 16, at 1366–68.

364. Nou, *supra* note 113; Jody Freeman & Jim Rossi, *Agency Coordination in Shared Regulatory Space*, 125 HARV. L. REV. 1131 (2011); Alejandro E. Camacho & Robert L. Glicksman, *Designing Regulation Across Organizations: Assessing the Functions and Dimensions of Governance,* 15 REG. & GOVERNANCE, Anniversary Issues, at S102 (2021).

365. Tabassi, *supra* note 301.

366. *Artificial Intelligence at NSF*, NAT'L SCI. FOUND. (May 4, 2023), https://www.nsf.gov/cise/ai.jsp [https://perma.cc/37W6-6J8J].

Generals, or the Administrative Conference of the United States.[367] It can also facilitate cross-fertilization of innovative programs, especially for agencies that have less technical competency, and allow them to gain knowledge from more experienced agencies such as HHS. While most of these are internal governmental endeavors, they are still external to the agency and can be required by presidential directives, and legislative action can enhance and facilitate them by creating frameworks for collaboration on AI and appropriating them.

5. Structural Reform Litigation

Class actions against public bureaucracies are a common tool to constrain administrative action and correct flaws where discernable harms are imposed on affected groups. Often, structural reform litigation propagates change by tying agencies to recurrent review through consent decrees and compelling them to resolve issues associated with the harms identified in litigation.[368] The literature is skeptical of the ability of such litigation to achieve outcomes that align with democratic objectives and consensus due, inter alia, to budgetary constraints and the ability of public managers to restructure internal agency operations.[369] Such concerns may in fact arise, as discussed in Section III.B.2, since reviewing courts are not well-positioned to interrogate agencies' internal operations and algorithmic systems. Nevertheless, there have been other, more optimistic voices pointing out the advantages structural litigation offers and the gap between perceived and real intrusiveness.[370] In the context of internal administrative law, structural litigation may allow courts to identify aggregate claims which get at the root of dysfunction rather than idiosyncratic cases that may lead to skewed outcomes[371] in accordance with the "hard cases makes bad law" maxim. In the algorithmic context, structural litigation may be beneficial in identifying common cases and classes of harms and delineating the contours of algorithmic harms.[372] Taken as a gradual, progressive effort and allowing agencies to structure their own accountability mechanisms against a certain benchmark may prove effective. So far, however, the few lawsuits brought against algorithmic systems in public bureaucracies have not proved very successful in inducing administrative agencies to improve operations and have resulted mostly in superficial inquiries into procurement practices or have evolved into civil litigation and blame-sharing between vendors and agencies.[373]

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367. GAO REPORT, *supra* note 24.

368. Anthony Michael Bertelli, *Strategy and Accountability: Structural Reform Litigation and Public Management*, 64 PUB. ADMIN. REV. 28 (2004).

369. *Id.*; Anthony M. Bertelli & Sven E. Feldmann, *Structural Reform Litigation: Remedial Bargaining and Bureaucratic Drift*, 18 J. THEORETICAL POL. 159 (2006).

370. John C. Jeffries Jr. & George A. Rutherglentt, *Structural Reform Revisited*, 95 CALIF. L. REV. 1387 (2007).

371. Ames et al., *supra* note 15, at 75.

372. Cuéllar & Huq, *supra* note 157.

373. *See generally* Calo & Citron, *supra* note 2.

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In short, despite the important role of internal law for algorithmic systems in administrative agencies, external public law—whether promulgated by legislative actions or induced by reviewing courts—will still maintain an important position in promoting accountability and guarding against the pitfalls of internal agency dynamics. It will do well not to do away with what internal governance mechanisms have to offer but rather adopt successful aspects and foster improvement through evaluation and reflection.

CONCLUSION

AI algorithms in administrative agencies are becoming a reality. They are gradually being embedded in the complex bureaucratic structures of the administrative state. The evident limitations of legal endeavors in achieving accountability and addressing other concerns and harms, by legislative action or judicial means, bring to the fore internal law as an alternative avenue for governance. Internal law has the potential to improve decision-making with AI because agencies have informational advantages in understanding bureaucratic structures and designing hybrid decision-making processes to improve overall outcomes. In this article I have therefore began to uncover the accumulating *internal law of administrative algorithms* and identified several main tenets and best practices that agencies, academics, and advocates have started to coalesce on.

This Article delineated some of the points of contention that will be raised with AI algorithms and outlined the doctrinal questions of administrative law that are likely to occupy judges and lawyers when dealing with AI in the government. As AI is in its early days in government, these questions will only become more prevalent and pressing. Algorithms will create serious challenges for the administration of justice. Internally robust processes that seek to ameliorate the risks algorithmic systems pose can mitigate some concerns, and legal discourse will benefit from continuing the endeavor of uncovering and developing the course.