

AI in Adjudication and Administration

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Artificial intelligence (AI) has begun to permeate many aspects of U.S. society.¹ In settings as varied as medicine, transportation, financial services, and entertainment, new digital technologies that rely on machine-learning algorithms to process vast quantities of data are making highly accurate predictions that often outperform humans in executing important tasks.² As a

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¹ Although a variety of definitions for the term “artificial intelligence” exist, a helpful one is “[t]he theory and development of computer systems able to perform tasks normally requiring human intelligence.” *Artificial Intelligence*, OXFORD DICTIONARIES, <https://www.oxfordreference.com/view/10.1093/oi/authority.20110803095426960> [<https://perma.cc/G6VX-AX6B>]. The terms “machine learning” and “artificial intelligence” are to some extent interchangeable and are used as such throughout this article. Cf. Cary Coglianese & David Lehr, *Transparency and Algorithmic Governance*, 71 ADMIN. L. REV. 1, 2 n.2 (2019) (“By ‘artificial intelligence’ and ‘machine learning,’ we refer . . . to a broad approach to predictive analytics captured under various umbrella terms For our purposes, we need not parse differences in the meaning of these terms, nor will we delve deeply into specific techniques within machine learning.”). For further discussion of how we define machine learning throughout this article, see *infra* notes 13–17 and accompanying text.

² See, e.g., Cary Coglianese, *Using Machine Learning to Improve the U.S. Government*, REG. REV. (Aug. 12, 2019), <https://www.theregreview.org/2019/08/12/coglianese-using-machine-learning-to-improve-us-government> [<https://perma.cc/PZD9-NTUG>]; Peter Dizikes, *AI, the Law, and Our Future*, MIT NEWS OFF. (Jan. 18, 2019), <http://news.mit.edu/2019/first-ai-policy-congress-0118> [<https://perma.cc/4B38-2A2B>]; Jillian D’Onfro, *AI 50: America’s Most Promising Artificial Intelligence Companies*, FORBES (Sept. 17, 2019), <https://www.forbes.com/sites/jilliandonfro/2019/09/17/ai-50-americas-most-promising-artificial-intelligence-companies/#54bfb84c565c> [<https://perma.cc/EV4Z-NC5A>]; Chris Weller, *A California Police Department is Using Software to Decide if You’re About to Commit a Crime*, BUS. INSIDER (Jan. 12, 2016), <https://www.businessinsider.com/intrado-beware-system-tracks-threat-levels-2016-1> [<https://perma.cc/2VMZ-C5XJ>] (“A new piece of software in place at the Fresno Police Department in central California uses huge batches of data, ranging from criminal

result, the potential utility of artificial intelligence in the legal field has not gone unnoticed, with scholars, attorneys, and judges beginning to examine the implications of these digital technologies for the U.S. legal system.³

This article seeks to capture the state of the art in current uses of digitization, algorithmic tools, and machine learning in domestic governance in the United States. It serves as a status report on nonmilitary governmental uses of artificial intelligence and its building blocks throughout state and federal courts and agencies.⁴ With responsibility for domestic governance divided in a federalist structure across fifty-one governments—fifty states plus

history to Twitter feeds, to assess how likely someone is to commit a crime and whether the police ought to keep tabs on them.”). Artificial intelligence tools have even proven useful in the fight against COVID-19. *See, e.g.*, Press Release, Nat’l Insts. of Health, NIH Harnesses AI for COVID-19 Diagnosis, Treatment, and Monitoring (Aug. 5, 2020), <https://www.nih.gov/news-events/news-releases/nih-harnesses-ai-covid-19-diagnosis-treatment-monitoring> [<https://perma.cc/2GFW-63CA>].

³ *See, e.g.*, Jens Frankenreiter & Michael A. Livermore, *Computational Methods in Legal Analysis*, 16 ANN. REV. L. & SOC. SCI. 39 (2020) (discussing how computational advances may affect legal interpretation); Daniel L. Chen, *Machine Learning and the Rule of Law* 4–7 (Working Paper, 2019), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3302507 [<https://perma.cc/7E8F-NSBS>] (noting that machine learning may be useful in detecting and adjusting for bias in judicial decision-making on asylum requests); Harry Surden, *Artificial Intelligence and Law: An Overview*, 35 GA. ST. U. L. REV. 1305, 1328 (2019) (discussing implications of having “AI-enabled computer systems . . . make their way into various facets of the legal system”).

⁴ We do not address military and security intelligence-gathering uses of AI both because they present distinctive policy implications beyond the scope of this article and because they may well be subject to security classification. For an in-depth, non-classified treatment of artificial intelligence in U.S. military applications, however, see PAUL SCHARRE, *ARMY OF NONE: AUTONOMOUS WEAPONS AND THE FUTURE OF WAR* (2018). We also do not address in this article the use of AI tools by legislatures, mainly because such use “remains something of a next frontier.” Monika Zalnieriute et al., *From Rule of Law to Statute Drafting: Legal Issues for Algorithms in Government Decision-Making*, in CAMBRIDGE HANDBOOK ON THE LAW OF ALGORITHMS: HUMAN RIGHTS, INTELLECTUAL PROPERTY, GOVERNMENT REGULATION 251–72 (Woodrow Barfield ed., 2021). AI tools make concrete, individual forecasts, which more naturally make them conducive to adjudicatory and administrative contexts where individualized determinations must be made. As one of us has noted elsewhere, “[a] bit more technical imagination and advancement may be required for machine learning to usher in automatic regulation”—or, for similar reasons, legislation. Coglianese & Lehr, *supra* note 1, at 9. That said, public support for such use may be growing. In one very small survey, at least forty percent of Americans reportedly favored replacing some of their legislators with AI systems (and fifty-one percent and seventy-five percent of the European and Chinese populations, respectively, did as well). Sam Shead, *More than Half of Europeans Want to Replace Lawmakers with AI, Study Says*, CNBC (May 27, 2021), <https://www.cnbc.com/2021/05/27/europeans-want-to-replace-lawmakers-with-ai.html> [<https://perma.cc/56X7-PAQX>]. Although the actual replacement of legislators with AI tools may be some time away, the involvement of legislatures in overseeing and crafting rules about the use of AI by others, including by courts and administrative agencies, is clearly already in taking place. *See, e.g.*, *State Artificial Intelligence Policy*, ELEC. PRIV. INFO. CTR., <https://epic.org/state-policy/ai/> [<https://perma.cc/6V2J-EGU5>]; Legislation Related to Artificial Intelligence, Nat’l Con. St. Legislatures, <https://www.ncsl.org/research/telecommunications-and-information-technology/2020-legislation-related-to-artificial-intelligence.aspx> [<https://perma.cc/2Q6Y-A7BR>].

the national government—the scope of this article’s coverage is vast.⁵ Its subject matter is also a rapidly changing one.

As new technologies and applications emerge in the private sector, both pressures and opportunities for the use of those technologies in public-sector settings continue to grow. The vast scope and fast pace of algorithmic governance make important the kind of stock-taking that this article provides. To assess the value that artificial intelligence holds, as well as to identify opportunities for its application in domestic governance, it is important to understand where and how AI is currently being used. Such a stock-taking can also facilitate future research evaluating current applications and generating recommendations for the diffusion of artificial intelligence in new settings.

An account of the use of AI in government is also valuable because there currently exists no centralized repository of applications of artificial intelligence by courts and administrative agencies.⁶ Given the federalist structure of the United States, the development and implementation of AI technology in the public sector is also not determined by any central institution. Technology decisions are made at the federal level in as many as several hundred separate administrative agencies.⁷ The number of comparable agencies at the state and local level surely runs into the tens of thousands. Even with respect simply to law enforcement agencies, it has been noted that “the decentralized, fragmented, and local nature of law enforcement in the United States makes it challenging to accurately count the number of agencies.”⁸

⁵ See generally, e.g., Robert A. Schapiro, *Toward a Theory of Interactive Federalism*, 91 IOWA L. REV. 243 (2005); Philip J. Weiser, *Federal Common Law, Cooperative Federalism, and the Enforcement of the Telecom Act*, 76 N.Y.U. L. REV. 1692 (2001).

⁶ One effort to provide such a repository can be found on the Penn Program on Regulation’s website on “Optimizing Government.” *Uses in Government*, PENN LAW: OPTIMIZING GOVERNMENT, <https://www.law.upenn.edu/institutes/ppr/optimizing-government-project/government.php#municipal> [https://perma.cc/SS39-4FJ6]. Another such project, which documents dozens of uses by local and state government agencies, is the Data-Smart City Solutions initiative run by Harvard University. *A Catalog of Civic Data Use Cases*, DATA-SMART CITY SOLS. (Apr. 9, 2021), <https://datasmart.ash.harvard.edu/news/article/how-can-data-and-analytics-be-used-to-enhance-city-operations-723> [https://perma.cc/65WG-878Z].

⁷ Indeed, just getting a count of the number of federal agencies is difficult. One scholarly report published by a governmental agency noted that “there is no authoritative list of government agencies. Every list of federal agencies in government publications is different.” DAVID E. LEWIS & JENNIFER L. SELIN, SOURCEBOOK OF UNITED STATES EXECUTIVE AGENCIES 14–15 (2012), https://www.acus.gov/sites/default/files/documents/Sourcebook-2012-Final_12-Dec_Online.pdf [https://perma.cc/CXL5-6UVA] (reporting estimates of the number of federal administrative agencies that range from 252 to 405).

⁸ U.S. DEPT OF JUST., NATIONAL SOURCES OF LAW ENFORCEMENT EMPLOYMENT DATA 1 (Oct. 2016), <https://www.bjs.gov/content/pub/pdf/nsleed.pdf> [https://perma.cc/NX8S-NR3S]. As a rough estimate of the number of law enforcement agencies, we note that

Decisions about digital technologies used by courts throughout the United States are similarly made by a plethora of institutions and actors. The federal court system comprises, in addition to one Supreme Court, a total of thirteen “circuits” in the federal appellate court system and ninety-four trial court “districts” (each with as many as dozens of trial judges, for a total number of more than 650 courtrooms).⁹ At the state level, the number of different courts proliferates even further—especially given that state governments further delegate their domestic authority to county and municipal governments that have their own courts. According to the National Center for State Courts, approximately 15,000 to 17,000 different state and municipal courts exist in the United States.¹⁰

Any one of these numerous judicial or administrative entities could in principle have its own policy with respect to electronic filing, digitization of documents, or the use of algorithms to support decision-making.¹¹ As a result, it is valuable for decision-makers in any of these settings, as well as scholars and practitioners, to have a source that catalogs current uses of artificial intelligence and its building blocks across the United States. Of course, any such survey of uses must be made with appropriate caution. As much as we have attempted to be exhaustive in cataloging domestic uses of AI, we can make no claim to have identified every use by any governmental entity. This article is based primarily on extensive searches of academic literature and media publications in our effort to identify current uses of machine-learning algorithms that aid decision-making within courts and agencies at both state and federal levels of government. We also spoke with court and agency officials who would be in a position to know about current uses of artificial intelligence and its building blocks by governmental entities, and we made contact with leading consultants and academic

approximately 18,000 different police departments and other law enforcement agencies responded to a federally sponsored Census of State and Local Law Enforcement Agencies in 2008. *Id.*

⁹ See, e.g., *Court Role and Structure*, U.S. CTS., <https://www.uscourts.gov/about-federal-courts/court-role-and-structure> [<https://perma.cc/EG2Q-NZPM>].

¹⁰ This estimate is based on a telephone and email exchange with NCSC staff, and it includes a vast number of municipal courts. Indeed, the uncertainty reflected in the range (rather than a point estimate) is apparently due to fairly regular changes in the size and organization of municipal courts.

¹¹ See, e.g., U.S. SUPREME COURT, RULES OF THE SUPREME COURT (Sept. 27, 2017), <https://www.supremecourt.gov/filingandrules/2017RulesoftheCourt.pdf> [<https://perma.cc/4EC9-HS4J>]; FED. R. CIV. P. 83(a) (“[A] district court, acting by a majority of its district judges, may adopt and amend rules governing its practice.”); FED. R. APP. P. 47(a)(1) (“Each court of appeals acting by a majority of its judges in regular active service may . . . make and amend rules governing its practice.”).

experts who are developing and studying such possible uses. Our research effort has produced a survey, as comprehensive as any we know, of judicial and administrative uses of machine learning across federal and state governments in the United States.¹²

The results of our research lead us to be confident in two overarching conclusions. First, no judicial or administrative body in the United States has yet instituted a system that provides for total decision-making by algorithm, such that a computer makes a fully independent determination (that is, a human “out of the loop” decision).¹³ Second, we are aware of no court that is currently relying in any way, even on a human-in-the-loop basis, on what we would consider to be machine-learning algorithms. That said, one state has a parole board using a system based on a machine-learning algorithm to support prisoner release decisions, and numerous other administrative agencies at the state and federal levels have deployed or are currently researching the use of machine learning in support of various administrative functions.¹⁴

In this article, we distinguish machine-learning algorithms—which we treat here as defining artificial intelligence—from two building blocks that might help lead to the eventual governmental use of artificial intelligence: digitization and algorithmic tools. Indeed, machine learning resides on the far end of a spectrum of digital technologies available to governments.

The closest point on that spectrum begins with simple *digitization*—or the use of electronic filing or other data systems to manage information in electronic format. Digitization is a building block toward artificial intelligence because it can facilitate the availability of the “big data” on which machine learning is based.

Next on the spectrum would be for governments to rely on what we call *algorithmic tools*—that is, traditional statistical models, indices, or scoring systems that are used as decision tools.

¹² Other such efforts have produced excellent resources on AI use by governments, but have tended to have a more limited scope, either institutionally (e.g., only focused on agencies) or on one level of government (e.g., federal). See, e.g., DAVID FREEMAN ENGSTROM ET AL., GOVERNMENT BY ALGORITHM: ARTIFICIAL INTELLIGENCE IN FEDERAL ADMINISTRATIVE AGENCIES (2020), <https://www-cdn.law.stanford.edu/wp-content/uploads/2020/02/ACUS-AI-Report.pdf> [<https://perma.cc/HD8M-M98T>]; HILA MEHR, ARTIFICIAL INTELLIGENCE FOR CITIZEN SERVICES AND GOVERNMENT (2017), https://ash.harvard.edu/files/ash/files/artificial_intelligence_for_citizen_services.pdf [<https://perma.cc/79GT-GE6Q>]. Of course, we cannot claim that we have ourselves identified or discussed in this article all of the uses of AI by governmental bodies in the United States, especially in such a fast-moving domain as information technology.

¹³ For a discussion of the difference between using algorithms on a supportive versus determinative basis, see Coglianese & Lehr, *supra* note 1, at 31, and Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 GEO. L.J. 1147, 1167–70 (2017).

¹⁴ See *infra* notes 43, 138–188 and accompanying text.

These traditional algorithmic or statistical tools rely on humans to select the specific variables to be included in a decision aid and the precise mathematical relationships between those variables.¹⁵

Only at the final step of the spectrum—*machine learning*—do governments rely on tools that constitute what we consider here to be artificial intelligence. Machine-learning algorithms essentially work “on their own” to process data and discover optimal mathematical relationships between them. These algorithms can take many forms, but in essence machine learning refers to an algorithm’s autonomous ability to detect patterns in large amounts of data. This functionality gives machine-learning algorithms not only their name but also their often superior performance in predictive accuracy over traditional, human-guided algorithmic tools.

Of course, even with machine learning, humans must specify the objective that the learning algorithm is supposed to forecast or optimize, then collect the data on which the algorithm will “learn,” and ultimately specify the general computational properties or architecture that the algorithm will deploy.¹⁶ Often, humans will also undertake a number of steps to “train” the algorithm and refine its operation.

Yet machine-learning algorithms are different than traditional statistical tools because the precise ways in which data are combined and analyzed are not fully determined in advance by a human analyst. These algorithms are also typically not as intuitively explainable after the fact. For this reason, machine-learning algorithms are often described as “black-box” algorithms. They do not afford a ready way of characterizing exactly how they work—that is, which variables matter and how those variables are weighed for any given output—even though the outputs can be quite accurate in terms of achieving or optimizing the objectives that the algorithms have been designed to achieve.¹⁷

¹⁵ A typical example of a traditional statistical tool would be ordinary least squares regression analysis, where a human selects the variables and the functional form of the model. Admittedly, some computer scientists might well consider even conventional regression analysis as a type of “machine” learning because a statistical software package computes the coefficients in the model. But what we and others mean by machine learning refers to nonparametric models or algorithms that do not involve a human in expressly specifying the model’s functional form or even at times the precise variables to use in generating a predictive output. See Coglianese & Lehr, *supra* note 13, at 1156–59.

¹⁶ For an excellent primer on machine learning, see David Lehr & Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. DAVIS L. REV. 653, 669 (2017).

¹⁷ For helpful discussions of some of the challenges associated with explaining outputs of machine-learning algorithms, see P. Jonathon Phillips et al., *Four Principles of Explainable Artificial Intelligence* (Aug. 2020), <https://www.nist.gov/system/files/documents/2020/08/17/NIST%20Explainable%20AI%20Draft%20NISTIR8312%20%281%29.pdf> [<https://perma.cc/ZGB5-L5TS>], and Lehr & Ohm, *supra* note 16, at 705–10.

In Part I of this article, we take up the status of artificial intelligence in the federal and state judiciaries. More precisely, we report on three building blocks that might eventually lead to the use of artificial intelligence in the courts: the increased digitization of court records; the use of algorithmic tools for risk assessment in aspects of the criminal justice process; and the growth of online dispute resolution outside of and parallel to the courts. The most widespread technological innovation in the courts in recent years has manifested in the use of various forms of digitization (such as electronic filing and case management), while some courts have relied on algorithmic tools to support pretrial, sentencing, or parole decisions. Some courts also recognize a role for online dispute resolution systems developed by the private sector.

We turn in Part II to a review of administrative agencies' uses of artificial intelligence. Many administrative systems have been digitized for some time, and administrative agencies have also long relied on traditional statistical analysis or algorithmic tools.¹⁸ But most relevant to the purposes of this article, some administrative agencies at the local, state, and federal levels are also starting to use machine-learning algorithms for certain analytical and decision support purposes. We thus devote our attention in Part II to these latter uses of machine learning in the administrative context.

In both parts of this article, we also highlight some of the legal issues, and at times the litigation and public controversy, that have surrounded certain applications of algorithmic tools or machine learning. Given the increased use of artificial intelligence in other facets of society, as well as in many other parts of the world, greater governmental reliance on machine learning in the United States will likely continue to increase. At some point in the

¹⁸ Government's use of digital computing emerged following World War II. *A Brief History of the U.S. Federal Government and Innovation*, INSIGHT (Aug. 1, 2011), <https://insight.ieeeusa.org/articles/a-brief-history-of-the-u-s-federal-government-and-innovation-part-iii-1945-and-beyond/> [<https://perma.cc/SV3C-2V97>]; Kenneth L. Kraemer & John Leslie King, *Management Science and Information Technologies in U.S. Local Governments: A Review of Use and Impact*, 7 COMPUT. ENV. URB. SYS. 7 (1982). The use of digital computing to perform domestic administrative tasks had permeated government in earnest starting in the 1970s, and by the 1990s it expanded further following the advent of the internet. See DARRELL M. WEST, *DIGITAL GOVERNMENT: TECHNOLOGY AND PUBLIC SECTOR PERFORMANCE* (2005); JANE FOUNTAIN, *BUILDING THE VIRTUAL STATE: INFORMATION TECHNOLOGY AND INSTITUTIONAL CHANGE* (2001). For further discussion, see *infra* notes 111–112 and accompanying text. When it comes to traditional statistical analysis, various types of legal and administrative decisions have been informed by the use of such tools over the last century. It was in 1897, after all, that Oliver Wendell Holmes, Jr., opined that, although “the black-letter [lawyer] may be the [lawyer] of the present, . . . the [lawyer] of the future is the [expert] of statistics and the master of economics.” Oliver W. Holmes, *The Path of the Law*, 10 HARV. L. REV. 457, 469 (1897).

not-too-distant future, autonomous decision-making systems based on machine learning may well begin to take the place of a government singularly and literally “of the people” and “by the people” in the United States.¹⁹

I. ARTIFICIAL INTELLIGENCE BUILDING BLOCKS IN THE COURTS

As of today, we know of no machine-learning tool that has been adopted in any court in the United States to make an ultimate, fully automated determination on a legal or factual question.²⁰ However, several emerging trends in recent years signal movement towards what may be the eventual use of automated adjudication via artificial intelligence. To date, the principal building blocks of artificial intelligence in the courts comprise the digitization of court filings and processes, the introduction of algorithmic tools for certain criminal court decisions, and the emergence of online dispute resolution as an alternative to traditional court proceedings for small claims.

A. *Digitization of Court Records*

Artificial intelligence depends on data.²¹ Increasingly, court systems in the United States have made data more easily accessible through the growing digitization of court documents.²²

¹⁹ Abraham Lincoln, Address Delivered at the Dedication of the Cemetery of Gettysburg (Nov. 19, 1863).

²⁰ See Richard C. Kraus, *Artificial Intelligence Invades Appellate Practice: The Here, The Near, and The Oh My Dear*, AM. BAR ASS'N (Feb. 5, 2019), https://www.americanbar.org/groups/judicial/publications/appellate_issues/2019/winter/artificial-intelligence-invades-appellate-practice-the-here-the-near-and-the-oh-my-dear/ [https://perma.cc/58HE-NAWP] (noting that in the United States, “the more fantastic ideas such as using AI to objectively decide cases by analyzing facts and applying law . . . are still figments of creative imaginations”).

²¹ See Willem Sundblad, *Data Is the Foundation for Artificial Intelligence and Machine Learning*, FORBES (Oct. 18, 2018), <https://www.forbes.com/sites/willemsundblad/europe/2018/10/18/data-is-the-foundation-for-artificial-intelligence-and-machine-learning/-4bd8c64051b4> [https://perma.cc/V43E-H8EU] (“[D]ata is both the most underutilized asset of manufacturers and the foundational element that makes AI so powerful.”).

²² See, e.g., Jenni Bergal, *Courts Plunge into the Digital Age*, PEW CHARITABLE TRS.: STATELINE (Dec. 8, 2014), <https://www.pewtrusts.org/en/research-and-analysis/blogs/stateline/2014/12/8/courts-plunge-into-the-digital-age> [https://perma.cc/2U44-PMVV] (noting that the status of courthouses’ digital use “has been changing dramatically in many courthouses across the country. States are moving to systems in which documents are submitted electronically, file rooms are disappearing and the judicial system is going paperless”); *Records/Document Management Resource Guide*, NAT’L CTR. FOR STATE CTS., <https://www.ncsc.org/Topics/Techology/Records-Documents-Management/Resource-Guide.aspx> [https://perma.cc/VR52-3VFN] (“Records and document management are at the core of most courts’ business processes [M]any state courts have implemented electronic court records (ECR) and electronic data management systems (EDMS) in an effort to improve court operations and manage unruly paperwork.”).

This digitization has in large part been internally driven by the courts. Courts at both the state and federal level, including the Supreme Court itself, have authorized electronic filing as one of several ways a party can submit motions or arguments to a court, or they have required it as the only method of submitting filings.²³ In addition, virtually every state and the federal government posts free forms online that can be downloaded and used by litigants.²⁴ Some courts have created “dedicated computer kiosks” specifically designed to help litigants who lack legal representation.²⁵ In California, for example, an “Online Self-Help Center” offers PDFs that can be filled in online and used for evictions, divorces, orders of protection, collection matters, small claims, and other issues.”²⁶

The federal judiciary has instituted an electronic case management system known as the Case Management/Electronic Case Files (CM/ECF) system that allows for convenient filing and organization of court documents, party pleadings, and other relevant materials.²⁷ In 2002, Congress directed the federal courts to ensure that, with exceptions for certain documents filed under seal, “any document that is filed electronically [is also] publicly available online.”²⁸ State and local courts have increasingly rolled out various electronic filing (or “e-filing”) software to replace paper submissions and docketing.²⁹ In Florida alone, individuals filed

²³ See, e.g., SUP. CT. R. 29 (requiring that in addition to filing documents with the Court Clerk, “all filers who are represented by counsel must submit documents to the [Supreme] Court’s electronic filing system”); 7TH CIR. R. 25 (“All documents must be filed and served electronically.”); E.D. PA. LOCAL R. 5.1.2 (“All civil and criminal cases filed in this court are required to be entered into the court’s Electronic Case Filing (“ECF”) System . . .”); CAL. R. CT. 2.253 (empowering courts to permit or require electronic filing).

²⁴ *Self Representation*, NAT’L CTR. FOR STATE CTS., <https://www.ncsc.org/Topics/Access-and-Fairness/Self-Representation/State-Links.aspx?cat=Court%20Forms> [https://perma.cc/4MVL-6X55].

²⁵ BENJAMIN H. BARTON & STEPHANOS BIBAS, *REBOOTING JUSTICE* 123 (2017).

²⁶ *Id.* at 119. Barton and Bibas report that in a single year more than four million people visited the California self-help portal. They also report successful experiences with other systems for “DIY” lawyering, such as a system in New York State. *Id.* at 119–23.

²⁷ *Case Management/Electronic Case Files*, PACER, <https://www.pacer.gov/cmecf/> [https://perma.cc/8AUY-S4A2]. Public access to PACER data is not free, which has generated some controversy. See, e.g., David Post, *Yes, PACER Stinks . . . But Is It Also Overcharging Its Customers?*, WASH. POST (Jan. 9, 2016), https://www.washingtonpost.com/news/volokh-conspiracy/wp/2016/01/09/yes-pacer-stinks-but-is-it-also-overcharging-its-customers/?utm_term=.49cf19383d86 [https://perma.cc/XG8X-EEHP]. Similar concerns have been expressed related to the video recording of judicial proceedings. See, e.g., Jonathan Sherman, *End the Supreme Court’s Ban on Cameras*, N.Y. TIMES (Apr. 24, 2015), <https://www.nytimes.com/2015/04/24/opinion/open-the-supreme-court-to-cameras.html> [https://perma.cc/2V3S-P8LZ].

²⁸ E-Government Act of 2002, 107 Pub. L. No. 347, § 205(c)(1), 116 Stat. 2899, 2914.

²⁹ *Electronic Filing*, NAT’L CTR. FOR ST. CTS., <https://www.ncsc.org/Topics/Technology/Electronic-Filing/State-Links.aspx> [https://perma.cc/B4H6-VXC8]. For examples of state

roughly 23.5 million documents totaling about 110 million pages from mid-2018 to mid-2019.³⁰ These systems have created massive repositories of filings from litigants, as well as judicial decisions and orders, all held in centralized databases.

In principle, artificial intelligence could take advantage of all this data.³¹ At private law firms, the increasing use of algorithmic tools, including those relying on machine-learning algorithms, supports the review of documents during the discovery process. This “e-discovery” practice has been shown to have a “strong impact” on reducing the need for human labor—and it has spawned services that seek to analyze trends and make legal forecasts.³²

In addition, artificial intelligence has been used by outside researchers in an attempt to predict courts’ decisions using data. In a 2017 study, a machine-learning statistical model correctly predicted the outcome of seventy percent of 28,000 U.S. Supreme Court decisions and seventy-two percent of individual Justices’ votes from 1816 to 2015.³³ With a growing amount of data available from courts at all levels across the country, and demands for courts to facilitate widespread public access to case records,³⁴ it is likely that such predictive efforts will only improve in the future. In time, it may also be possible that artificial intelligence tools will have gained enough “experience” in document review to step into the role

court “e-filing” systems, see *eCourts*, N.J. CTS., <https://njcourts.gov/attorneys/ecourts.htm> [<https://perma.cc/54GH-E3X8>]; *Electronic Filing in the Delaware Judiciary*, DEL. CTS., <https://courts.delaware.gov/efiling/> [<https://perma.cc/S8GP-TZLL>]; *Active Courts*, ODYSSEY EFILEGA, <http://www.odysseyefilega.com/active-courts.htm> [<https://perma.cc/2V2Y-8FG2>]; EFILETEXAS, <https://www.efiletexas.gov/> [<https://perma.cc/4Z73-NS9U>]; *Superior Court Electronic Case Filing*, N.H. JUD. BRANCH, <https://www.courts.state.nh.us/nh-e-court-project/superior-attorneys.htm> [<https://perma.cc/B3WH-637M>] (noting that e-filing in the New Hampshire Superior Court became mandatory in September 2018).

³⁰ 2018-2019 Annual Statistics, FLA. CTS. E-FILING PORTAL (June 25, 2019), <https://www.flcourts.org/Publications-Statistics/Publications/2018-19-Annual-Report> [<https://perma.cc/Q24Q-HDUX>].

³¹ In fact, a project out of Northwestern University, the Systematic Content Analysis of Litigation Events (SCALES) initiative, is currently working to use large sets of data from court records to develop AI tools that can facilitate greater analysis of the workings of the federal judiciary. See SCALES, <https://scales-okn.org/> [<https://perma.cc/AM9Y-ZXQU>].

³² See, e.g., Dana Remus & Frank Levy, *Can Robots Be Lawyers: Computers, Lawyers, and the Practice of Law*, 30 GEO. J. LEGAL ETHICS 501, 515–16 (2017). Various private sector efforts are underway to make use of court data for predictive analytic purposes. One service is Lex Machina, <https://lexmachina.com/> [<https://perma.cc/B9JD-2682>], which is used by law firms. Another service, Docket Navigator, <http://brochure.docketnavigator.com/> [<https://perma.cc/4MXB-G44L>], performs basic analytics (albeit not machine learning) in intellectual property cases.

³³ See Matthew Hutson, *Artificial Intelligence Prevails at Predicting Supreme Court Decisions*, SCIENCE (May 2, 2017), <https://www.sciencemag.org/news/2017/05/artificial-intelligence-prevails-predicting-supreme-court-decisions> [<https://perma.cc/XT6U-TU24>].

³⁴ See, e.g., Open Courts Act of 2021, S. 2614, 117th Cong. § 3(a) (1st Session 2021) (seeking to eliminate the fees charged for access to federal court records).

of judges. Rather than just predicting judicial outcomes, perhaps these tools will use the large troves of data available in electronic filing systems to help in making actual judicial determinations. Such a step would, of course, mark a considerable transformation in how judicial functions are performed, presenting potential implications for lawyering, judging, and public attitudes toward the courts.³⁵

B. Risk Assessment Algorithms

Algorithmic tools have taken root in some court systems at least as aids to human decision-making in criminal cases with respect to questions of bail, sentencing, and parole. But so far, virtually none of these tools appear to rely on *machine-learning* algorithms.

An algorithmic tool for bail decisions before trial that was originally developed by the Arnold Foundation has now been adopted by at least four states (Arizona, Kentucky, New Jersey, and Utah) and about a dozen municipal courts, largely in major metropolitan areas.³⁶ According to a recent report by two media justice advocacy organizations, all but four states have apparently adopted some kind of risk assessment formula or aid in sentencing decisions.³⁷ More than half of the states use some

³⁵ In a judiciary more reliant on AI tools to adjudicate disputes, systems that can sift through data and help make decisions could ultimately make the legal profession less labor-intensive, requiring fewer humans to review and analyze the thousands of documents that can be produced in the lifecycle of a case—thus potentially reducing the number of lawyers and support staff needed to handle the litigation process. *See, e.g.*, Remus & Levy, *supra* note 32, at 535–36 (predicting that the adoption of advanced legal technology all at once would reduce attorney hours by thirteen percent, or by two and one-half percent a year if adopted over the course of five years); Anthony E. Davis, *The Future of Law Firms (and Lawyers) in the Age of Artificial Intelligence*, 27 PROF. LAW. 3, 6 (2020) (“The drudge work traditionally done by new lawyers is already vanishing and will ultimately disappear almost entirely.”). In addition, future automation of various judicial tasks could affect the nature or quality of court decisions and litigants’ experiences interacting with the judiciary. For various perspectives on such a potential future, see, for example, Benjamin Minhao Chen et al., *Having Your Day in Robot Court* (UCLA Sch. of L. Pub. L. & Legal Theory Rsch. Paper, Paper No. 21-20, 2021), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3841534 [<https://perma.cc/6ZCU-MC3F>], KATHERINE B. FORREST, WHEN MACHINES CAN BE JUDGE, JURY, AND EXECUTIONER: JUSTICE IN THE AGE OF ARTIFICIAL INTELLIGENCE (2021), Anthony J. Casey & Anthony Niblett, Will Robot Judges Change Litigation and Settlement Outcomes?, MIT COMPUTATIONAL L. REP. (Aug. 14, 2020), <https://law.mit.edu/pub/willrobotjudgeschangelitigationandsettlementoutcomes/release/1> [<https://perma.cc/LQ8Y-22PH>], Aziz Z. Huq, *A Right to a Human Decision*, 105 VA. L. REV. 611 (2020), Eugene Volokh, *Chief Justice Robots*, 68 DUKE L. J. 1135 (2019), and Andrea L. Roth, *Trial by Machine*, 104 GEO. L. J. 1245 (2016).

³⁶ *See* ARNOLD VENTURES, PUBLIC SAFETY ASSESSMENT FAQs (“PSA 101”) (Mar. 18, 2019), https://craftmediabucket.s3.amazonaws.com/uploads/Public-Safety-Assessment-101_190319_140124.pdf [<https://perma.cc/TQ6X-ZUYU>].

³⁷ *National Landscape*, MAPPING PRETRIAL INJUSTICE, <https://pretrialrisk.com/national-landscape/> [<https://perma.cc/E2U3-E7S2>]. Just six years ago, it was reported that only twenty states used such tools. *See* Sonja Starr, *Evidence-Based Sentencing and the Scientific Rationalization of Discrimination*, 66 STAN. L. REV. 803, 809 (2014). Federal courts, meanwhile, must consider the Sentencing Guidelines, which set out suggested sentence ranges for federal

form of algorithmic tool for purposes of parole decision-making.³⁸ The federal government has recently announced an algorithmic tool for parole decisions: Prisoner Assessment Tool Targeting Estimated Risk and Needs (PATTERN).³⁹ The PATTERN system was developed in response to the First Step Act of 2018, which called for the use of risk assessment in federal parole decisions.⁴⁰ Similarly, some state statutes encourage or require the use of these algorithmic tools,⁴¹ while in other instances these tools are selected at the discretion of state or local judges.⁴²

As best we can determine, only one jurisdiction (Pennsylvania) has implemented any risk assessment tool in criminal justice that is based on machine learning.⁴³ Despite

offenses depending on a variety of factors—a somewhat crude, if older and nondigital style of algorithm. See U.S. SENTENCING GUIDELINES MANUAL (U.S. SENTENCING COMM’N 2018); see also *Kimbrough v. United States*, 552 U.S. 85, 108–09 (2007) (noting that the Sentencing Guidelines are advisory but still should play a “key role” in judges’ considerations).

³⁸ BERNARD E. HARCOURT, AGAINST PREDICTION: PROFILING, POLICING, AND PUNISHING IN AN ACTUARIAL AGE 77 (2007) (noting twenty-eight states were using an algorithmic risk assessment tool for parole decision-making as of 2004).

³⁹ U.S. DEPT OF JUST., THE FIRST STEP ACT OF 2018: RISK AND NEEDS ASSESSMENT SYSTEM (2019), https://nij.ojp.gov/sites/g/files/xyckuh171/files/media/document/the-first-step-act-of-2018-risk-and-needs-assessment-system_1.pdf [<https://perma.cc/GXU4-QC9D>]; see also Brandon Garrett & John Monahan, *Assessing Risk: The Use of Risk Assessment in Sentencing*, JUDICATURE (Summer 2019), <https://judicature.duke.edu/articles/assessing-risk-the-use-of-risk-assessment-in-sentencing/> [<https://perma.cc/3HUF-7YVY>] (noting that the First Step Act “mentions risk no less than 100 times”).

⁴⁰ See NAT’L INST. OF JUST., U.S. DEPT OF JUST., 2020 REVIEW AND REVALIDATION OF THE FIRST STEP ACT RISK ASSESSMENT TOOL 1–4 (2021), <https://www.ojp.gov/pdffiles1/nij/256084.pdf> [<https://perma.cc/6LJ4-BDTJ>] (discussing First Step Act of 2018, Pub. L. No. 115-391, § 101, 132 Stat. 5194, 5195–96).

⁴¹ See, e.g., ALA. STAT. § 12-25-33(6) (instructing the Alabama Sentencing Commission to create an instrument to be “predictive of the relative risk that a felon will become a threat to public safety”); KY. REV. STAT. ANN. § 532.007(3)(a) (“Sentencing judges shall consider . . . the results of a defendant’s risk and needs assessment included in the presentence investigation”); OHIO REV. CODE ANN. § 5120.114(A) (allowing for use of risk assessment tool by adjudicatory bodies in the criminal justice system); OKLA. STAT. tit. 22, § 988.18 (requiring courts to use a risk assessment tool in determining an offender’s eligibility for a sentence of community service); 42 PA. CONS. STAT. § 2154.7 (requiring the Pennsylvania Commission on Sentencing to adopt a tool to “be used as an aide in evaluating the relative risk that an offender will reoffend and be a threat to public safety”); W. VA. CODE § 62-12-6(a)(2) (instructing probation officers to “[c]onduct a standardized risk and needs assessment” of probationers); see also ARIZ. CODE OF JUD. ADMIN. § 6-201.01(J)(3) (“For all probation eligible cases, presentence reports shall [] contain case information related to criminogenic risk and needs as documented by the standardized risk assessment and other file and collateral information.”).

⁴² See, e.g., BD. OF DIRS. OF THE JUD. CONF. OF IND., POLICY FOR INDIANA RISK ASSESSMENT SYSTEM (Apr. 23, 2010), <https://www.in.gov/judiciary/cadp/files/prob-risk-iras-2012.pdf> [<https://perma.cc/33WW-EXG7>]; R.I. DEPT OF CORR., LEVEL OF SERVICE INVENTORY-REVISED: A PORTRAIT OF RIDOC OFFENDERS (Apr. 2011), <http://www.doc.ri.gov/administration/planning/docs/LSINewsletterFINAL.pdf> [<https://perma.cc/6MRV-LLM6>].

⁴³ See generally Richard Berk, *An Impact Assessment of Machine Learning Risk Forecasts on Parole Board Decisions and Recidivism*, 13 J. EXPT. CRIM. 193 (2017). And technically this use in Pennsylvania is by an agency, not a court: the Pennsylvania Board of Probation and Parole. Another state, Maryland, has apparently looked into using machine learning for parole, but does not appear to have implemented it.

somewhat frequent claims to the contrary in the popular media,⁴⁴ all other algorithmic tools used by courts appear to be based on standard indices or conventional logistic regression models—not machine-learning algorithms.

For example, one of the more popular non-learning algorithmic tools for bail decisions, the Arnold Foundation's Public Safety Assessment, considers nine factors, including: the defendant's age; current violent offense; pending charges at the time of the offense; prior misdemeanor, felony, and violent convictions; prior failure to appear in the past; and prior sentences to incarceration. It then weighs these factors in varying proportions to determine scores from one to six that purport to predict the defendant's likelihood of new criminal activity, new violent criminal activity, and failure to appear in court, which a judge can then use in determining whether to grant pretrial release.⁴⁵

Another non-learning algorithmic tool, known as the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS), has been adopted by several state court systems for pretrial decisions. It involves an extensive questionnaire that covers issues such as the defendant's prior criminal history, compliance with probation, substance abuse, relationships with others who have been arrested or sent to jail, home and work environment, and personality.⁴⁶ The algorithm uses these data points to place the defendant along several "risk scales" purporting to predict the defendant's relative likelihood of pretrial failure (including failure to appear and new felony arrest after pretrial release) and recidivism.⁴⁷ In deciding whether to approve a defendant for pretrial release or in determining an appropriate sentence, judges and other officials

⁴⁴ See, e.g., Matt O'Brien & Dake Kang, *AI in the Court: When Algorithms Rule on Jail Time*, ASSOCIATED PRESS (Jan. 31, 2018), <https://apnews.com/article/ae7b23e20c874800aa5746b92210a2dc> [<https://perma.cc/C9JF-E4ZP>].

⁴⁵ *Risk Factors and Formulas*, PUB. SAFETY ASSESSMENT, <https://www.psa-pretrial.org/about/> [<https://perma.cc/N3PZ-YVDJ>]; see also, e.g., N.J. CTS., PUBLIC SAFETY ASSESSMENT: NEW JERSEY RISK FACTOR DEFINITIONS 1–4 (Dec. 2018), <https://njcourts.gov/courts/assets/criminal/psariskfactor.pdf> [<https://perma.cc/2E5P-JM39>].

⁴⁶ See generally NORTHPOINTE INC., PRACTITIONER'S GUIDE TO COMPAS CORE (Mar. 19, 2015), http://www.northpointeinc.com/files/technical_documents/Practitioners-Guide-COMPAS-Core-_031915.pdf [<https://perma.cc/LC2R-588T>]. Although details about COMPAS are proprietary, investigative journalists at ProPublica uncovered the underlying questionnaire used in Wisconsin. See *Risk Assessment*, <https://www.documentcloud.org/documents/2702103-Sample-Risk-Assessment-COMPAS-CORE.html> [<https://perma.cc/5PN5-UU6U>]. Other states' courts have adopted COMPAS as well, including Florida, Michigan, New Mexico, and Wyoming. See *Algorithms in the Criminal Justice System*, ELEC. PRIV. INFO. CTR., <https://epic.org/algorithmic-transparency/crim-justice/> [<https://perma.cc/5WM7-3V8A>].

⁴⁷ See PRACTITIONER'S GUIDE TO COMPAS CORE, *supra* note 46.

can take the values reached by these algorithms into account.⁴⁸ For instance, the New York Appellate Division reversed the New York State Board of Parole's decision to deny an inmate release on parole, finding that the decision was "irrational[] bordering on improp[er]"—a conclusion the appellate court reached in part by looking to the inmate's COMPAS risk assessment, which labeled him "low' for all risk factors."⁴⁹

Yet another basic algorithmic tool, LSI-R (Level of Service Inventory-Revised), aims to predict a defendant's risk of recidivism by weighing a number of factors. These factors include criminal history, educational and employment background, financial, mental, and familial state, substance abuse, and other personal details.⁵⁰ The Rhode Island Department of Corrections has adopted this test, as have courts in a number of states, including California, Colorado, Delaware, Hawaii, Iowa, Oklahoma, and Washington.⁵¹

In addition to these examples of common risk assessment algorithms, some individual states have also adopted their own unique algorithms.⁵² Again, to be clear, none of these are artificial intelligence *per se*, in the sense of machine-learning algorithms. These risk assessment algorithms are instead

⁴⁸ See, e.g., Adam Liptak, *Sent to Prison by a Software Program's Secret Algorithms*, N.Y. TIMES (May 1, 2017), <https://www.nytimes.com/2017/05/01/us/politics/sent-to-prison-by-a-software-programs-secret-algorithms.html> [<https://perma.cc/B7C7-5YKA>]; O'Brien & Kang, *supra* note 44; Ellora Thadaneey Israni, *When an Algorithm Helps Send You to Prison*, N.Y. TIMES (Oct. 26, 2017), <https://www.nytimes.com/2017/10/26/opinion/algorithm-compas-sentencing-bias.html> [<https://perma.cc/LL6P-FX9Y>] ("Use of a computerized risk assessment tool somewhere in the criminal justice process is widespread across the United States . . . States trust that even if they cannot themselves unpack proprietary algorithms, computers will be less biased than even the most well-meaning humans.").

⁴⁹ *Rivera v. Stanford*, 172 A.D.3d 872, 876–77 (N.Y. App. Div. 2019).

⁵⁰ Anthony W. Flores et al., *Predicting Outcome with the Level of Service Inventory-Revised: The Importance of Implementation Integrity*, 34 J. CRIM. JUST. 523, 524 (2006).

⁵¹ See R.I. DEP'T OF CORRS., *supra* note 42; *Algorithms in the Criminal Justice System*, *supra* note 46.

⁵² See, e.g., BD. OF DIRS. OF THE JUD. CONF. OF IND., *supra* note 42; Susan Turner et al., *Development of the California Static Risk Assessment (CSRA): Recidivism Risk Prediction in the California Department of Corrections and Rehabilitation* 5–6 (U.C. Irvine Ctr. for Evidence-Based Corrections, Working Paper, 2013), <https://ucicorrections.seweb.uci.edu/files/2013/12/Development-of-the-CSRA-Recidivism-Risk-Prediction-in-the-CDCR.pdf> [<https://perma.cc/RG4B-KV93>] (listing factors considered by the California Static Risk Assessment tool); LA. SENTENCING COMM'N, RECOMMENDATIONS OF THE LOUISIANA SENTENCING COMMISSION FOR THE 2010 AND 2011 TERMS 14 (Mar. 1, 2012), http://www.lcle.state.la.us/sentencing_commission/2012_biannual_report_lsc_final.pdf [<https://perma.cc/VZD2-ELCC>] (noting that Louisiana uses risk assessment tools for "both inmate management and programming . . . for persons held in state adult correctional facilities and supervision planning . . . for persons under probation or parole supervision provided by the Department"); THE COUNCIL OF STATE GOV'TS JUS. CTR., MONTANA COMMISSION ON SENTENCING 41 (Mar. 1–2, 2016), <https://csgjusticecenter.org/publications/montana-commission-on-sentencing-third-meeting/> [<https://perma.cc/34RS-TG49>] (noting the use of the Montana Offender Reentry Risk Assessment).

formulas developed after studying large data sets using conventional statistical analysis, and then the formulas are applied to inputs given for each defendant. They are not algorithms that engage in autonomous inductive “learning” to figure out what scores to give defendants.

Nevertheless, the existing risk assessment algorithms used by courts in many states have not avoided scrutiny. Some scholars, lawyers, and concerned citizens have challenged the lack of transparency behind some of these algorithms, as some are created by private consultants who claim commercial secrecy protection to avoid disclosure.⁵³ Idaho, in fact, passed a law requiring that all pretrial risk assessment tools be transparent, compelling the builders of these tools to make their algorithms’ inputs open to public inspection and allow criminal defendants to request access to the calculations and data that determine their risk assessment scores.⁵⁴

Even when the parameters used in the analysis underlying these algorithms are publicly known, the owners of a risk assessment system will often decline to explain how exactly the factors that go into assessing an individual’s likelihood of recidivism or pretrial misbehavior are weighted.⁵⁵

⁵³ See, e.g., Cade Metz & Adam Satariano, *An Algorithm that Grants Freedom, or Takes it Away*, N.Y. TIMES (Feb. 7, 2020), <https://www.nytimes.com/2020/02/06/technology/predictive-algorithms-crime.html> [<https://perma.cc/C6PD-MBZV>].

⁵⁴ IDAHO CODE § 19-1910.

⁵⁵ See, e.g., Judge Noel L. Hillman, *The Use of Artificial Intelligence in Gauging the Risk of Recidivism*, AM. BAR ASS’N (Jan. 1, 2019), https://www.americanbar.org/groups/judicial/publications/judges_journal/2019/winter/the-use-artificial-intelligence-gauging-risk-recidivism/ [<https://perma.cc/LVG2-C9C2>] (“[P]redictive technology becomes another witness against the defendant without a concomitant opportunity to test the data, assumptions, and even prejudices that underlie the conclusion.”). Some have raised concerns about the secrecy that the creators of these risk assessment tools maintain over the inner workings of their products:

No one knows exactly how COMPAS works; its manufacturer refuses to disclose the proprietary algorithm. We only know the final risk assessment score it spits out . . . Something about this story is fundamentally wrong: Why are we allowing a computer program, into which no one in the criminal justice system has any insight, to play a role in sending a man to prison?

See Israni, *supra* note 48; see also Deirdre K. Mulligan & Kenneth A. Bamberger, *Procurement as Policy: Administrative Process for Machine Learning*, 34 BERKELEY TECH. L.J. 781, 786 (2019) (noting that “government agencies purchasing and using [algorithmic] systems most often have no input into—or even knowledge about—their design or how well that design aligns with public goals and values” and “know nothing about the ways that the system models the phenomena it seeks to predict, the selection and curation of training data, or the use of that data”). For discussion of how governments can overcome the propensity of contractors to want to protect the secrecy of their AI systems, see, for example, Lavi M. Ben Dor & Cary Coglianese, *Procurement as AI Governance*, 2 IEEE TRANSACTIONS TECH. & SOC. 192 (2021), Hannah Bloch-Wehba, *Access to Algorithms*, 88 FORDHAM L. REV. 1265, 1307–08 (2020), Cary Coglianese & Erik Lamppmann, *Contracting for Algorithmic Accountability*, 6 ADMIN. L. REV. ACCORD 175 (2021), and David S. Rubenstein, *Acquiring Ethical AI*, 73 FLA. L. REV. 747, 811–13 (2021).

As Judge Noel L. Hillman of the United States District Court for the District of New Jersey has put it, “[a] predictive recidivism score may emerge oracle-like from an often-proprietary black box. Many, if not most, defendants . . . will lack the resources, time, and technical knowledge to understand, probe, and challenge” the use of these tools.⁵⁶

A widely discussed 2016 ProPublica investigation purportedly showed that the COMPAS tool systematically found Black defendants to be at a higher risk of recidivism than similarly situated white defendants—even though twice as many Black defendants designated as high-risk never actually recidivated compared with high-risk white defendants who never recidivated.⁵⁷ The ProPublica investigation has raised significant questions about the wisdom of integrating algorithms into judicial decision-making.⁵⁸ A more recent study by economists Megan Stevenson and Jennifer Doleac, meanwhile, has found that the use of an algorithmic risk assessment tool by Virginia state court judges failed to lower incarceration or recidivism rates and that racial disparities in sentencing increased among the judges who most relied on the tool.⁵⁹

To date, the courts have only started to grapple with the legal implications of these kinds of findings about algorithmic tools.⁶⁰ Most prominently, in *State v. Loomis*, a defendant in

⁵⁶ See Hillman, *supra* note 55; cf. Judge Stephanie Domitrovich, *Artificial Intelligence Stepping into Our Courts: Scientific Reliability Gatekeeping of Risk Assessments*, AM. BAR ASS'N (Feb. 3, 2020), https://www.americanbar.org/groups/judicial/publications/judges_journal/2020/winter/artificial-intelligence-stepping-our-courts-scientific-reliability-gatekeeping-risk-assessments/#2 [<https://perma.cc/6ZB2-HAY9>] (urging the adoption of best practices to validate risk assessment tools and ensure their reliability).

⁵⁷ See Julia Angwin et al., *Machine Bias*, PROPUBLICA (May 23, 2016), <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing> [<https://perma.cc/5M44-LC53>]; see also Israni, *supra* note 48; Liptak, *supra* note 48; Ed Yong, *A Popular Algorithm Is No Better at Predicting Crimes Than Random People*, ATLANTIC (Jan. 17, 2018), <https://www.theatlantic.com/technology/archive/2018/01/equivalent-compas-algorithm/550646/> [<https://perma.cc/5MU4-3QVL>].

⁵⁸ See, e.g., Sandra G. Mayson, *Bias In, Bias Out*, 128 YALE L.J. 2218 (2019) (discussing inequities in algorithmic prediction); Cynthia Rudin et al., *The Age of Secrecy and Unfairness in Recidivism Prediction* 1 (Duke Univ., Working Paper, 2019), <https://arxiv.org/pdf/1811.00731.pdf> [<https://perma.cc/SL2L-J8PK>] (discussing concerns about proprietary algorithms); Anne L. Washington, *How to Argue with an Algorithm: Lessons from the COMPAS-ProPublica Debate*, 17 COLO. TECH. L.J. 131, 154–59 (2018) (providing a framework for evaluating the integrity of predictive algorithms). We note, of course, that just because one (non-learning) algorithm such as COMPAS may have problems does not mean that other algorithms might not perform better.

⁵⁹ Megan T. Stevenson & Jennifer L. Doleac, *Algorithmic Risk Assessment in the Hands of Humans* 1–6, 36 (Working Paper, 2019), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3489440 [<https://perma.cc/N3UB-T76E>].

⁶⁰ For instance, one D.C. juvenile court judge found that a risk assessment tool intended to predict a defendant's risk of future violence was inadmissible at sentencing, in part because some of the factors it considered reflected and amplified racial

Wisconsin state court challenged the state's use of the COMPAS algorithm at his sentencing after he pleaded guilty.⁶¹ Loomis's COMPAS risk scores indicated that he had a high risk of recidivism; at sentencing, the court relied in part on the fact that he had been "identified, through the COMPAS assessment, as an individual who is at high risk to the community."⁶²

In a post-conviction challenge to his sentence, Loomis argued that using the risk assessment violated his due process rights to (1) be sentenced based upon accurate information, (2) receive an individualized sentence, and (3) avoid being sentenced on the basis of his gender.⁶³ The trial court denied the motion, holding that it had "used the COMPAS risk assessment to corroborate its findings and that it would have imposed the same sentence regardless of whether it considered the COMPAS risk scores."⁶⁴

The Wisconsin Supreme Court affirmed the lower court.⁶⁵ It rejected Loomis's due process challenges, noting that the variables that the COMPAS algorithms used were publicly available and that the risk assessment's outcome was based fully on either the defendant's answers to the questions or on publicly available information about his criminal history.⁶⁶ As a result, the use of COMPAS complied with due process, since the defendant had the "opportunity to verify that the questions and answers listed on the report were accurate."⁶⁷ The court further held that, although the use of the risk assessment tool did involve group data, its inclusion among a mix of factors still achieved an individualized sentence for the defendant.⁶⁸ Finally, the inclusion of gender in the COMPAS algorithm's analysis did not violate any due process rights absent any proof that the court

disparities; however, the judge limited his holding so it only prohibited the algorithm's use in that particular case. See AI NOW INST., LITIGATING ALGORITHMS 2019 REPORT 9–10, 29 (2019), <https://ainowinstitute.org/litigatingalgorithms-2019-us.pdf> [<https://perma.cc/8GNG-7A6V>].

⁶¹ State v. Loomis, 881 N.W.2d 749 (Wis. 2016).

⁶² *Id.* at 755.

⁶³ *Id.* at 757.

⁶⁴ *Id.*

⁶⁵ *Id.*

⁶⁶ *Id.* at 761.

⁶⁷ *Id.*

⁶⁸ *Id.* at 764–65. However, the Wisconsin Supreme Court warned lower courts to be careful given the group-based nature of the COMPAS assessment. *Id.* An appellate court in Michigan reached the same basic holding on a similar due process argument: it found that because a trial court is not bound by a risk assessment tool's recommendations at sentencing and determines how heavily or lightly to weigh those recommendations, and because a risk assessment report that incorporates information about the population at large is "similar to the opinions of probation agents that are routinely" considered at sentencing, the use of COMPAS does not violate a defendant's right to an individualized sentence. People v. Younglove, No. 341901, 2019 WL 846117, at *3 (Mich. Ct. App. Feb. 21, 2019) (per curiam).

actually relied on gender as a factor in sentencing, since the algorithm simply accounted for differences in recidivism rates between men and women.⁶⁹

Loomis appealed to the United States Supreme Court.⁷⁰ The Court invited the Solicitor General to weigh in, often a sign that the Court recognizes the potential significance of the case.⁷¹ The Solicitor General's Office argued that the Court should not grant the petition, noting that no division of authority yet existed on the validity of the use of these algorithms and asserting that "[t]he issues that this petition raises . . . would benefit from further percolation."⁷² Ultimately, the Court declined to take up the case, leaving the issue of a defendant's due process rights when confronted with a risk assessment algorithm yet to be settled by the nation's highest court.⁷³

Other litigation, though, has continued to proceed in various state courts. In *Malenchik v. State*, for example, the defendant, who had pled guilty to a felony and admitted to being a habitual offender, challenged the trial court's use of the results of two risk assessment tests (one of which was the LSI-R) in determining his sentence.⁷⁴ The tests' results indicated that Malenchik was at high risk of recidivism.⁷⁵ The Indiana Supreme Court emphasized that Malenchik's sentence had been based on factors other than the risk assessments, since the trial court had also relied on the defendant's prior criminal history and refusal to accept responsibility for his actions and change

⁶⁹ See *Loomis*, 881 N.W.2d at 765–67.

⁷⁰ Petition for Writ of Certiorari, *Loomis v. Wisconsin*, 2017 U.S. LEXIS 4204 (June 26, 2017) (No. 16-6387).

⁷¹ See *Loomis v. Wisconsin*, 137 S. Ct. 1240 (2017). The Solicitor General handles all litigation on behalf of the United States in the U.S. Supreme Court. See *Office of the Solicitor General*, U.S. DEP'T OF JUST., <https://www.justice.gov/osg> [<https://perma.cc/M2JG-GFLN>]. For discussions of the role of the Solicitor General in influencing the Court's docket and merits decision, see, for example, Ryan C. Black & Ryan J. Owens, *Solicitor General Influence and Agenda Setting on the U.S. Supreme Court*, 64 POL. RSCH. Q. 765, 766 (2011) ("[W]e find strong support for [Solicitor General] influence. Justices who completely disagree with the [Solicitor General] nevertheless follow her recommendations 35 percent of the time, a number we take to be powerful evidence of influence."), and Margaret Meriwether Cordray & Richard Cordray, *The Solicitor General's Changing Role in Supreme Court Litigation*, 51 B.C. L. REV. 1323, 1324 (2010) ("The U.S. Solicitor General, as the U.S. Supreme Court's premier advocate, has long exerted significant influence over both the Court's case selection decisions and its substantive decisions on the merits.").

⁷² Brief for the United States as Amicus Curiae at 21–22, *Loomis v. Wisconsin*, 2017 U.S. LEXIS 4204 (June 26, 2017) (No. 16-6387).

⁷³ See *Loomis*, 2017 U.S. LEXIS 4204, at *1. For a general discussion of due process and the government's reliance on algorithms, see Coglianese & Lehr, *supra* note 13, at 1184–91; Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249 (2008).

⁷⁴ *Malenchik v. State*, 928 N.E.2d 564, 566–67 (Ind. 2010).

⁷⁵ *Id.*

his behavior, and it had not used the algorithm's output as an independent aggravating factor.⁷⁶ The court noted that such tools are neither "intended nor recommended to substitute for the judicial function of determining the length of sentence," but are instead "significant sources of valuable information for judicial consideration in deciding whether to suspend all or part of a sentence, how to design a probation program for the offender, whether to assign an offender to alternative treatment facilities or programs, and other such corollary sentencing matters."⁷⁷ As a result, the Indiana Supreme Court held that a trial court can properly "supplement and enhance" its evaluation of the evidence before it at sentencing by considering the results of a risk assessment, which can "provide usable information based on extensive penal and sociological research to assist the trial judge in crafting individualized sentencing schemes with a maximum potential for reformation."⁷⁸

Another case, *State v. Walls*, addressed a defendant's right to access a risk assessment tool used during sentencing.⁷⁹ The defendant Walls received a LSI-R score indicating that he was a "high-risk, high-needs probation candidate."⁸⁰ The trial court decided, "based on this assessment," to sentence him to probation supervised by community correctional officers, rather than by court services.⁸¹ Although the defendant's counsel asked the court to share the LSI-R assessment report, the court refused to do so.⁸² In addition to holding that this refusal contravened Kansas law and was an abuse of discretion, the Kansas Court of Appeals found that the trial court had violated the defendant's due process rights, since depriving him of the LSI-R report "necessarily denied him the opportunity to challenge the accuracy of the information upon which the court was *required* to rely in determining the conditions of his probation."⁸³ Since a defendant has a right to an "effective opportunity to rebut the allegations likely to affect the sentence," the trial court's withholding of the output of the risk assessment tool on which it had relied in setting Walls' sentence deprived him of due process.⁸⁴

⁷⁶ *Id.* at 568.

⁷⁷ *Id.* at 573.

⁷⁸ *Id.* at 573–75.

⁷⁹ *State v. Walls*, No. 116027, 2017 WL 2709819, at *1 (Kan. Ct. App. June 23, 2017) (per curiam).

⁸⁰ *Id.*

⁸¹ *Id.*

⁸² *Id.*

⁸³ *Id.* at *4.

⁸⁴ *Id.* at *2, *4 (quoting *State v. Easterling*, 213 P.3d 418, 425–26 (Kan. 2009)).

In yet another case, *State v. Rogers*, the question arose as to whether a court's *failure to use* a risk assessment tool in sentencing a defendant contravened his due process rights. The Supreme Court of Appeals of West Virginia rejected the claim because the defendant failed to enter a proper objection at the time of initial sentencing. But Justice Loughry, in a separate concurring opinion, argued that a risk assessment algorithm is "merely a tool that may be used by [trial court] judges during sentencing," a process over which judges have broad discretion and that courts are under no obligation to use an algorithm.⁸⁵

In addition to these cases, in a few other criminal appeals, defendants have questioned whether prosecutors must disclose the results of algorithmic facial recognition or risk assessment tools to defense counsel as part of their duty to turn over exculpatory evidence under *Brady v. Maryland*.⁸⁶ The courts that have handled these cases have avoided delving into issues concerning the algorithmic nature of any of the particular tools, since they have concluded either that the tools were not actually used in prosecuting the defendant or that the failure to disclose their use did not prejudice the defendant.⁸⁷

Finally, in *People v. Wakefield*, a defendant challenged the admissibility of the DNA matching software used to convict him.⁸⁸ After law enforcement collected a sample of his DNA, a private company ran it through software that compared the defendant's DNA to a sample from the scene of the crime using an algorithm that relied on "a certain degree of artificial intelligence."⁸⁹ The defendant objected to his lack of access to the algorithm's source code, claiming that it violated his Sixth Amendment right to confront the witnesses against him.⁹⁰ Although the Appellate Division concluded that the report reflecting the algorithm's match between the two DNA samples was testimonial since the analysis was conducted to further law enforcement goals, it held that the source code was not a declarant and rejected the defendant's Confrontation Clause

⁸⁵ *State v. Rogers*, No. 14-0373, 2015 WL 869323, at *2 (W. Va. Jan. 9, 2015); *id.* at *4–5 (Loughry, J., concurring).

⁸⁶ For a discussion of these appeals, see AI NOW INST., *supra* note 60, at 30. The Supreme Court's decision in *Brady v. Maryland* can be found at 373 U.S. 83 (1963).

⁸⁷ See AI NOW INST., *supra* note 60; see also *Lynch v. State*, 260 So. 3d 1166, 1169–70 (Fla. Dist. Ct. App. 2018), *review denied*, 2019 WL 3249799 (Fla. July 19, 2019).

⁸⁸ *People v. Wakefield*, 175 A.D.3d 158 (N.Y. App. Div. 2019).

⁸⁹ *Id.* at 160–62.

⁹⁰ *Id.* at 165. The Confrontation Clause prohibits introduction of out-of-court testimonial statements against a defendant unless the declarant is unavailable and the defendant has had a prior opportunity to cross-examine that person. *Id.* at 168 (citing *People v. John*, 27 N.Y.3d 294, 303 (2016), and *Bullcoming v. New Mexico*, 564 U.S. 647, 657 (2011)).

argument.⁹¹ The court acknowledged that it might be possible for an artificial intelligence tool to be a declarant independent of its human creator, since such algorithms involve “distributed cognition between technology and humans,” but it ultimately found that the system at issue operated under sufficient human input and supervision such that the true speaker behind the report was the algorithm’s creator.⁹²

Although it is still early in courts’ assessment of judicial use of algorithmic tools, it seems noteworthy that, in all the cases decided to date that have actually wrestled with the issues, courts appear to have taken pains to emphasize that such tools only serve as one of multiple factors that a judge takes into account in reaching a decision. Perhaps this suggests that, as long as humans remain in the loop, whether with standard algorithmic tools or even with machine-learning algorithms, courts’ use of algorithms will continue to win approval.⁹³

C. *Online Dispute Resolution*

At the limit of courts’ exploration of the precursors to automated decision-making, online dispute resolution (ODR) promises eventually to take humans out of the loop. ODR has emerged in recent years as a tool for resolving disagreements among parties using technology, growing in part out of prior developments in the field of alternative dispute resolution (ADR). ADR is a term that refers to a range of methods such as mediation and arbitration that aim to settle disputes without the use of litigation and the court system.⁹⁴ ODR mechanisms first mimicked ADR approaches to conflict resolution before evolving into their current forms, which harness the advantages of technology to aid their mission.⁹⁵

⁹¹ *Id.* at 168–69.

⁹² *Id.* at 169–70.

⁹³ See, e.g., *Malenchik v. State*, 928 N.E.2d 564, 568 (Ind. 2010) (“[T]he trial court’s sentencing decision was clearly based on factors apart from the defendant’s LSI-R and SASSI results The trial judge did not rely on either the LSI-R or SASSI as an independent aggravating factor in deciding to impose more than the advisory sentence.”). See generally Melissa Hamilton, *Risk-Needs Assessment: Constitutional and Ethical Challenges*, AM. CRIM. L. REV. 231 (2015); Roger K. Warren, *Evidence-Based Sentencing: The Application of Principles of Evidence-Based Practice to State Sentencing Practice and Policy*, 43 U.S.F. L. REV. 585 (2009).

⁹⁴ See ETHAN KATSH & ORNA RABINOVICH-EINY, DIGITAL JUSTICE 33–34 (2017); *Online Dispute Resolution Moves From E-Commerce to the Courts*, PEW CHARITABLE TRS. (June 4, 2019), <https://www.pewtrusts.org/en/research-and-analysis/articles/2019/06/04/online-dispute-resolution-moves-from-e-commerce-to-the-courts> [https://perma.cc/5AWA-SA6M] [hereinafter *Online Dispute Resolution I*]; *Alternative Dispute Resolution*, LEGAL INFO. INST., https://www.law.cornell.edu/wex/alternative_dispute_resolution [https://perma.cc/92XH-U9MM].

⁹⁵ See KATSH & RABINOVICH-EINY, *supra* note 94; *Online Dispute Resolution I*, *supra* note 94.

The initial growth of ODR has been largely driven by the private sector.⁹⁶ Most notably, eBay and PayPal have developed ODR systems to handle the millions of disputes that regularly arise on their platforms from and among users.⁹⁷ Realizing that they could not afford to hire enough human mediators to resolve all of these disputes or arrange for parties to video-conference with each other, these companies leveraged the extensive amounts of data they had collected on consumer behavior and usage.⁹⁸ Their ODR systems aim to prevent as many disputes as possible and to resolve the remainder quickly and amicably. To do so, these systems first diagnose the problem, working directly with the complainant, and then move to direct negotiations (aided by technology) and ultimately allow the company to decide the issue if the parties are not able to resolve matters on their own.⁹⁹ As the success of these systems has inspired other firms to develop similar and increasingly sophisticated programs, algorithms have become a more prominent dispute resolution solution, allowing companies to automate away many (if not all) of the steps of the adjudicatory process.¹⁰⁰ Amazon, for example, has developed algorithms that can resolve a consumer complaint about a defective product without requiring any human intervention.¹⁰¹

Some courts have also begun experimenting with ODR as a mechanism to attempt to resolve lawsuits without requiring the use of judicial decision-making. Although much of the innovation in this area has occurred in other parts of the world, dozens of state and local courts in the United States, including in Michigan, Ohio, California, and Utah, have adopted some form of “court ODR” in cases involving small claim civil matters, traffic violations, outstanding warrant cases, and low-conflict family court cases.¹⁰² What counts as an ODR system can vary

⁹⁶ See *Online Dispute Resolution I*, *supra* note 94.

⁹⁷ See BARTON & BIBAS, *supra* note 25, at 111; KATSH & RABINOVICH-EINY, *supra* note 94, at 34–35.

⁹⁸ See BARTON & BIBAS, *supra* note 25, at 111; KATSH & RABINOVICH-EINY, *supra* note 94, at 34–35.

⁹⁹ COLIN RULE & AMY J. SCHMITZ, THE NEW HANDSHAKE: ONLINE DISPUTE RESOLUTION AND THE FUTURE OF CONSUMER PROTECTION 37 (2017) (“Each stage acted like a filter, with the objective being to minimize the flow of cases that made it to the end.”); see also BARTON & BIBAS, *supra* note 25, at 111–15; KATSH & RABINOVICH-EINY, *supra* note 94, at 34–36. We note that Colin Rule helpfully describes the stages of an ODR process using the “DNMEA” mnemonic: Diagnosis, Negotiation, Mediation, Evaluation, and Appeal.

¹⁰⁰ See KATSH & RABINOVICH-EINY, *supra* note 94, at 46–48.

¹⁰¹ *Id.* at 48.

¹⁰² See *id.* at 161–62; *Online Dispute Resolution Offers a New Way to Access Local Courts*, PEW CHARITABLE TRS. (Jan. 4, 2019), <https://www.pewtrusts.org/en/research-and-analysis/fact-sheets/2019/01/online-dispute-resolution-offers-a-new-way-to-access-local-courts> [<https://perma.cc/FLV8-UJA2>] [hereinafter *Online Dispute Resolution II*].

from a simple website that facilitates entering pleas for traffic tickets online to an online portal for engaging in asynchronous negotiations.¹⁰³ These mechanisms are not mandatory in any jurisdiction of which we are aware but instead are offered as an option to avoid appearing in court. In jurisdictions with these systems, parties are notified of the ODR option via mailings or websites.¹⁰⁴ Parties can access the ODR system at any time, and with the more interactive systems they can communicate and negotiate with each other, obtain legal information and suggested resolutions from the system, and easily manage electronic documents—all without having to see the inside of a courtroom.¹⁰⁵ These systems can usually reach resolution faster and at a lower cost to the parties than traditional court-centered adjudication, and they are far more accessible too.¹⁰⁶

ODR provides an emerging avenue for litigants and courts to engage in dispute resolution outside of the presence of a courtroom and absent a human judge. Courts' currently optional ODR systems, as well as the private-sector iterations that have inspired them, increasingly have adopted automated processes and rely on algorithmic tools to aid in reaching what some observers characterize as fair and low-cost solutions to the parties' disputes.¹⁰⁷ As some researchers have already begun to observe, court systems could take these algorithms to the next level of autonomy by integrating artificial intelligence into ODR processes, which would allow for more completely automated forms of decision-making within the nation's courtrooms.¹⁰⁸

¹⁰³ See, e.g., KATSH & RABINOVICH-EINY, *supra* note 94, at 161–62; *Online Dispute Resolution II*, *supra* note 102; see also, e.g., *Online Services*, SUPERIOR CT. CAL., CNTY. L.A., <https://www.lacourt.org/online/traffic> [<https://perma.cc/C4V4-MCK4>]; *Online Dispute Resolution (ODR) Pilot Project*, UTAH CTS., <https://www.utcourts.gov/smallclaimsodr/> [<https://perma.cc/LD6P-7MGF>].

¹⁰⁴ See KATSH & RABINOVICH-EINY, *supra* note 94, at 161–62; *Online Dispute Resolution II*, *supra* note 102.

¹⁰⁵ See *Online Dispute Resolution II*, *supra* note 102.

¹⁰⁶ See *Online Dispute Resolution I*, *supra* note 94.

¹⁰⁷ See KATSH & RABINOVICH-EINY, *supra* note 94, at 163 (“The use of ODR in courts is also introducing algorithms into the judicial decision-making process.”); Loïc E. Coutelier, *The New Frontier of Online Dispute Resolution: Online Divorce Mediation*, AM. BAR ASS’N (Apr. 1, 2016), https://www.americanbar.org/groups/young_lawyers/publications/tyl/topics/dispute-resolution/new-frontier-online-dispute-resolution-online-divorce-mediation [<https://perma.cc/A9C8-7PX2>] (discussing a form of ODR used in divorce mediation that relies on “an innovative algorithm that uses game theory negotiation to maximize the return for divorcing couples who are dividing assets”).

¹⁰⁸ See generally Arno R. Lodder & John Zeleznikow, *Artificial Intelligence and Online Dispute Resolution*, in *ONLINE DISPUTE RESOLUTION: THEORY AND PRACTICE* 73–94 (Mohamed S. Abdel Wahab et al. eds., 2012).

II. ARTIFICIAL INTELLIGENCE IN THE ADMINISTRATIVE STATE

In contrast with the nascent digitization efforts in the courts, which might eventually move in the direction of full use of AI, administrative agencies have long used information technology to support vital services and programs. In recent years, this has included reliance on machine-learning algorithms.

Even outside of the military, intelligence-gathering, and space exploration contexts, computers have been used for decades by government agencies to support administration and data management for various tasks, including tax collection and the operation of large national benefits programs such as Social Security and Medicare.¹⁰⁹ The technologies used by government have tended to lag behind those deployed in the private sector. Federal and state agencies relied on mainframe computers, for example, long after the personal computer revolution hit the private sector in the 1980s, and they continue to remain behind the innovation curve today.¹¹⁰ Many government computer systems have grown quite antiquated. As of 2016, auditors reported that three-quarters of annual federal spending on computer technology in the United States was devoted to “legacy systems” that are “increasingly obsolete” due to “outdated software languages and hardware parts that are unsupported.”¹¹¹

Still, the internet revolution in the 1990s did prompt state and federal government agencies to begin to digitize many of their services and make greater use of the worldwide web. Initially, of course, the movement was slow. According to one survey, by the year 2000, states had websites containing an average of only about four automated or online governmental services each.¹¹² The most popular digitized service at that time was applying for a state government job (then available in thirty-two states).¹¹³ The second most popular was electronic

¹⁰⁹ Harold C. Relyea & Henry B. Hogue, *A Brief History of the Emergence of Digital Government in the United States*, in DIGITAL GOVERNMENT 16 (Alexei Pavlichev & G. David Garson eds., 2004).

¹¹⁰ Jack Moore, *The Crisis in Federal IT that's Scarier than Y2K Ever Was*, NEXTGOV (Nov. 20, 2015), <http://www.nextgov.com/cio-briefing/2015/11/crisis-federal-it-rivals-y2k/123908/> [<https://perma.cc/L8YH-2VGM>]; Tod Newcombe, *The Complicated History of Government Technology*, GOVERNING (Oct. 2, 2017), <https://www.govtech.com/computing/The-Complicated-History-of-Government-Technology.html> [<https://perma.cc/BM69-Y498>].

¹¹¹ U.S. GOV'T ACCOUNTABILITY OFF., GAO-16-696T, INFORMATION TECHNOLOGY: FEDERAL AGENCIES NEED TO ADDRESS AGING LEGACY SYSTEMS (2016), <https://www.gao.gov/assets/680/677454.pdf> [<https://perma.cc/H2AW-GUQB>] (testimony of David A. Powner, Director, Information Technology Management Issues).

¹¹² Jane E. Fountain, *The Virtual State: Transforming American Government?*, 90 NAT'L CIV. REV. 241, 242 (2001).

¹¹³ *Id.*

filing of income taxes (twenty-four states), and the third most popular was the online renewal of drivers licenses (seventeen states).¹¹⁴ Today, all states have these basic services digitized—and many more services as well.

The federal government adopted the E-Government Act of 2002 “to develop and promote electronic Government services and processes” and “[t]o promote use of the Internet and other information technologies to provide increased opportunities for citizen participation in Government.”¹¹⁵ The E-Government Act established a federal Office of Electronic Government, imposed a duty on all federal agencies to make vast quantities of government information available online, and generally required agencies to accept online submissions of public comments on proposed regulations.¹¹⁶ The federal government has since created portals such as *Regulations.gov* and *Data.gov* to make available massive amounts of information previously housed in paper records or internal government computers.¹¹⁷

Today, the United States is regarded as among the nations that have made considerable progress in implementing e-government practices. According to the United Nations’ ranking of countries’ progress in e-government, the United States places ninth among all countries for “e-government development.”¹¹⁸ It also ranks first in the world for “e-participation,” tied with Estonia and the Republic of Korea.¹¹⁹

These rankings suggest that, even if administrative agencies in the United States may have been slower out of the starting gate than the private sector in their use of information technology, they appear ahead of many counterpart government bodies elsewhere in the world. Administrative agencies have also moved to digitize their operations and services much earlier than has the U.S. court system. In this respect, administrative agencies are well along a path that will support greater use of machine learning.

Some agencies have undertaken targeted efforts to make data more easily accessible for use in machine-learning applications. For example, officials at the Federal Deposit Insurance Corporation have expressly focused on developing

¹¹⁴ *Id.*

¹¹⁵ E-Government Act of 2002, 107 Pub. L. No. 347, § 2, 116 Stat. 2899, 2900–01.

¹¹⁶ *Id.* § 3602.

¹¹⁷ For discussion of these and related efforts, see WHITE HOUSE ARCHIVES, THE OBAMA ADMINISTRATION’S COMMITMENT TO OPEN GOVERNMENT: A STATUS REPORT (2011), https://obamawhitehouse.archives.gov/sites/default/files/opengov_report.pdf [<https://perma.cc/T8MG-GMG2>].

¹¹⁸ U.N., UNITED NATIONS E-GOVERNMENT SURVEY 2020, at 12 (2020).

¹¹⁹ *Id.* at 120.

“the back-end disciplines of in-memory analytics, big data, and data quality.”¹²⁰ Staff at the Federal Communications Commission (FCC) established a Data Innovation Initiative with similar goals.¹²¹ Financial regulators have worked to create a dedicated “legal entity identifier” to be able to link disparate transactional and other data to the corresponding business entities.¹²² The Environmental Protection Agency has built databases that can be used to train algorithms,¹²³ while the Food and Drug Administration has tapped into cloud storage capacity to give the agency the ability to analyze big data.¹²⁴

Beyond these data-centered building blocks of artificial intelligence, U.S. administrative agencies are generally light-years ahead of the U.S. judicial system in terms of employing algorithmic tools. After all, algorithmic tools of the traditional statistical kind have long been a staple of administrative decision-making, especially when agencies set policies and regulations.¹²⁵ Some government agencies, such as the U.S. Department of Commerce, even count data collection and analysis as among their principal responsibilities.¹²⁶

As a result, it is not surprising that administrative agencies are ahead of the courts in terms of their use of full-fledged machine-learning tools as well, something that the courts have yet to deploy. Admittedly, the use of machine learning within administrative agencies is not yet as extensive

¹²⁰ U.S. FED. DEPOSIT INS. CORP., BUSINESS TECHNOLOGY STRATEGIC PLAN 2013–2017 (2013), https://www.fdic.gov/about/strategic/it_plan/BusinessTechnologyStrategicPlan2013-2017.pdf [<https://perma.cc/3NSB-UZXX>].

¹²¹ See Michael Byrne, *Big Data*, FCC BLOG (Oct. 28, 2010, 1:06 PM), <https://www.fcc.gov/news-events/blog/2010/10/28/big-data> [<https://perma.cc/9HAQ-U8QR>].

¹²² See Matthew Reed, *Legal Entity Identifier System Turns a Corner*, FINRESEARCH.GOV (July 3, 2014), <https://financialresearch.gov/from-the-management-team/2014/07/03/legal-entity-identifier-system-turns-a-corner/> [<https://perma.cc/5VZD-94DM>].

¹²³ See *EPA’s Cross-Agency Data Analytics and Visualization Program*, EPA, <https://web.archive.org/web/20160414154548/https://www.epa.gov/toxics-release-inventory-tri-program/epas-cross-agency-data-analytics-and-visualization-program> [<https://perma.cc/PB8J-UV8E>].

¹²⁴ See Taha Kass-Hout, *FDA Leverages Big Data via Cloud Computing*, FDA VOICE (June 19, 2014), <http://blogs.fda.gov/fdavoices/index.php/2014/06/fda-leverages-big-data-via-cloud-computing> [<https://perma.cc/9AEP-SH52>]. “Big data” is a generic term that refers to massive datasets that are analyzed using machine-learning tools. See Chitrai Mani, *How Is Big Data Analytics Using Machine Learning?*, FORBES (Oct. 20, 2020), <https://www.forbes.com/sites/forbestechcouncil/2020/10/20/how-is-big-data-analytics-using-machine-learning/?sh=2eb75ab471d2> [<https://perma.cc/HTL6-3KWP>].

¹²⁵ For more recent discussions of the use of algorithmic analysis in public administration, see generally, for example, ROBERT D. BEHN, *THE PERFORMANCESTAT POTENTIAL: A LEADERSHIP STRATEGY FOR PRODUCING RESULTS* (2014); DONALD F. KETTL, *LITTLE BITES OF BIG DATA FOR PUBLIC POLICY* (2018); MONEYBALL FOR GOVERNMENT (Jim Nussle & Peter Orszag eds., 2014).

¹²⁶ See generally MICHAEL LEWIS, *THE FIFTH RISK* (2018).

as it is in the private sector, but artificial intelligence is beginning to emerge to assist with important administrative functions—even though, again, we know of no example where artificial intelligence has fully replaced human decision-making.

We also know of no comprehensive survey of all uses of machine learning by administrative agencies at both the state and federal levels. In 2020, however, a team of researchers from Stanford University and New York University (NYU) completed a multi-year effort to survey the use of machine learning by the *federal* government and develop a series of case studies.¹²⁷ A research team of more than two dozen members with backgrounds in law and computer science looked carefully through a broad range of public sources in search of references to possible machine-learning uses at about 140 of the largest federal agencies, yielding a total of 157 “use cases” at sixty-four agencies involving some reliance on artificial intelligence or machine-learning algorithms.¹²⁸ However, these examples were not distributed evenly across agencies: the Securities and Exchange Commission, for example, had ten distinct use cases, while about half of the agencies in the study had none.¹²⁹ Furthermore, when team members with computer science backgrounds looked closely at each use, they could find only about twelve percent that could be ranked as having a higher level of sophistication,¹³⁰ suggesting that “[w]hile the deep learning revolution has rapidly transformed the private sector, it appears to have only scratched the surface in public sector application.”¹³¹ In a potentially promising sign, however, most of

¹²⁷ See generally ENGSTROM ET AL., *supra* note 12. In the early part of this century, the federal Government Accountability Office (GAO) conducted a survey of more than 125 federal agencies and reported that fifty-two relied on some form of “data mining,” which the GAO defined broadly “as the application of database technology and techniques—such as statistical analysis and modeling—to uncover hidden patterns and subtle relationships in data and to infer rules that allow for the prediction of future results.” U.S. GOV’T ACCOUNTABILITY OFF., GAO-04-548, DATA MINING: FEDERAL EFFORTS COVER A WIDE RANGE OF USES 4 (2004), <https://www.gao.gov/assets/gao-04-548.pdf> [<https://perma.cc/T9QD-KCWN>]. The GAO did not report whether any of these applications relied on machine learning rather than traditional analytic tools.

¹²⁸ The researchers searched for the use of algorithms at 142 of the largest federal agencies, with at least 400 full-time equivalent employees each. See ENGSTROM ET AL., *supra* note 12, at 15. The researchers were not able to assess algorithmic sophistication for the vast majority of the use cases. *Id.* at 20. For the roughly forty percent of the tools for which they could make a determination, they coded roughly equal shares as falling in the “lower,” “medium,” and “higher” ranges of sophistication, with about twenty use cases in each category. *Id.*

¹²⁹ See ENGSTROM ET AL., *supra* note 12, at 16. The researchers found that only sixty-four of the 142 agencies (forty-five percent) had even a single use of an algorithmic tool. *Id.*

¹³⁰ See *supra* note 128.

¹³¹ See ENGSTROM ET AL., *supra* note 12, at 20.

the algorithms the researchers discovered had been developed internally by staff at the agencies rather than by private contractors, reflecting a “substantial creative appetite within agencies.”¹³² Finally, the Stanford-NYU team appeared not entirely confident that all of the use cases they found actually entailed full machine-learning systems, as they reported “some degree of puffery amongst agencies when they describe the adoption of machine learning and AI tools.”¹³³ For a majority of the use cases, a lack of publicly available documentation rendered the team unable to determine the exact nature of the methods that the algorithms deployed.¹³⁴

The precise stage of implementation of the systems identified by the Stanford-NYU team varied across the cases, as only fifty-three use cases, roughly one-third of the total, were fully deployed, while the rest remained in the planning or piloting stages or were only partially deployed.¹³⁵ Still, the team’s finding of 157 use cases across the federal government at least suggests a plausible upper bound of the current extent of uses of machine learning at the federal level. Obviously, still more uses exist at the state and local government levels. We cannot purport to chronicle all instances of administrative machine learning in this article, but instead we provide a range of examples to convey the variety of uses to which machine learning is being put by various agencies throughout the United States.

It is revealing that, among the use cases the Stanford-NYU team identified, roughly one-third were devoted to enforcement targeting—that is, helping to identify cases of possible fraud or regulatory violations in a way that would then allow human auditors or inspectors to follow up and investigate.¹³⁶ The research team also found that the policy area with the most frequent use of AI was law enforcement, which made up roughly one-fifth of the total use cases.¹³⁷ We thus first proceed in the next section to provide illustrative instances of machine learning used in the context of enforcement. We then proceed with examples in government services and program administration. Finally, we turn to a discussion of some of the merits, controversies, and legal issues surrounding the use of artificial intelligence in the administrative setting. Our discussion throughout all three sections includes

¹³² *Id.*

¹³³ Dan Ho, Remarks at the 71st Plenary Session of the Administrative Conference of the United States (June 13, 2019) (transcript on file with authors).

¹³⁴ See ENGSTROM ET AL., *supra* note 12, at 20.

¹³⁵ *Id.* at 18.

¹³⁶ *Id.* at 17.

¹³⁷ *Id.*

examples of machine learning and other algorithmic tools deployed at the federal, state, and local levels of government.

A. *Enforcement*

It is a common refrain that administrative agencies have more problems to deal with than they have resources to solve. Perhaps nowhere could this refrain be more accurate than in the context of administrative enforcement. Agencies have a limited number of auditors, inspectors, and other enforcement personnel who must oversee a vast number of individuals and businesses to ensure their compliance with myriad pages of laws and regulations. The federal Occupational Safety and Health Administration, for instance, has no more than about two thousand inspectors who oversee more than eight million workplaces employing about 130 million workers.¹³⁸ To deploy these limited oversight resources optimally, agencies need to know which businesses or individuals are most likely to require oversight. Machine-learning algorithms can provide forecasts of the likelihood of violations, thus helping agencies allocate resources better when deciding which regulated entities to target for human inspection and auditing.

For example, in 2001, the U.S. Internal Revenue Service (IRS) began developing machine-learning risk tools to integrate data from prior tax records, as well as data from other government agencies, to help it predict cases of possible tax fraud and prioritize which taxpayers to target for auditing.¹³⁹ More recently, the IRS developed a machine-learning program that uses credit card information and other third-party data to forecast the probability of underreporting by businesses.¹⁴⁰

¹³⁸ *Commonly Used Statistics*, OCCUPATIONAL SAFETY & HEALTH ADMIN., <https://www.osha.gov/oshstats/commonstats.html> [<https://perma.cc/5TEE-UZL6>].

¹³⁹ See JANE MARTIN & RICK STEPHENSON, RISK-BASED COLLECTION MODEL DEVELOPMENT AND TESTING 142 (June 7, 2005), <http://www.irs.gov/pub/irs-soi/05stephen.pdf> [<https://perma.cc/6FYX-CHD3>]; DAVID DEBARR & MAURY HARWOOD, RELATIONAL MINING FOR COMPLIANCE RISK 183 (June 2, 2004), <http://www.irs.gov/pub/irs-soi/04debarr.pdf> [<https://perma.cc/R5XL-GSLS>].

¹⁴⁰ See Chris Wagner et al., *IRS Policy Implementation Through Systems Programming Lacks Transparency and Precludes Adequate Review*, in 2010 ANNUAL REPORT TO CONGRESS 71, 76 (2010), http://www.irs.gov/pub/irs-utl/2010arcmsp5_policythruprogramming.pdf [<https://perma.cc/Y8R6-F52Q>]; U.S. TREASURY INSPECTOR GEN. FOR TAX ADMIN., 2014-20-088, THE INFORMATION REPORTING AND DOCUMENT MATCHING CASE MANAGEMENT SYSTEM COULD NOT BE DEPLOYED (2014), <https://www.treasury.gov/tigta/auditreports/2014reports/201420088fr.pdf> [<https://perma.cc/FEX4-GGYT>]; cf. Lynnley Browning, *Computer Scientists Wield Artificial Intelligence to Battle Tax Evasion*, N.Y. TIMES (Oct. 9, 2015), <https://www.nytimes.com/2015/10/10/business/computer-scientists-wield-artificial-intelligence-to-battle-tax-evasion.html> [<https://perma.cc/PD4J-B5XU>] (discussing a study that developed an artificial intelligence tool that the IRS could use to detect certain tax shelters used by corporate entities).

The Securities and Exchange Commission similarly uses machine learning and natural language processing to identify potential instances of insider trading, “bad apple” investment advisers and brokers, and accounting and financial reporting fraud.¹⁴¹ Meanwhile, the federal agency that oversees Medicare relies in part on machine-learning algorithms to help it identify possible leads for its fraud investigators to pursue.¹⁴² Federal immigration agencies have also increasingly relied on automated processes in identifying, monitoring, and apprehending immigrants who are unlawfully in the United States.¹⁴³ A range of other agencies, including the Environmental Protection Agency, the Department of Labor, and the Consumer Product Safety Commission, are currently developing or deploying algorithms to predict regulatory infractions across a variety of policy areas.¹⁴⁴

Local governments have also embraced the use of artificial intelligence to support efforts to promote regulatory compliance. The New York City Fire Department, for example, uses machine-learning algorithms to allocate and target a limited number of building inspectors who check for compliance with fire-related ordinances.¹⁴⁵ In Chicago, machine-learning tools assign health inspections of restaurants based on algorithmic forecasts of establishments posing the greatest risks.¹⁴⁶

A number of state and local law enforcement authorities also use algorithmic tools—some of which appear to be based on machine learning—when deciding where to send general police patrols. Starting with a widely discussed CompStat initiative in New York City in the 1990s (which was not based on machine learning), many

¹⁴¹ See ENGSTROM ET AL., *supra* note 12, at 22–29; Pam Karlan & Joe Bankman, *Artificial Intelligence and the Administrative State with Guests David Engstrom and Cristina Ceballos*, STAN. LEGAL (2019), <https://law.stanford.edu/stanford-legal-on-siriusxm/artificial-intelligence-and-the-administrative-state-with-guests-david-engstrom-and-cristina-ceballos/> [https://perma.cc/UFY8-UVLC]; David Freeman Engstrom & Daniel E. Ho, *Algorithmic Accountability in the Administrative State*, 37 YALE J. ON REG. 800, 816–19 (2020).

¹⁴² David Engstrom, Remarks at the 71st Plenary Session of the Administrative Conference of the United States (June 13, 2019) (transcript on file with authors).

¹⁴³ Anil Kalhan, *Immigration Policing and Federalism Through the Lens of Technology, Surveillance, and Privacy*, 74 OHIO ST. L. REV. 1105, 1122–34 (2013); see also ENGSTROM ET AL., *supra* note 12, at 30–36.

¹⁴⁴ See ENGSTROM ET AL., *supra* note 12, at 27.

¹⁴⁵ Brian Heaton, *New York City Fights Fire with Data*, GOV'T TECH. (May 15, 2015), <http://www.govtech.com/public-safety/New-York-City-Fights-Fire-with-Data.html> [https://perma.cc/QQ2T-HS2W].

¹⁴⁶ Stephen Goldsmith, *Chicago's Data-Powered Recipe for Food Safety*, DATA-SMART CITY SOLS. (May 21, 2015), <https://datasmart.ash.harvard.edu/news/article/chicagos-data-powered-recipe-for-food-safety-688> [https://perma.cc/K2PJ-RBH2]. Boston developed similar restaurant-inspection algorithms through a crowdsourcing project. See generally Edward Glaeser et al., *Crowdsourcing City Government: Using Tournaments to Improve Inspection Accuracy*, 106 AM. ECON. REV. 114 (2016).

police departments across the United States have taken a more systematic approach to allocating law enforcement resources by using performance metrics and data analysis.¹⁴⁷

Today, similar “moneyballing” efforts include a variety of predictive policing tools.¹⁴⁸ Some of these tools help police identify areas of a city that have a greater propensity for crime and may merit greater police patrols. For example, the City of Los Angeles Police Department has used a machine-learning tool called Real-Time Analysis Critical Response (RACR).¹⁴⁹ At least a dozen or more cities use a vendor-developed software called PredPol, which relies on a proprietary algorithm to identify sections of a city that may be more prone to criminal activity so that additional police resources can be allocated to those areas.¹⁵⁰ Dozens of cities have adopted another tool, ShotSpotter, which relies on algorithms to process sounds and alerts police to the locations of shootings based on the sound of gunfire.¹⁵¹ Still other algorithmic tools, such as the New York City Police Department’s Patternizr,¹⁵² seek to identify alleged

¹⁴⁷ By the end of the 1990s, a third of the largest police departments in the United States reported using a program like CompStat. DAVID WEISBURD ET AL., POLICE FOUNDATION REPORT: THE GROWTH OF COMPSTAT IN AMERICAN POLICING (Apr. 2004), https://www.researchgate.net/profile/James-Willis-5/publication/252109584_The_Growth_of_CompStat_in_American_Policing/links/5579a6c808ae75363756f5ab/The-Growth-of-CompStat-in-American-Policing.pdf [https://perma.cc/6VDJ-NQXJ].

¹⁴⁸ For a discussion of moneyballing in the public sector generally, see MONEYBALL FOR GOVERNMENT (Jim Nussle & Peter Orszag eds., 2d ed. 2015). For a distinction between place-based and person-based prediction in policing systems, see Ángel Díaz, *New York City Police Department Surveillance Technology*, BRENNAN CTR. FOR JUST. (Oct. 7, 2019), https://www.brennancenter.org/sites/default/files/2019-10/2019_NewYorkPolicyTechnology.pdf [https://perma.cc/3L6G-W8FF].

¹⁴⁹ Nate Berg, *Predicting Crime, LAPD-Style*, GUARDIAN (June 25, 2014), <https://www.theguardian.com/cities/2014/jun/25/predicting-crime-lapd-los-angeles-police-data-analysis-algorithm-minority-report>.

¹⁵⁰ Randy Rieland, *Artificial Intelligence Is Now Used to Predict Crime. But Is it Biased?*, SMITHSONIAN (Mar. 5, 2018), <https://www.smithsonianmag.com/innovation/artificial-intelligence-is-now-used-predict-crime-is-it-biased-180968337/> [https://perma.cc/6K49-TMZF]; see also ANDREW GUTHRIE, THE RISE OF BIG DATA POLICING SURVEILLANCE, RACE, AND THE FUTURE OF LAW ENFORCEMENT (2017); Erica Goode, *Sending the Police Before There’s a Crime*, N.Y. TIMES (Aug. 15, 2011), <https://www.nytimes.com/2011/08/16/us/16police.html> [https://perma.cc/2KBQ-BJSZ]; cf. United States v. Curry, 965 F.3d 313, 347 (4th Cir. 2020) (Wilkinson, J., dissenting) (“While predictive policing programs are subject to modification and differ in their details, they share a common premise: through smart policies, law enforcement can affirmatively prevent crime from happening, rather than just solve it.”).

¹⁵¹ Chris Weller, *There’s a Secret Technology in 90 US Cities That Listens for Gunfire 24/7*, BUS. INSIDER (June 27, 2017), <https://www.businessinsider.com/how-shotspotter-works-microphones-detecting-gunshots-2017-6> [https://perma.cc/9AMM-T22R].

¹⁵² J. Brian Charles, *NYPD’s Big Artificial-Intelligence Reveal*, GOVERNING (Mar. 19, 2019), <https://www.governing.com/archive/gov-new-york-police-nypd-data-artificial-intelligence-patternizr.html> [https://perma.cc/D3L8-5Z9Y].

perpetrators by integrating information, detecting patterns in crime incidents, and finding linkages between incidents.¹⁵³

Recent reports indicate that the Federal Bureau of Investigation, Immigration and Customs Enforcement, U.S. Postal Inspection Service, and hundreds of state and local law enforcement agencies are using facial recognition tools marketed by private-sector firms in an effort to identify criminal suspects.¹⁵⁴ In May 2019, San Francisco became the first major U.S. city to place restrictions on law enforcement's use of facial recognition and other surveillance tools.¹⁵⁵ In light of heightened concerns about racial discrimination by law enforcement officers, a number of technology companies, such as Apple, Microsoft, and IBM, announced in June 2020 that they would halt sales of their facial recognition technologies to police departments.¹⁵⁶ Although a number of other providers have continued to offer such tools to law enforcement agencies,¹⁵⁷ a growing number of cities such as Boston, Minneapolis, San Francisco, Oakland, and Portland have enacted restrictions to keep their police forces from using facial recognition technology—either in body cameras or more generally—amid heightened concerns

¹⁵³ Phil Goldstein, *How Pattern Recognition and Machine Learning Helps Public Safety Departments*, STATETECH (May 3, 2019), <https://statetechmagazine.com/article/2019/05/how-pattern-recognition-and-machine-learning-helps-public-safety-departments-perfcon> [<https://perma.cc/V83E-FNRR>]; Caroline Haskins, *Dozens of Cities Have Secretly Experimented with Predictive Policing Software*, VICE (Feb. 6, 2019), https://www.vice.com/en_us/article/d3m7jq/dozens-of-cities-have-secretly-experimented-with-predictive-policing-software [<https://perma.cc/R8YE-44GE>].

¹⁵⁴ See, e.g., Jared Council, *ICE Signs Contract with Facial Recognition Company Clearview AI*, WALL ST. J. (Aug. 14, 2020), <https://www.wsj.com/articles/ice-signs-contract-with-facial-recognition-company-clearview-ai-11597452727> [<https://perma.cc/75YQ-4W3U>]; Kashmir Hill, *The Secretive Company That Might End Privacy as We Know It*, N.Y. TIMES (Feb. 10, 2020), <https://www.nytimes.com/2020/01/18/technology/clearview-privacy-facial-recognition.html> [<https://perma.cc/G3H8-49AS>]; Jon Schuppe, *How Facial Recognition Became a Routine Policing Tool in America*, NBC NEWS (May 11, 2019), <https://www.nbcnews.com/news/us-news/how-facial-recognition-became-routine-policing-tool-america-n1004251> [<https://perma.cc/6T8A-AGT7>]; Jana Winter, *Facial Recognition, Fake Identities and Digital Surveillance Tools: Inside the Post Office's Covert Internet Operations Program*, YAHOO! NEWS (May 18, 2021), <https://news.yahoo.com/facial-recognition-fake-identities-and-digital-surveillance-tools-inside-the-post-offices-covert-internet-operations-program-214234762.html> [<https://perma.cc/CS9G-744H>].

¹⁵⁵ San Francisco Ordinance on Acquisition of Surveillance Technology, No. 190110 (May 6, 2019), <https://sfgov.legistar.com/View.ashx?M=F&ID=7206781&GUID=38D37061-4D87-4A94-9AB3-CB113656159A> [<https://perma.cc/V2S7-NETA>].

¹⁵⁶ See Jonathan Vananian, *Microsoft Follows IBM and Amazon in Barring Police from Using Its Facial-Recognition Technology*, FORTUNE (June 11, 2020), <https://fortune.com/2020/06/11/microsoft-ibm-amazon-facial-recognition-police/> [<https://perma.cc/MTT6-KXJA>].

¹⁵⁷ See Jared Council, *Facial Recognition Companies Commit to Police Market After Amazon, Microsoft Exit*, WALL ST. J. (June 12, 2020), <https://www.wsj.com/articles/facial-recognition-companies-commit-to-police-market-after-amazon-microsoft-exit-11591997320> [<https://perma.cc/X62Y-C2G8>].

about privacy violations and racial bias.¹⁵⁸ State legislatures in Virginia, California, New York, New Hampshire, Oregon, and Vermont have also curbed or banned law enforcement use of facial recognition software.¹⁵⁹ At the federal level, a number of police reform bills would prevent federal law enforcement agencies from using facial recognition tools.¹⁶⁰ Those tools, however, continue to attract interest from government, notwithstanding the increased scrutiny. A survey of federal agencies found that at least eighteen agencies used facial recognition systems in 2020, and at least ten plan to expand their use of facial recognition over the next few years, largely for law enforcement and national security purposes.¹⁶¹

B. *Service Delivery and Program Administration*

Just as city police departments have deployed machine-learning tools to assist with law enforcement efforts, cities are also using machine learning to support other key governmental functions.¹⁶² To manage a variety of algorithmic efforts, New York City has established an entire Office of Data Analytics, which works to integrate data from across the city and develop a variety of “analytics tools to prioritize risk more strategically, deliver services more efficiently, enforce laws more effectively and increase transparency.”¹⁶³ Other cities have similarly created special offices or teams devoted to data analysis and prediction.¹⁶⁴

¹⁵⁸ See Sidney Fussell, *The Next Target for a Facial Recognition Ban? New York*, WIRED (Jan. 28, 2021), <https://www.wired.com/story/next-target-facial-recognition-ban-new-york/> [https://perma.cc/GPL4-8PAY]; Libor Jany, *Minneapolis Passes Restrictive Ban on Facial Recognition Use by Police, Others*, STAR TRIB. (Feb. 12, 2021), <https://www.startribune.com/minneapolis-passes-restrictive-ban-on-facial-recognition-use-by-police-others/600022551/> [https://perma.cc/3V27-YRCJ]; see also Joseph Choi, *Officials Halting Facial Recognition System that Identified Lafayette Square Protester*, HILL (May 18, 2021), <https://thehill.com/homenews/state-watch/554118-officials-halting-facial-recognition-system-that-identified-lafayette> [https://perma.cc/A5EH-LJCM] (discussing discontinuation of D.C.-area facial recognition program).

¹⁵⁹ See Denise Lavoie, *Virginia Lawmakers Ban Police Use of Facial Recognition*, ABC NEWS (Mar. 29, 2021), <https://abcnews.go.com/Politics/wireStory/virginia-lawmakers-ban-police-facial-recognition-76753765> [https://perma.cc/NVV4-HRRZ].

¹⁶⁰ See Tate Ryan-Mosley, *We Could See Federal Regulation on Face Recognition as Early as Next Week*, MIT TECH. REV. (May 21, 2021), <https://www.technologyreview.com/2021/05/21/1025155/amazon-face-recognition-federal-ban-police-reform/> [https://perma.cc/X25Z-K9ZD].

¹⁶¹ U.S. GOV'T ACCOUNTABILITY OFF., GAO-21-526, FACIAL RECOGNITION TECHNOLOGY: CURRENT AND PLANNED USES BY FEDERAL AGENCIES 10–14, 26–27 (2021), <https://www.gao.gov/assets/gao-21-526.pdf> [https://perma.cc/Y7TX-QAJ2].

¹⁶² See, e.g., Hannah Bloch-Wehba, *Access to Algorithms*, 88 FORDHAM L. REV. 1265, 1273–83 (2020).

¹⁶³ *About the Office of Data Analytics*, NYC ANALYTICS, <https://www1.nyc.gov/site/operations/research/mayor-office-of-data-analytics.page> [https://perma.cc/2DPV-F684].

¹⁶⁴ See, e.g., *Analytics Team*, CITY OF BOS., <https://www.boston.gov/departments/analytics-team> [https://perma.cc/F253-9AJD]; *Data Science*, CITY OF CHI., <https://data.cityofchicago.org/>

Los Angeles has established a Data Science Federation, a formal partnership with local colleges and universities aiming to promote “predictive . . . analysis that will help drive data driven decision making within the city.”¹⁶⁵ Similarly, Chicago worked with a consortium of university partners to create a SmartData Platform that helps facilitate the use of machine learning in support of city services.¹⁶⁶

Local governments have employed machine-learning tools for a variety of purposes related to service delivery and program administration. Both Chicago and Washington, D.C., are using machine learning to optimize rodent bait placement throughout their cities.¹⁶⁷ In Flint, Michigan, following a major fiasco in the management of the city’s water supply, officials have benefited from machine-learning predictions to identify priorities for replacing pipes contributing to lead contamination in homes throughout the city.¹⁶⁸ Johnson County, Kansas has used algorithmic determinations of risk to determine how to allocate its social service counselors and mental health professionals.¹⁶⁹ Allegheny County in Pennsylvania has relied on machine learning to help screen phone referrals made to the county’s child protective services hotline for risk of future abuse or neglect and then to assess which complaints might merit further intervention.¹⁷⁰

Artificial intelligence is also working on the ground to help make roadways safe. In Los Angeles, traffic lights operate automatically based on a machine-learning system that optimizes for congestion avoidance using data fed by a network of sensors

www.chicago.gov/city/en/depts/doi/provdrs/data_sciences.html [https://perma.cc/4P8R-VQ93].

¹⁶⁵ *About Us*, DATA SCIENCE, <https://datasciencefederation.lacity.org/about-us> [https://perma.cc/GY6V-79ZT].

¹⁶⁶ Ash Center Mayor’s Challenge Research Team, *Chicago’s SmartData Platform: Pioneering Open Source Municipal Analytics*, DATA-SMART CITY SOLS. (Jan. 8, 2014), <http://datasmart.ash.harvard.edu/news/article/chicago-mayors-challenge-367> [https://perma.cc/P8N7-Y7GJ].

¹⁶⁷ Linda Poon, *Will Cities Ever Outsmart Rats?*, CITYLAB (Aug. 9, 2017), <https://www.citylab.com/solutions/2017/08/smart-cities-fight-rat-infestations-big-data/535407/> [https://perma.cc/3S9F-RNS5].

¹⁶⁸ Gabe Cherry, *Google, U-M to Build Digital Tools for Flint Water Crisis*, UNIV. OF MICH. NEWS (May 3, 2016), <http://ns.umich.edu/new/multimedia/videos/23780-google-u-m-to-build-digital-tools-for-flint-water-crisis> [https://perma.cc/7WR2-W8K7].

¹⁶⁹ Robert Sullivan, *Innovations in Identifying People Who Frequently Use Criminal Justice and Healthcare Systems*, POL’Y RSCH. ASSOCS. (May 16, 2018), <https://www.prainc.com/innovations-identification-cj-healthcare/> [https://perma.cc/4UFP-JG7D].

¹⁷⁰ RHEMA VAITHIANATHAN ET AL., DEVELOPING PREDICTIVE RISK MODELS TO SUPPORT CHILD MALTREATMENT HOTLINE SCREENING DECISIONS 1 (2019), www.alleghenycountyanalytics.us/wp-content/uploads/2019/05/16-ACDHS-26_PredictiveRisk_Package_050119_FINAL-2.pdf [https://perma.cc/V2JT-F75K]; see also Dan Hurley, *Can an Algorithm Tell When Kids Are in Danger?*, N.Y. TIMES (Jan. 2, 2018), <https://www.nytimes.com/2018/01/02/magazine/can-an-algorithm-tell-when-kids-are-in-danger.html> [https://perma.cc/LJJ6-AJRG].

in the city's streets.¹⁷¹ Pittsburgh has also adopted an AI-driven tool that has cut vehicle travel time by twenty-five percent by optimizing the city's traffic light system.¹⁷² Georgia is developing a "smart highway" system that will use data obtained from vehicles with smart sensors to detect weather and road conditions, sharing that information with other drivers and roadway operators to reduce traffic and prevent car accidents.¹⁷³

The innovative use of data analytics by local governments is now the centerpiece of a Data-Smart City Solutions initiative at Harvard University's John F. Kennedy School of Government.¹⁷⁴ This initiative has cataloged more than seventy-five uses of data analytics by local governments, some but not all involving machine learning.¹⁷⁵ Its list includes tasks as varied as identifying children who could benefit from mentoring programs, targeting businesses that might be underpaying taxes, and prioritizing trees for trimming.¹⁷⁶

Similarly, the Penn Program on Regulation's Optimizing Government project has chronicled local government efforts that rely on machine learning or other predictive analytics tools. These efforts include: early intervention academic support for public school students; detection of problems with water infrastructure, waste, and pollution; economic blight prevention; detection of risks to police officers from interactions with members of the public; and improvement of city services, public transportation, and public health.¹⁷⁷

¹⁷¹ Ian Lovett, *To Fight Gridlock, Los Angeles Synchronizes Every Red Light*, N.Y. TIMES (Apr. 1, 2013), <http://www.nytimes.com/2013/04/02/us/to-fight-gridlock-los-angeles-synchronizes-every-red-light.html> [https://perma.cc/S5HE-FENE]; David Z. Morris, *How Swarming Traffic Lights Could Save Drivers Billions of Dollars*, FORTUNE (July 13, 2015, 4:47 PM), <http://fortune.com/2015/07/13/swarming-traffic-lights> [https://perma.cc/2FZU-TWN5].

¹⁷² GWANHOO LEE, IBM CTR. FOR THE BUS. OF GOV'T, CREATING PUBLIC VALUE USING THE AI-DRIVEN INTERNET OF THINGS 19–22 (2021), <http://www.businessofgovernment.org/sites/default/files/Creating%20Public%20Value%20using%20the%20AI-Driven%20Internet%20of%20Things.pdf> [https://perma.cc/W9HC-9ESG].

¹⁷³ See *id.*, at 26–29.

¹⁷⁴ *Data-Smart City Solutions: Our Mission*, DATA-SMART CITY SOLS., <https://datasmart.ash.harvard.edu/data-smart-city-solutions> [https://perma.cc/3J28-B4KG].

¹⁷⁵ *A Catalog of Civic Data Use Cases*, DATA-SMART CITY SOLS. (Apr. 9, 2021), <https://datasmart.ash.harvard.edu/news/article/how-can-data-and-analytics-be-used-to-enhance-city-operations-723> [https://perma.cc/CQ3V-K2TU].

¹⁷⁶ *Id.*

¹⁷⁷ See *Uses in Government*, *supra* note 6. We acknowledge, however, that descriptive materials available on these various uses do not always make it entirely clear which of these efforts involved actual machine learning versus other kinds of predictive analytic techniques. For example, although a 2017 survey of local governments by the National League of Cities indicated that sixty-six percent of local governments have invested in "smart city" technologies, many of these uses include applications that likely do not involve machine-learning algorithms in assisting with government decisions, such as "WiFi kiosks" and "E-governance applications." NICOLE DUPUIS & BROOKS RAINWATER, NAT'L LEAGUE OF CITIES, CITIES AND THE INNOVATION ECONOMY: PERCEPTIONS OF LOCAL LEADERS 14 (2017),

At the federal level, predictive analytic tools, including ones relying on machine learning, have been put to varied service-related uses. One of the earliest uses of machine learning by the federal government actually helped spur innovation in AI technology: the U.S. Postal Service's use of machine learning to support automatic handwriting detection and mail sorting.¹⁷⁸ In addition, scientists at the National Oceanic and Atmospheric Administration have relied on machine learning for weather forecasting.¹⁷⁹ Risk analysts at the Environmental Protection Agency have used machine-learning algorithms to forecast the likelihood that certain chemicals are toxic and need further study and management.¹⁸⁰ The Food and Drug Administration has employed artificial intelligence to extract information from adverse event reports about drugs.¹⁸¹ Similarly, the Bureau of Labor Statistics uses machine learning to code survey results about workplace injuries,¹⁸² and the Consumer Financial Protection Bureau relies on natural language processing to categorize and identify patterns in consumer complaints.¹⁸³ The Federal Communications Commission has used natural language processing to analyze millions of public comments submitted in response to its proposed net neutrality rulemakings.¹⁸⁴ The U.S. Patent and Trademark Office is exploring how machine learning could identify existing literature that may be novelty-defeating "prior art" to patent

https://www.nlc.org/wp-content/uploads/2017/10/NLC_CitiesInnovationEconomy_pages1.pdf [<https://perma.cc/G8S7-4BAJ>].

¹⁷⁸ One of the first automatic techniques for detecting handwriting emerged in the late 1980s in the context of mail sorting. See Ching-Huei Wang & Sargur Srihari, *A Framework for Object Recognition in a Visually Complex Environment and Its Application to Locating Address Blocks on Mail Pieces*, 2 INT'L J. COMP. VISION 125, 125 (1988); OFER MATAN ET AL., HANDWRITTEN CHARACTER RECOGNITION USING NEURAL NETWORK ARCHITECTURES (Nov. 1990), <http://yann.lecun.com/exdb/publis/pdf/matan-90.pdf> [<https://perma.cc/9HGT-CRDE>].

¹⁷⁹ David John Gagne et al., *Day-Ahead Hail Prediction Integrating Machine Learning with Storm-Scale Numerical Weather Models* (2015), <https://www.aaai.org/ocs/index.php/IAAI/IAAI15/paper/viewFile/9724/9898> [<https://perma.cc/K745-MHPY>].

¹⁸⁰ Richard S. Judson et al., *Estimating Toxicity-Related Biological Pathway Altering Doses for High-Throughput Chemical Risk Assessment*, 24 CHEM. RSCH. TOXICOLOGY 451, 457–60 (2011); Robert Kavlock et al., *Update on EPA's ToxCast Program: Providing High Throughput Decision Support Tools for Chemical Risk Management*, 25 CHEM. RSCH. TOXICOLOGY 1287, 1295 (2012); Matthew Martin et al., *Economic Benefits of Using Adaptive Predictive Models of Reproductive Toxicity in the Context of a Tiered Testing Program*, 58 SYS. BIOLOGY REPROD. MED. 3, 4–6 (2012).

¹⁸¹ *Impact Story: Capturing Patient Experience Through Deep Learning*, U.S. FOOD & DRUG ADMIN., <https://www.fda.gov/drugs/regulatory-science-action/impact-story-capturing-patient-experience-through-deep-learning> [<https://perma.cc/QG8Q-PK39>]; see also ENGSTROM ET AL., *supra* note 12, at 53–58.

¹⁸² Alex Measure, *Machine Learning: How Bureau of Labor Statistics Did It*, DIGITAL.GOV (July 25, 2019), <https://digital.gov/event/2019/07/25/machine-learning-how-bureau-labor-statistics-did-it/> [<https://perma.cc/YS64-3E5V>].

¹⁸³ See ENGSTROM ET AL., *supra* note 12, at 61–62.

¹⁸⁴ *Id.* at 60–61.

applications.¹⁸⁵ U.S. Customs and Border Protection uses facial-recognition algorithms at airports to identify people when they arrive in the United States from international flights.¹⁸⁶ The Social Security Administration uses a natural language processing tool based on machine learning that helps flag initial decisions adjudicating disability claims for further quality review.¹⁸⁷

As this review of the many public sector uses of AI makes clear, local, state, and federal agencies have embraced the potential that algorithmic tools have to offer, deploying these tools in a variety of contexts to conduct their operations and provide services to the public.¹⁸⁸ These uses of AI systems promise to improve aspects of governmental performance, but they have also at times raised some legal and policy concerns.

C. *Impacts and Issues*

The principal advantages of artificial intelligence in the administrative context are similar to those in the private sector: accuracy and efficiency.¹⁸⁹ Machine-learning algorithms can

¹⁸⁵ See generally Arti Kaur Rai, *Machine Learning at the Patent Office: Lessons for Patents and Administrative Law*, 104 IOWA L. REV. 2617 (2019); see also ENGSTROM ET AL., *supra* note 12, at 46–52.

¹⁸⁶ See Karlan & Bankman, *supra* note 141 (interview with David Engstrom).

¹⁸⁷ GERALD RAY & GLENN SKLAR, AN OPERATIONAL APPROACH TO ELIMINATING BACKLOGS IN THE SOCIAL SECURITY DISABILITY PROGRAM 31–34 (2009), http://www.crfb.org/sites/default/files/An_Operational_Approach_to_Eliminating_Backlogs_in_the_Social_Security_Disability_Program.pdf [<https://perma.cc/65BA-UELV>]; Judge Paul Armstrong, *Artificial Intelligence: From Law Office to Administrative Proceedings*, AM. BAR ASS'N (Feb. 3, 2020), https://www.americanbar.org/groups/judicial/publications/judges_journal/2020/winter/artificial-intelligence-law-office-administrative-proceedings/ [<https://perma.cc/C4Q6-RXDE>] (noting that “the Social Security Administration (SSA) has taken an active role in promoting the use of AI, first in its appeals process and then as an aid in writing and editing its ALJ decisions themselves”); see also Engstrom & Ho, *supra* note 141, at 9–11.

¹⁸⁸ Many governments are relying on AI to help manage the inflow of contacts from the public. Following the economic fallout from the COVID-19 pandemic, for example, the Illinois Department of Employment Security implemented an AI system to help manage incoming calls seeking assistance with filing unemployment benefits. Brent Mitchell, *Artificial Intelligence Can Help States Manage the Unemployment Crisis*, STATETECH (Feb. 25, 2021), <https://statetechmagazine.com/article/2021/02/artificial-intelligence-can-help-states-manage-unemployment-crisis> [<https://perma.cc/6X8R-PNEH>]. Other agencies have implemented AI-based chatbots to assist in fielding inquiries from the public. Carlos Meléndez, *Chatbots: The New Government Official in the Fight Against Coronavirus*, NEXTGOV (June 10, 2020), <https://www.nextgov.com/ideas/2020/06/chatbots-new-government-official-fight-against-coronavirus/165966/> [<https://perma.cc/6NB2-AEU9>]. For further discussion of governmental use of AI, see DARRELL M. WEST & JOHN R. ALLEN, TURNING POINT: POLICYMAKING IN THE ERA OF ARTIFICIAL INTELLIGENCE (2020).

¹⁸⁹ See, e.g., CARY COGLIANESE, A FRAMEWORK FOR GOVERNMENTAL USE OF MACHINE LEARNING 34–37 (2020), <https://www.acus.gov/sites/default/files/documents/Coglianese%20ACUS%20Final%20Report%20w%20Cover%20Page.pdf> [<https://perma.cc/C98E-RZU6>] (noting that the use of AI in governmental decision-making offers the

make more accurate forecasts that can aid in governmental decision-making. For example, researchers have shown that if the U.S. Environmental Protection Agency were to use a machine-learning algorithm to assign its water pollution inspectors instead of just identifying facilities at random to inspect, the agency could increase the accuracy of finding violations of the Clean Water Act by 600 percent.¹⁹⁰ A separate analysis of a machine-learning tool used to identify potentially toxic chemicals showed that it could save the government nearly \$980,000 for every toxic chemical identified.¹⁹¹

In addition to improving the allocation of scarce administrative resources, machine-learning systems may eventually help reduce some of the inevitable biases and inconsistencies that arise from human judgment.¹⁹² For example, with the Social Security Administration's disability adjudications, some research suggests that human decisions reflect racial disparities that tend to disfavor claimants of color.¹⁹³ Another study of just a single office within the Social Security Administration found vastly disparate rates of benefits awards, with "judge grant rates in this single location rang[ing] . . . from less than 10 percent being granted to over 90 percent."¹⁹⁴ If machine-learning tools are used as substitutes for—or even just as complements to—human decision-making, they could potentially reduce inconsistencies and other foibles that permeate human judgment.¹⁹⁵

Notwithstanding this potential, the use of machine learning in governmental settings has not escaped controversy.

potential to increase the accuracy, capacity, speed, and consistency of agencies' decisions).

¹⁹⁰ See generally Miyuki Hino et al., *Machine Learning for Environmental Monitoring*, 1 NATURE SUSTAINABILITY 583 (2018).

¹⁹¹ Matthew Martin et al., *Economic Benefits of Using Adaptive Predictive Models of Reproductive Toxicity in the Context of a Tiered Testing Program*, 58 SYS. BIOLOGY REPROD. MED. 3, 4–6 (2012).

¹⁹² On human biases, see DANIEL KAHNEMAN, THINKING, FAST AND SLOW (2011); DANIEL KAHNEMAN ET AL., NOISE: A FLAW IN HUMAN JUDGMENT (2021); and Cary Coglianese & Alicia Lai, *Algorithm vs. Algorithm*, DUKE L.J. (forthcoming).

¹⁹³ See U.S. GOV'T ACCOUNTABILITY OFF., GAO/HRD-92-56, SOCIAL SECURITY: RACIAL DIFFERENCES IN DISABILITY DECISIONS WARRANTS FURTHER INVESTIGATION 75 (1992), <https://www.gao.gov/assets/160/151781.pdf> [<https://perma.cc/63X6-U5Sj>]. See generally Erin Godtland et al., *Racial Disparities in Federal Disability Benefits*, 25 CONTEMP. ECON. POL. 27 (2007).

¹⁹⁴ TRAC, SOCIAL SECURITY AWARDS DEPEND MORE ON JUDGE THAN FACTS: DISPARITIES WITHIN SSA DISABILITY HEARING OFFICES GROW (2011), <https://trac.syr.edu/tracreports/ssa/254/> [<https://perma.cc/U5YH-DWAV>].

¹⁹⁵ See, e.g., Jon Kleinberg et al., *Algorithms as Discrimination Detectors*, 117 PROC. NAT'L. ACAD. SCI. 30096 (Dec. 1, 2020); Sendhil Mullainathan, *Biased Algorithms Are Easier to Fix Than Biased People*, N.Y. TIMES (Dec. 6, 2019), <https://www.nytimes.com/2019/12/06/business/algorithm-bias-fix.html> [<https://perma.cc/8FFD-WQCY>].

If the underlying data contain biases—which may occur if they derive from human practices and systems that themselves reflect biases and prejudices—then machine learning might reify the inequities built into the data.¹⁹⁶

For example, concerns have arisen about inherent biases built into facial recognition algorithms, given their potential utility for law enforcement agencies.¹⁹⁷ A recent study by the National Institute of Standards and Technology ran millions of photographs obtained from government databases through almost 200 different commercial facial-recognition algorithms.¹⁹⁸ The study found that U.S.-developed algorithms tended to have higher rates of false positives for Asian and Black faces than for white ones (by a factor of between 10 and 100) and more frequent false positives for women than for men.¹⁹⁹

Moreover, if algorithms rely on underlying data that are limited, or if algorithms are not designed or tested well, they may lead to a false sense of accuracy—perhaps even making decision-making more error-prone. For instance, Indiana’s experiment with automating the distribution of public benefits reportedly resulted in widespread inaccuracies that erroneously deprived many people of public assistance.²⁰⁰ Another error arising from an algorithm occurred when a man in Michigan faced what appears to have been the first wrongful arrest caused by a faulty facial recognition system.²⁰¹

Reliance on algorithms that process large amounts of data gives rise to other concerns. Some of these concerns center

¹⁹⁶ For recent discussions, compare CATHY O’NEIL, *WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY* (2016), with MICHAEL KEARNS & AARON ROTH, *THE ETHICAL ALGORITHM: THE SCIENCE OF SOCIALLY AWARE ALGORITHM DESIGN* (2019).

¹⁹⁷ See Natasha Singer & Cade Metz, *Many Facial-Recognition Systems Are Biased, Says U.S. Study*, N.Y. TIMES (Dec. 19, 2019), <https://www.nytimes.com/2019/12/19/technology/facial-recognition-bias.html> [<https://perma.cc/58N7-EH54>].

¹⁹⁸ *NIST Study Evaluates Effects of Race, Age, Sex on Face Recognition Software*, NIST (Dec. 19, 2019), <https://www.nist.gov/news-events/news/2019/12/nist-study-evaluates-effects-race-age-sex-face-recognition-software> [<https://perma.cc/NL95-K44Y>].

¹⁹⁹ *Id.*

²⁰⁰ See VIRGINIA EUBANKS, *AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR* 39–83 (2018). In addition, an automated digital system for identifying unemployment insurance fraud in Michigan made tens of thousands of false fraud accusations against unemployment insurance recipients. See Ryan Felton, *Criminalizing the Unemployed*, DETROIT METRO TIMES (July 1, 2015), <https://www.metrotimes.com/detroit/criminalizing-the-unemployed/Content?oid=2353533> [<https://perma.cc/8M4A-DM83>]; Allie Gross, *Update: UIA Lawsuit Shows How the State Criminalizes the Unemployed*, DETROIT METRO TIMES (Oct. 5, 2015), <https://www.metrotimes.com/news-hits/archives/2015/10/05/ui-a-lawsuit-shows-how-the-state-criminalizes-the-unemployed> [<https://perma.cc/5CUR-S349>].

²⁰¹ See Kashmir Hill, *Wrongfully Accused by an Algorithm*, N.Y. TIMES (Aug. 3, 2020), <https://www.nytimes.com/2020/06/24/technology/facial-recognition-arrest.html> [<https://perma.cc/YC3R-DL3N>].

on potential violations of privacy.²⁰² Other apprehensions focus on the possibility of irresponsible or oppressive governmental actors using algorithms to abuse their power.²⁰³

In addition, in the governmental setting, these concerns are exacerbated by the “black box” character of machine-learning algorithms, which seems to raise particular worries about transparency and accountability. These issues have driven calls for increased oversight over the use of algorithms in governmental decisionmaking.²⁰⁴ The way that such algorithms optimize outcomes and the solutions they support may not be readily apparent to those whom they affect, which has suggested to some observers either that these tools should be avoided by government agencies or that officials should take extra steps to explain what these algorithms do.²⁰⁵

Such concerns have motivated government bodies to scrutinize more closely how they use artificial intelligence tools—and to lay out principles that they will follow when establishing automated decisionmaking processes. City and local governments have begun to formulate frameworks for how they will use AI to aid in decisionmaking.²⁰⁶ In addition, a

²⁰² See, e.g., Cameron F. Kerry, *Protecting Privacy in an AI-Driven World*, BROOKINGS INSTITUTION (Feb. 10, 2020), <https://www.brookings.edu/research/protecting-privacy-in-an-ai-driven-world/> (“As artificial intelligence evolves, it magnifies the ability to use personal information in ways that can intrude on privacy interests.”).

²⁰³ See, e.g., Rashida Richardson et al., *Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, And Justice*, 94 N.Y.U. L. REV. 192, 192 (2019) (raising concerns about the use of “dirty data” from corrupt, racially biased, or unlawful police practices in algorithmic tools to support predictive policing, which can further perpetuate the biases and misbehavior inherent in the data); Shibani Mahtani, *Chicago Police Take a Page From “Minority Report,”* WALL ST. J. (May 12, 2017), <https://www.wsj.com/articles/chicago-police-take-a-page-from-minority-report-1494581400> [<https://perma.cc/S85Q-HTDB>]; Ali Winston & Ingrid Burrington, *A Pioneer in Predictive Policing Is Starting a Troubling New Project*, VERGE (Apr. 27, 2018), <https://www.theverge.com/2018/4/26/17285058/predictive-policing-predpol-pentagon-ai-racial-bias> [<https://perma.cc/954H-9JDY>]; see also *United States v. Curry*, 965 F.3d 313, 344–46 (4th Cir. 2020) (Thacker, J., concurring) (highlighting the potential for harm from predictive policing algorithms that may use data that reflects and reinforces racial biases).

²⁰⁴ For instance, New York City was the first in the country to set up a task force to oversee the use of automated decision systems by city agencies. See generally N.Y.C. AUTOMATED DECISION SYS. TASK FORCE, NEW YORK CITY AUTOMATED DECISION SYSTEMS TASK FORCE REPORT 5 (2019), <https://www1.nyc.gov/assets/adstaskforce/downloads/pdf/ADS-Report-11192019.pdf> [<https://perma.cc/8BCZ-C6CM>].

²⁰⁵ See AI NOW INST., AI NOW 2019 REPORT 14 (2019), https://ainow.institute.org/AI_Now_2019_Report.pdf [<https://perma.cc/3TAM-VFNT>] (flagging a variety of concerns about the “black box” nature of algorithms and the potential for harm and abuse if they are used by government agencies without fully accounting for built-in biases).

²⁰⁶ See, e.g., *supra* note 204 and accompanying text; VT. ARTIFICIAL INTELLIGENCE TASK FORCE, FINAL REPORT 16–22 (2020), <https://legislature.vermont.gov/assets/Legislative-Reports/Artificial-Intelligence-Task-Force-Final-Report-1.15.2020.pdf> [<https://perma.cc/Z7W8-8QNL>].

number of initiatives at the federal level have sought to establish guidelines for responsible use of AI. An executive order issued in December 2020 urges federal agencies to use AI responsibly.²⁰⁷ The Administrative Conference of the United States has adopted a slate of guidelines for agencies deploying AI tools, encouraging administrative officials to consider issues such as transparency, bias, technical capacity, procurement, privacy, security, decisional authority, and oversight.²⁰⁸ The Government Accountability Office, for its part, has issued a detailed “accountability framework” that identifies “key practices to help ensure accountability and responsible AI use by federal agencies and other entities involved in the design, development, deployment, and continuous monitoring of AI systems.”²⁰⁹

Congress has encouraged additional efforts to promote responsible use of AI in government. The AI in Government Act of 2020 created an AI Center for Excellence within the General

²⁰⁷ Promoting the Use of Trustworthy Artificial Intelligence in the Federal Government, Exec. Order No. 13,960, 85 Fed. Reg. 78,939, 78,940–41 (Dec. 3, 2020). As of the writing of this article, President Biden does not appear to have rescinded this executive order. The December 2020 order followed initiatives by individual agencies to identify and commit to standards for their own adoption of machine-learning systems. See, e.g., OFF. OF THE DIR. OF NAT’L INTEL., PRINCIPLES OF ARTIFICIAL INTELLIGENCE FOR THE INTELLIGENCE COMMUNITY (2020), https://www.dni.gov/files/ODNI/documents/Principles_of_AI_Ethics_for_the_Intelligence_Community.pdf; Press Release, U.S. Dep’t of Defense, DOD Adopts Ethical Principles for Artificial Intelligence (Feb. 24, 2020), <https://www.defense.gov/Newsroom/Releases/Release/Article/2091996/dod-adopts-ethical-principles-for-artificial-intelligence/> [<https://perma.cc/M8VW-RBPV>].

²⁰⁸ Admin. Conf. of the U.S., Statement Number 20, Agency Use of Artificial Intelligence, 86 Fed. Reg. 6616 (Jan. 22, 2021). These initiatives focus merely on government’s own use of AI—to say nothing of how government will regulate private-sector uses. See, e.g., Memorandum from Russell T. Vought, Acting Director, Off. of Mgmt. & Budget, to Heads of Executive Departments and Agencies, Guidance for Regulation of Artificial Intelligence Applications (Nov. 17, 2020), <https://www.whitehouse.gov/wp-content/uploads/2020/11/M-21-06.pdf> [<https://perma.cc/AEF9-5TE9>] (setting out “policy considerations” for federal agencies’ “regulatory and non-regulatory approaches to AI applications developed and deployed outside of the Federal government”). At the state level, California and Virginia have recently become the first two states to adopt data privacy laws requiring companies that use consumers’ data—including providers of AI tools—to disclose those uses and allow consumers to opt out of having their data used. See Stephan Zoder, *California’s Privacy Rights Act: What Does It Mean For Your Organization?*, FORBES (Jan. 28, 2021), <https://www.forbes.com/sites/stephanzoder/2021/01/28/californias-privacy-rights-act-what-does-it-mean-for-your-organization/?sh=6a42725a1a38> [<https://perma.cc/G3G4-R67S>]; Cat Zakrzewski, *Virginia Governor Signs Nation’s Second State Consumer Privacy Bill*, WASH. POST (Mar. 2, 2021), <https://www.washingtonpost.com/technology/2021/03/02/privacy-tech-data-virginia/> [<https://perma.cc/R9LT-DH7M>]. Efforts by government to oversee uses of AI beyond government itself have also gained traction around the world. The European Union has proposed a sweeping regulation that would impose a heavy regulatory burden on all AI systems used within the bloc. See Mark MacCarthy & Kenneth Popp, *Machines Learn that Brussels Writes the Rules: The EU’s New AI Regulation*, BROOKINGS (May 4, 2021), <https://www.brookings.edu/blog/techtank/2021/05/04/machines-learn-that-brussels-writes-the-rules-the-eus-new-ai-regulation/> [<https://perma.cc/K48Z-RQ8Z>].

²⁰⁹ U.S. GOV’T ACCOUNTABILITY OFF., ARTIFICIAL INTELLIGENCE: AN ACCOUNTABILITY FRAMEWORK FOR FEDERAL AGENCIES AND OTHER ENTITIES (June 2021), <https://www.gao.gov/assets/gao-21-519sp.pdf> [<https://perma.cc/ZE7R-2BQ7>].

Services Administration and called for the Office of Management and Budget to develop further guidance on best practices in governmental use of AI.²¹⁰ The National Artificial Intelligence Initiative Act of 2020 instructed the National Institute of Standards and Technology to develop a voluntary risk management framework for the use of AI by both the public and private sectors.²¹¹

Guidelines such as the ones that Congress has called for, along with ones already developed, are undoubtedly welcome because the deployment of artificial intelligence tools in the public sector can present a number of challenges in practice. Indeed, the use of algorithms in government already has led to some controversies and disputes.

The public school district in Boston, for example, worked with researchers at the Massachusetts Institute of Technology on a machine-learning algorithm intended to inform the redesign of school schedules and bus routes. The initial algorithm-informed redesign, which would have changed the starting times for many schools, was expected to save the district up to \$15 million in annual expenses and produce schedules that were healthier for students, better for the environment, and more equitable for minority students.²¹² But the system's scheduling "overhaul was introduced with insufficient explanation or opportunity for citizen interaction with the model," and it prompted a "public pushback [that] was strong and swift."²¹³ The school district dropped the proposed scheduling changes in the face of the opposition.²¹⁴ It did, however, proceed to use digital algorithms to reprogram the specific routes traveled by the district's buses, still saving taxpayers considerable money on fuel costs and substantially reducing emissions.²¹⁵

In Houston, a school district ended up in court after relying on a complex algorithm—albeit not a machine-learning

²¹⁰ Consolidated Appropriations Act, 2021, Pub. L. No. 116-260, Division U, Title I, §§ 101–105, 134 Stat. 1182, 2286–89.

²¹¹ William M. (Mac) Thornberry National Defense Authorization Act for Fiscal Year 2021, Division E, Pub. L. No. 116-283, §§ 5001–5501, 134 Stat. 3388, 4523–47.

²¹² ELLEN GOODMAN, *THE CHALLENGE OF EQUITABLE ALGORITHMIC CHANGE* (2019), <https://www.theregreview.org/wp-content/uploads/2019/02/Goodman-The-Challenge-of-Equitable-Algorithmic-Change.pdf> [<https://perma.cc/YPS9-596R>].

²¹³ *Id.* at 3, 7.

²¹⁴ Emma Coleman, *How One City Saved \$5 Million by Routing School Buses with an Algorithm*, ROUTE FIFTY (Aug. 12, 2019), <https://www.route-fifty.com/tech-data/2019/08/boston-school-bus-routes/159113/> [<https://perma.cc/67UG-6DKD>].

²¹⁵ Sean Fleming, *This U.S. City Put an Algorithm in Charge of its School Bus Routes and Saved \$5 Million*, WORLD ECON. F. (Aug. 22, 2019), <https://www.weforum.org/agenda/2019/08/this-us-city-put-an-algorithm-in-charge-of-its-school-bus-routes-and-saved-5-million/> [<https://perma.cc/9PJR-JNGF>].

one—to rate teachers’ performance and justify the dismissal of teachers whom the algorithm rated poorly.²¹⁶ The district relied on a private consulting firm to develop and run the algorithm, but the firm considered its “algorithms and software as trade secrets, refusing to divulge them to either [the district] or the teachers themselves.”²¹⁷ The teachers’ union and several teachers filed a lawsuit against the school district, arguing that the algorithm deprived them of procedural due process.²¹⁸ The teachers argued that, without “access to the computer algorithms and data necessary to verify the accuracy of their scores,” the district deprived them of their constitutional rights. The trial court issued only an interim decision, ruling that the procedural due process claim could possibly have merit and that the teachers were entitled to take their case to a jury. The court held that “without access to . . . proprietary information—the value-added equations, computer source codes, decision rules, and assumptions—[the teachers’] scores will remain a mysterious ‘black box,’ impervious to challenge.”²¹⁹ Although the court recognized that the consulting firm relied on by the school district may well have been within its rights to keep its algorithms secret, it held that a jury could still consider whether “a policy of making high stakes employment decisions based on secret algorithms [is] incompatible with minimum due process.”²²⁰ Of course, the preliminary nature of the trial court’s decision cannot rule out the possibility that, had the matter gone to a jury, the school officials might have been able to put forth additional evidence that could have satisfied the teachers’ due process rights while still protecting the firm’s trade secrets.²²¹

A handful of other cases in recent years have similarly raised due process and transparency concerns over states’ use of non-learning algorithms in making decisions about individuals’ Medicaid or disability benefits. In Idaho, lawyers acting on behalf of a group of people with developmental disabilities filed suit against the state over reductions in Medicaid payments for

²¹⁶ *Hous. Fed’n of Teachers, Local 2415 v. Hous. Indep. Sch. Dist.*, 251 F. Supp. 3d 1168, 1171 (S.D. Tex. 2017); *see also* Coglianese & Lehr, *supra* note 1, at 37–38.

²¹⁷ *Hous. Fed’n of Teachers*, 251 F. Supp. at 1176–77.

²¹⁸ *Id.* at 1171–73.

²¹⁹ *Id.* at 1179.

²²⁰ *Id.* at 1179–80.

²²¹ The case settled in October 2017; in that settlement, the school district noted that it had already terminated the vendor of the algorithm and agreed that it would never again fire a teacher based on a “value-added” scoring system of the kind it had used, “so long as the value-added score assigned to the teacher remains unverifiable.” Settlement and Full and Final Release Agreement at 1–2, *Hous. Fed’n of Teachers*, 251 F. Supp. 3d 1168 (S.D. Tex. 2017), https://www.aft.org/sites/default/files/settlementagreement_houston_100717.pdf [<https://perma.cc/3V2V-NHM7>].

long-term institutional services.²²² The state had relied on a proprietary algorithm used in setting individual budgets for claimants' required care and in calculating Medicaid benefits.²²³ Idaho initially argued that the methodology used by the non-learning algorithm was a "trade secret" and refused to disclose it to the plaintiffs unless they signed a confidentiality agreement.²²⁴ The court rejected that assertion, and the parties ultimately stipulated to a preliminary injunction under which Idaho agreed to make details about its budget calculation tool available to participants in the program upon request.²²⁵

The West Virginia Department of Health and Human Resources was also sued over its use of a non-learning algorithm that determined Medicaid recipients' budgets for the care they needed.²²⁶ When the algorithmically determined budgets resulted in significant benefits reductions for the plaintiffs, they filed a class action against the state agency. Because the plaintiffs had no way of knowing what criteria the algorithm had relied on to determine their budgets and therefore lacked meaningful opportunities to contest its determinations, they alleged violations of due process and sought to enjoin the use of the algorithm.²²⁷ The court agreed and issued a preliminary injunction prohibiting the algorithm's use, since the agency failed to disclose the algorithm's overarching methodology, the variables it used, or how it weighed these variables.²²⁸ The court lifted its injunction after West Virginia developed and made publicly available an alternative system that relied on identifiable matrices and allowed recipients to contest the accuracy of the variables and the overall use of the matrices.²²⁹

²²² See generally *K.W. v. Armstrong*, 298 F.R.D. 479, 494 (D. Idaho 2014); *Schultz v. Armstrong*, No. 3:12-CV-00058-BLW, 2012 WL 3201223 (D. Idaho Aug. 2, 2012). For a discussion of this litigation, see Bloch-Wehba, *supra* note 162, at 1279, 1296.

²²³ See Bloch-Wehba, *supra* note 162, at 1279.

²²⁴ *Id.*

²²⁵ *Id.* In subsequent litigation, the plaintiffs moved to certify a class of similarly situated individuals; the court granted the motion and expanded the injunction to reach the entire class. *K.W. v. Armstrong*, 298 F.R.D. 479, 494 (D. Idaho 2014). On appeal, the Ninth Circuit affirmed, holding that the district court did not abuse its discretion in finding that the notices informing the plaintiffs of the reduction in their benefits as a result of the algorithm's determinations failed to lay out properly the agency's rationale for the reductions. *K.W. ex rel. D.W. v. Armstrong*, 789 F.3d 962, 971–74, 976 (9th Cir. 2015).

²²⁶ *Michael T. v. Bowling*, No. 2:15-cv-09655, 2016 WL 4870284, at *1–4 (S.D. W. Va. Sept. 13, 2016), *modified sub nom.* *Michael T. v. Crouch*, 2018 WL 1513295 (S.D. W. Va. Mar. 26, 2018).

²²⁷ *Id.* at *4, *7–9.

²²⁸ *Id.* at *10–12, *15.

²²⁹ *Crouch*, 2018 WL 1513295, at *6–13; see also Bloch-Wehba, *supra* note 162, at 1276–79.

Individuals and advocacy groups in Arkansas, Michigan, Oregon, and Florida have also brought similar claims alleging constitutional or statutory process violations.²³⁰ In the majority of these suits, the plaintiffs were at least partially successful in obtaining either a court order in their favor or a settlement with the state government that stopped the use of the algorithm or required greater disclosure about its operations. It seems clear from the Idaho and West Virginia cases that government agencies will be on the shakiest of legal grounds when they disclose absolutely nothing about the algorithms they use. But both of those cases involved algorithms made up of a limited number of fully known variables that had been assigned specific weights.²³¹ It remains to be seen what courts will demand that states disclose when they rely on complex, machine-learning algorithms that are not easily or intuitively explainable. Given that due process calls for a balancing of factors by the courts,²³² it may be that the Houston school district case comes the closest to the potential outcomes in any future procedural due process challenges to the administrative use of machine-learning algorithms—where the ultimate judgment about the due process calculus and the balancing of interests at stake will be one for a jury to make.²³³

In addition to lawsuits raising procedural due process claims, administrative agencies that rely on machine-learning algorithms could possibly face objections based on federal antidiscrimination statutes, such as Title VI of the Civil Rights

²³⁰ See, e.g., *Barry v. Lyon*, 834 F.3d 706 (6th Cir. 2016); *Brandy C. v. Palmer*, No. 4:17cv226-RH/CAS, 2018 WL 4689464 (N.D. Fla. Sept. 29, 2018); Order on Motion for Preliminary Injunction, *C.S. v. Saiki*, No. 6:17-cv-00564-MC (D. Or. Apr. 19, 2017); *Cahoo v. SAS Inst. Inc.* (Cahoo I), 322 F. Supp. 3d 772, 786 (E.D. Mich. 2018), *aff'd in part, reversed in part*, 912 F.3d 887 (6th Cir. 2019); *Ark. Dep't of Human Servs. v. Ledgerwood*, 530 S.W.3d 336, 342–43 (Ark. 2017); *Bauserman v. Unemployment Ins. Agency*, No. 333181, 2019 WL 6622945 (Mich. Ct. App. Dec. 5, 2019); see also *AI Now Inst.*, *supra* note 60, at 7–9; *AI NOW INST.*, *supra* note 205, at 35–36; CTR. FOR DEMOCRACY & TECH., CHALLENGING THE USE OF ALGORITHM-DRIVEN DECISION-MAKING IN BENEFITS DETERMINATIONS AFFECTING PEOPLE WITH DISABILITIES (2020), <https://cdt.org/wp-content/uploads/2020/10/2020-10-21-Challenging-the-Use-of-Algorithm-driven-Decision-making-in-Benefits-Determinations-Affecting-People-with-Disabilities.pdf> [<https://perma.cc/S72V-V2YU>]; Kate Crawford & Jason Schultz, *AI Systems as State Actors*, 119 COLUM. L. REV. 1941, 1944–57 (2019).

²³¹ The cases discussed in Part I of this article addressing judicial use of algorithms are also obviously relevant to the administrative use of algorithms. Just as here, however, none of those cases addressed any truly *machine-learning* algorithms.

²³² Under current federal law, courts are expected to determine what procedural due process requires by balancing three factors: the interests of the private individual; the risk of erroneous decisions; and the interests of the government. See *Mathews v. Eldridge*, 424 U.S. 319, 334–35 (1976). For elaboration on due process balancing in the context of algorithmic tools, see *Coglianesi & Lehr*, *supra* note 1, at 40–42.

²³³ As noted, the algorithm at the center of the Houston case was also not a machine-learning one.

Act of 1964.²³⁴ The Due Process Clause of the Constitution's Fifth Amendment and the Equal Protection Clause of the Fourteenth Amendment also prohibit the federal and state governments, respectively, from engaging in intentionally discriminatory practices. If agencies are neglectful or malicious, they could certainly use machine-learning tools in ways that offend existing principles of constitutional or statutory law.²³⁵

Nevertheless, although it is possible for government agencies to deploy machine-learning algorithms in a manner that leads to judicial disapproval, it seems likely that the responsible use of machine learning will in most cases be accommodated under existing principles of U.S. law.²³⁶ Agencies obviously cannot expect to have their decisions unchallenged if they fail to provide any information about how a machine-learning system operates. But it would seem that, so long as agencies avoid stonewalling and provide perhaps even a modicum of transparency, many if not most agency uses of artificial intelligence could well withstand judicial scrutiny.²³⁷ Moreover, as AI tools generally gain more widespread use in the private sector, it is perhaps likely that members of the public will come to accept them more in the public sector too—if not even to expect that governmental institutions will rely on them.²³⁸

²³⁴ 42 U.S.C. § 2000d *et seq.* Title VI prohibits state and local governments that receive federal financial assistance from engaging in practices that have disparate impacts on protected classes. See 28 C.F.R. § 42.104(b)(2).

²³⁵ Other possible objections, for example, might purport to be based on the Fourth Amendment of the Constitution or on considerations of the Administrative Procedure Act (APA). See, e.g., Michael L. Rich, *Machine Learning, Automated Suspicion Algorithms, and the Fourth Amendment*, 164 U. PA. L. REV. 871 (2016) (arguing that using algorithms in police investigations could raise significant Fourth Amendment concerns that have yet to be examined by courts); Mulligan & Bamberger, *supra* note 55, at 782–83, 808–29 (raising the possibility that government actions that derive from machine learning might give rise to arbitrary and capricious claims under the APA). Even if such objections are raised, this does not mean that they will be found valid nor, even if found valid, that they will permanently block the application of machine learning to governmental administration. See, e.g., Steven M. Appel & Cary Coglianese, *Algorithmic Governance and Administrative Law*, in *THE CAMBRIDGE HANDBOOK OF THE LAW OF ALGORITHMS* (Woodrow Barfield ed., 2021) (“Governmental use of machine-learning algorithms—even to automate key governmental decisions—can be readily accommodated by current administrative law doctrines.”); Aziz Z. Huq, *Artificial Intelligence and the Rule of Law*, in *THE ROUTLEDGE HANDBOOK OF THE RULE OF LAW* (Michael Sevel ed., forthcoming) (“There is no reason to think that the problems besetting early adopters of a new governance tools will persist in later adoptions.”).

²³⁶ See generally Coglianese & Lehr, *supra* note 1; Coglianese & Lehr, *supra* note 13. For an argument that courts should demand more of the government when it uses AI tools, see Ashley Deeks, *The Judicial Demand for Explainable Artificial Intelligence*, 119 COLUM. L. REV. 1829 (2019).

²³⁷ See generally Coglianese & Lehr, *supra* note 1.

²³⁸ See Cary Coglianese, *Administrative Law in the Automated State*, 150 DÆDALUS 104, 113 (2021); Cary Coglianese & Katelyn Hefter, *From Negative to Positive AI Rights*, WM. & MARY BILL RIGHTS J. (forthcoming). Public acceptance of governmental

CONCLUSION

Although the day when a judge's role is fully supplanted by an algorithm is surely still one that is far in the future, if it should ever completely arrive,²³⁹ the building blocks that could eventually give rise to a world of increased use of artificial intelligence by governmental entities have already started to emerge in state and federal legal systems across the United States. The widespread adoption of risk assessment tools in criminal cases in courts at every level of government appears to reflect some tentative comfort with allowing algorithms to inform judicial decisions. Increasing digitization of records could potentially provide courts with troves of data for artificial intelligence programs that could analyze and possibly even facilitate automated adjudication. The growing adoption of online dispute resolution by some courts on an optional basis, as well as its use by private organizations, could also eventually make the public more comfortable with fully computerized and automated adjudication. The opportunities for successful application of artificial intelligence are perhaps even greater in administrative agencies, where government officials are already beginning to rely on machine-learning tools to inform enforcement decisions, allocate social services, and manage programs.

Overall, these tools appear to offer great promise. As with any tool, of course, if they are not used with care, they may create problems and generate conflict and litigation. Public concerns have already arisen over the use of algorithms in facial recognition software and in other uses in the criminal law system more generally. The few court cases decided to date, though, do not suggest that the judiciary will categorically disapprove of machine-learning tools—especially when they are responsibly designed and implemented and are not kept entirely secret. It is certainly beyond the limits of any kind of intelligence, human or artificial, to forecast with precision what the future will hold for governmental use of

use of AI could very well also extend to the reliance on automation for judging by courts. As Tim Wu has noted (albeit with some skepticism), "it is possible that our taste for human adjudication might be fleeting; perhaps it is akin to an old-fashioned taste for human travel agents." Tim Wu, *Will Artificial Intelligence Eat the Law? The Rise of Hybrid Social-Ordering Systems*, 119 COLUM. L. REV. 2001, 2023 (2019).

²³⁹ See, e.g., Dave Orr and Colin Rule, *Artificial Intelligence and the Future of Online Dispute Resolution 10* (unpublished manuscript), <http://www.newhandshake.org/SCU/ai.pdf> [<https://perma.cc/HL6X-YRN8>] ("We are still a long way away from giving an AI Lexis-Nexis access and then asking it to serve on the Supreme Court."); Wu, *supra* note 238, at 2008 (noting that "software remains in the early stages of replacing the law").

machine learning in the United States. Yet with the continued reliance on machine learning in other spheres of life, the public acceptability of, if not demand for, its use in the governmental sector may only increase.