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FROM NEGATIVE TO POSITIVE ALGORITHM RIGHTS

Cary Coglianese* and Kat Hefter**

In 1958, the British philosopher, Isaiah Berlin, delivered a lecture at Oxford in which he distinguished *negative* liberty from *positive* liberty.¹ The former refers to freedom from governmental action that constrains individual choice, while the latter demands access to governmental action that protects citizens and ensures their ability to pursue their own life plans.² Berlin's distinction tracks a similar negative-versus-positive dichotomy in legal rights, with U.S. constitutional law focusing almost exclusively on negative rights—that is, rights to be protected *from* the government.³ The Bill of Rights and the Fourteenth Amendment's rights to due process and equal protection limit the government's ability to take actions harming individuals or constraining their choices, such as over speech or religion.⁴ Much political and legal discourse in the United States emphasizes protecting individuals from governmental actions impinging on their liberty and harming their interests.⁵

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¹ See generally ISAIAH BERLIN, TWO CONCEPTS OF LIBERTY: AN INAUGURAL LECTURE DELIVERED BEFORE THE UNIVERSITY OF OXFORD ON 31 OCTOBER 1958 (1958).

² *Id.*

³ See, e.g., Aziz Huq, *Constitutional Rights in the Machine-Learning State*, 105 CORNELL L. REV. 1875, 1876 (2020) (“A deep skepticism of the state lies at the heart of American constitutionalism.”).

⁴ As Judge Richard Posner has noted, the U.S. Constitution “is a charter of negative rather than positive liberties. . . . The men who wrote the Bill of Rights were not concerned that government might do too little for the people but that it might do too much to them.” Jackson v. City of Joliet, 715 F.2d 1200, 1203 (7th Cir. 1983).

⁵ This is not to say that some scholars and advocates have not proposed positive constitutional rights. See generally, e.g., Michael J. Gerhardt, *The Ripple Effects of Slaughter-House: A Critique of a Negative Rights View of the Constitution*, 43 VANDERBILT L. REV. 409 (1990). Rather, it is simply to note that the general thrust of constitutional discourse in the United States has been focused on negative rights, with the Constitution viewed primarily as a shield to protect against state interference with the individual. See generally, e.g., David P. Currie, *Positive and Negative Constitutional Rights*, 53 U. CHI. L. REV. 864 (1986).

With a constitutional tradition deeply rooted in negative rights, it is hardly surprising that much contemporary political and legal discourse surrounding artificial intelligence (AI) and its use by the government has sought, in a negative rights fashion, to protect individuals from governmental use of this technology.⁶ Critics of AI seek to keep this technology from intruding on individuals' liberty and equal treatment—that is, they advocate for a negative right of individuals to be free from having AI or machine-learning algorithms used to augment or replace human judgment by government officials.⁷ A growing movement opposed to algorithmic governance in the United States—and, frankly, around the world—focuses on the dangers posed by governmental action that misuses or abuses these digital tools. This movement seeks to protect individuals from governmental action based on algorithmic tools,⁸ and its adherents even call for banning the use of AI and preserving what some have called a right to a human decision.⁹

These calls for limitations on governmental use of AI are certainly understandable given that the irresponsible or abusive use of algorithmic tools can result in harm, whether from biases or other errors in the automated algorithmic tools or from the tools' ability to help illiberal governmental officials deploy governmental power unjustly.¹⁰ To prevent harms and abuses from the use of algorithmic tools, a negative rights approach that places limits on this use may well be appropriate at the present time.

But even if so, it remains undeniable that the status quo—a world that depends on human-based decision-making—is also far from ideal.¹¹ Human decision-making

⁶ For general background on the constitutional conception of negative and positive rights, see Currie, *supra* note 5.

⁷ A negative rights approach is expressed in proposed legislation introduced at all levels of government in the United States. *See, e.g.*, Justice Against Malicious Algorithms Act of 2021, H.R. 5596, 117th Cong. (2021); H. 263, 2021 Gen. Assemb., Reg. Sess. (Vt. Feb. 12, 2021); *AG Racine Introduces Legislation to Stop Discrimination in Automated Decision-Making Tools that Impact Individuals' Daily Lives*, OFF. OF THE ATT'Y GEN. FOR D.C. (Dec. 9, 2021), <https://oag.dc.gov/release/ag-racine-introduces-legislation-stop>.

⁸ For example, in *Houston Fed'n of Tchrs., Loc. 2415 v. Houston Indep. Sch. Dist.*, 251 F. Supp. 3d 1168 (S.D. Tex. 2017), public school teachers argued that their public employer's use of a machine-learning algorithm to grade their performance was a violation of due process and equal protection rights. The case eventually settled, and the school discontinued its use of the software. *Id.* at 1183 n.8.

⁹ *See generally* Aziz Z. Huq, *A Right to a Human Decision*, 106 VA. L. REV. 611 (2020); *cf.* Margot E. Kaminski & Jennifer M. Urban, *The Right to Contest AI*, 121 COLUM. L. REV. 1957 (2021) (describing a similar, related right to contest AI-based decisions).

¹⁰ *See* Clare Garvie, *Garbage In, Garbage Out: Face Recognition on Flawed Data*, GEO. L. CTR. PRIV. & TECH. (May 16, 2019), <https://www.flawedfacedata.com/>; Laura Moy, *Facing Injustice: How Face Recognition Technology May Increase the Incidence of Misidentifications and Wrongful Convictions*, 30 WM. & MARY BILL RTS. J. 337 (2021).

¹¹ *See* Cary Coglianese & Alicia Lai, *Algorithm vs. Algorithm*, 72 DUKE L.J. 1281, 1288–1304 (2022) (discussing the wide range of factors that detract from human decision-making, including individual cognitive biases and collective decision-making challenges);

has perpetuated many injustices. Moreover, the implicit biases embedded in human decision-making can be even more difficult to identify and eradicate than any associated with the use of algorithms.¹² As a result, a negative right for individuals to be free of AI-based decisions will leave individuals still susceptible to imperfect and potentially unjust decisions made by humans with their own deeply engrained biases, cognitive limitations, and group decision-making pathologies. Given the undesirable aspects of the status quo, a full consideration of the use of AI by government ought to take into account whether individuals have, or should have at some point, an expectation that the government affirmatively rely on algorithmic tools when making decisions that affect them. In other words, we might ask if, in the future, members of the public might justifiably come to expect a *positive* right to governmental use of algorithmic tools that overcome the limitations of human decision-making.

We consider this issue here and suggest that the current calls for a negative right to be free from AI could very well transform over time into positive claims that demand the use of algorithmic tools by government officials.¹³ In Part I, we begin

Eric Colson, *What AI-Driven Decision Making Looks Like*, HARV. BUS. REV. (July 8, 2019), <https://hbr.org/2019/07/what-ai-driven-decision-making-looks-like> (comparing AI-driven decisions to the “all too human” errors that affect decision-making, including cognitive bias). On limitations to human judgment more generally, see, e.g., DANIEL KAHNEMAN, OLIVIER SIBONY & CASS R. SUNSTEIN, *NOISE: A FLAW IN HUMAN JUDGMENT* (2021); William M. Grove & Paul E. Meehl, *Comparative Efficiency of Informal (Subjective, Impressionistic) and Formal (Mechanical, Algorithmic) Prediction Procedures: The Clinical-Statistical Controversy*, 2 PSYCH., PUB. POL. & L. 293 (1996).

¹² With digital algorithms, uncovering algorithmic bias is a matter of statistics; models can be mathematically tweaked or given constraints that will alter their outcomes. Human motivations and intentions, by contrast, are much harder to uncover and more challenging to combat. See, e.g., Coglianese & Lai, *supra* note 11, at 1314 (explaining why “digital algorithms can be easier to debias” than humans); Sendhil Mullainathan, *Biased Algorithms Are Easier to Fix Than Biased People*, N.Y. TIMES (Dec. 6, 2019) (describing the process of “uncovering algorithmic discrimination” as “a statistical exercise” that is “far more straightforward” than uncovering and eradicating human prejudice); Alex Miller, *Want Less-Biased Decisions? Use Algorithms*, HARV. BUS. REV. (July 26, 2018), <https://hbr.org/2018/07/want-less-biased-decisions-use-algorithms> (collecting examples showing that digital algorithms can be developed that overcome the biases in human decision-making).

¹³ As should be evident from the discussion that follows, we conceive of the negative-versus-positive rights dichotomy in more than just constitutional terms. Sometimes negative-rights claims might well sound in constitutional terms, such as due process or equal protection, but the legal manifestation of such an approach might also take the form of statutory or regulatory law—or even just accepted good-government practices. Similarly, while it is plausible to conceive in constitutional terms of a positive right to algorithmic decision-making, such as when due process might demand the reliance on an AI tool if such a tool is demonstrably more fair than human decision-making, we also mean to include the possibility that a positive right could be based on other legal or policy grounds. A future of positive rights to algorithmic governance, thus, would not require any transformation in the U.S. constitutional tradition that has historically emphasized negative rights. Nor would it require that AI tools

by sketching the current landscape surrounding the adoption of AI by government. That landscape is characterized by strong activist and scholarly voices expressing a pronounced aversion to the use of digital algorithms—and taking a decidedly negative rights tone. In Part II, we show that, although aversion to complex technology might be understandable, that aversion is neither inevitable nor impossible to overcome. We offer several examples of advanced technologies and analytic techniques that in the past have emerged in the face of significant criticism, but which have come to be widely accepted. In fact, there now exists an affirmative expectation—even at times a legal one—that government should use these technologies when making consequential decisions affecting people’s interests.

Given the possibility of legal and, more broadly, public insistence on the use of at least certain kinds of advanced technologies, we put forward in Part III a set of factors that may help lead eventually to widespread acceptance of algorithmic technologies similar to the acceptance of the technologies discussed in Part II. We suggest that a path forward exists that might build a general acceptance of the use of algorithmic tools by governmental entities, a path that would represent a shift from present-day calls for negative-rights protections against AI to eventual positive-rights expectations that good government practices routinely involve the use of AI.

I. ALGORITHMIC HARMS AND NEGATIVE RIGHTS

Although the use of AI has become widespread over the past decade, especially in the private sector, this use increasingly meets resistance from a growing chorus of critics concerned about the fairness and transparency of algorithmic tools and the privacy of the data on which they rely.¹⁴ These concerns about the use of algorithmic tools by private sector actors tend to be amplified when governmental entities use these tools to make decisions affecting individual liberty or involving other fundamental interests. Critics making the case for freedom from governmental use of AI have already succeeded in banning or severely restricting at least some uses of it by public entities in various places throughout the United States.¹⁵ In this Part, our aim

be demanded as a matter of *constitutional* right. Instead, a positive right to governmental reliance on AI could manifest in statutory or regulatory rights or in widely accepted expectations of how government should operate.

¹⁴ See generally, e.g., Karen Yeung, *Algorithmic Regulation: A Critical Interrogation*, 12 REGUL. & GOVERNANCE 505 (2018); Aaron M. Bornstein, *Are Algorithms Building the New Infrastructure of Racism?*, NAUTILUS (Dec. 21, 2017), <https://nautil.us/are-algorithms-building-the-new-infrastructure-of-racism-6874/>; Julia Angwin et al., *Machine Bias*, PRO PUBLICA (May 23, 2016), <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing>; FRANK PASQUALE, BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION (2015); see also *infra* Section I.A.

¹⁵ A number of city ordinances, for example, have restricted the use of AI-based facial recognition software. See, e.g., S.F., Cal., Ordinance No. 103-19 (May 21, 2019); Bos., Mass., Ordinance 16-62 (June 24, 2020); Portland, Or., Ordinance No. 190113 (Sept. 9, 2020); New

is to highlight the criticisms to show that, while research and development in AI has blazed forward in recent years, a substantial degree of resistance has grown up alongside the technological advancements.

A. Alarm Bells Over Algorithms

Over the past decade, the private sector's deployment of AI has started to touch most people's lives on a regular basis. Apple has reported, for example, that more than 500 million people in 2018 used Siri, its AI personal assistant.¹⁶ In 2020, Google reported that about the same number were using its Google Assistant.¹⁷ AI routinely influences the content people see on internet browsers, social media, streaming services, and online shopping outlets.¹⁸ Banks, hospitals, and businesses alike rely on machine-learning algorithms for a variety of managerial tasks, including marketing and risk management.¹⁹

But in recent years, a growing chorus of journalists, activists, academics, and politicians have pushed back against the notion of governmental reliance on digital algorithms, raising alarm bells about their use.²⁰ Increasingly, civil rights groups warn of the dangers of these algorithms.²¹ The titles of popular books reflect this

Orleans, La., Ordinance No. 28559; Pittsburgh, Pa., Ordinance 2020-0647 (Sept. 22, 2020); cf. *infra* notes 59–60 and accompanying text.

¹⁶ *Siri Now Actively Used on More than 500M Devices, up from 375M in June*, APPLEINSIDER (Jan. 24, 2018), <https://appleinsider.com/articles/18/01/24/siri-now-actively-used-on-more-than-500m-devices-up-from-375m-in-june> [<https://perma.cc/SE79-9HQW>].

¹⁷ Lisa Eadicicco, *Google Assistant Now Has 500 Million Users, Rivaling Amazon Alexa*, BUS. INSIDER (Jan. 7, 2020, 1:00 PM), <https://www.businessinsider.com/google-assistant-500-million-users-challenges-amazon-alexa-2020-1> [<https://perma.cc/9VQG-XR9Z>].

¹⁸ See, e.g., Sara Brown, *Machine Learning, Explained*, MIT SLOAN SCH. MGMT. (Apr. 21, 2021), <https://mitsloan.mit.edu/ideas-made-to-matter/machine-learning-explained> [<https://perma.cc/PEG5-XERM>] (discussing a wide range of uses of AI in private sector).

¹⁹ Eleni Digalaki, *The Impact of Artificial Intelligence in the Banking Sector & How AI Is Being Used in 2021*, BUS. INSIDER (Feb. 2, 2022, 2:04 PM), <https://www.businessinsider.com/ai-in-banking-report>; Jessica Kent, *90% of Hospitals Have Artificial Intelligence Strategies in Place*, HEALTH IT ANALYTICS (Mar. 11, 2021), <https://healthitanalytics.com/news/90-of-hospitals-have-artificial-intelligence-strategies-in-place>; Rebecca Bakken, *Business Applications for Artificial Intelligence: An Update for 2020*, HARV. DIV. OF CONTINUING EDUC. (Mar. 18, 2019), <https://professional.dce.harvard.edu/blog/business-applications-for-artificial-intelligence-an-update-for-2020/>.

²⁰ See *infra* Section I.A.

²¹ See, e.g., Dillon Reisman et al., *Algorithms Are Making Government Decisions. The Public Needs to Have a Say*, ACLU (Apr. 10, 2018, 10:00 AM), <https://www.aclu.org/issues/privacy-technology/surveillance-technologies/algorithms-are-making-government-decisions>; *Civil Rights Group Calls for Strong Guardrails in Hiring Assessment Technologies*, NAACP LEGAL DEF. & EDUC. FUND (July 29, 2020), <https://www.naacpldf.org/press-release/civil-rights-groups-call-for-strong-guardrails-in-hiring-assessment-technologies/>; Letter from ACLU, Ctr. Race, Ineq. & L., The Just. Roundtable, The Leadership Conf. Educ. Fund, The

anxiety: *Weapons of Math Destruction*,²² *Automating Inequality*,²³ and *Algorithms of Oppression*, to name a few.²⁴ An award-winning documentary—*Coded Bias*—shows how AI tools “infringe dangerously on people’s liberties,”²⁵ offering a glimpse into a “scary” and “dystopian future” where “you can walk down the street[, be] labeled a terrorist, [and] then rounded up[,] arrested, and traumatized before anyone has a chance to prove your innocence.”²⁶

Among the criticisms of AI, three prominent concerns about algorithmic governance tend to dominate: a lack of transparency, insufficient accountability, and a propensity for unfairness or biased decision-making.²⁷ Taken together, these concerns provide the foundation for a negative rights approach to algorithms. After all, it is only because of the potential harms from algorithms that individuals might need to be protected from them.

Concerns about transparency, accountability, and bias derive in part from the fact that algorithmic tools can crowd out or substitute for human decision-making—and then can introduce their own problems.²⁸ The degree and nature of this substitution effect can vary depending on the type of algorithm, and differences in the type of algorithm can also affect the degree or nature of the concerns.

Leadership Conf. Civ. & Hum. Rts., Media Mobilizing Project, and Upturn, to David B. Mulhausen, Director, Nat’l Inst. Just. (Sept. 3, 2019), <http://civilrightsdocs.info/pdf/policy/letters/2019/The%20Leadership%20Conference%20et%20al%20Comment%20Letter%20to%20Department%20of%20Justice%20on%20PATTERN%20%20First%20Step%20Act%209%203%202019.pdf> [<https://perma.cc/P2F8-GYL4>].

²² CATHY O’NEIL, *WEAPONS OF MATH DESTRUCTION* (2016).

²³ VIRGINIA EUBANKS, *AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR* (2018).

²⁴ SAFIYA UMOJA NOBLE, *ALGORITHMS OF OPPRESSION* (2018).

²⁵ Devika Garish, ‘*Coded Bias*’ Review: *When the Bots Are Racist*, N.Y. TIMES (Nov. 11, 2021), <https://www.nytimes.com/2020/11/11/movies/coded-bias-review.html> [<https://perma.cc/VJX4-RCU4>].

²⁶ Valerie Complex, ‘*Coded Bias*’: *Film Review*, VARIETY (Feb. 12, 2020, 7:03 PM), <https://variety.com/2020/film/reviews/coded-bias-review-1203502855/> [<https://perma.cc/J8Y3-RBWA>].

²⁷ This trio of concerns has even been encapsulated in the name of an annual computer science conference on “fairness, accountability, and transparency” launched in 2018. ACM CONF. ON FAIRNESS, ACCOUNTABILITY, & TRANSPARENCY (ACM FACCT), <https://facctconference.org/2021/index.html> [<https://perma.cc/GB5C-7KVS>] (last visited Apr. 26, 2022).

²⁸ This point is axiomatic. After all, as Nick Bostrom has observed, if an AI system were to be “kept in complete physical and informational isolation,” then “such an isolated system would be rather useless.” NICK BOSTROM, *SUPERINTELLIGENCE: PATHS, DANGERS, STRATEGIES* 131 (2014). It is only when digital systems are useful, in the sense of influencing or replacing human decision-making, that they will make a difference and thereby raise concerns. *Cf.* *State v. Loomis*, 881 N.W.2d 749, 764 (Wis. 2016) (upholding a state court’s use of a risk assessment algorithm in criminal sentencing against a due process challenge because the algorithm was not “determinative” and therefore did not displace human judgment).

In the most general sense, an algorithm is simply a “step-by-step procedure for solving a problem or accomplishing some end.”²⁹ The term “algorithm” is often used interchangeably with the terms “artificial intelligence” and “machine learning” because these techniques or technologies rely on particular kinds of sophisticated algorithms, namely those which rely on computer-driven methods to derive relational information from different variables.³⁰ But algorithms can also be specified entirely by humans instead of computers.³¹ Indeed, whenever people follow a recipe in a cookbook or apply laws and procedures in a courtroom, they are following human-specified algorithms.³²

Even when computers are involved, algorithms can still be fully specified by humans; the computers just carry out the steps. For instance, the traffic signals on street corners can rely on computers to change their lights from red to green without humans needing to flip a switch. But they still can follow human-specified instructions that dictate their timing, such as to change color every three minutes during the morning rush hour and then every five minutes during the rest of the day. In such instances, the computer merely tracks the time and transmits electronic pulses so that the lights follow the human-specified instructions.

A more complex traffic-signaling algorithm—but one still influenced by humans—could specify the timing of light changes by assigning predetermined weights to inputs provided by the activation of pedestrian buttons and embedded street sensors that detect the presence of vehicles. In either case, the traffic lights, while operating automatically, still rely on algorithms fully specified by humans and expressed in reasonably comprehensible terms.

²⁹ *Algorithm*, MERRIAM-WEBSTER DICTIONARY, <https://www.merriam-webster.com/dictionary/algorithm> (last visited Apr. 26, 2022); see also MELANIE MITCHELL, *ARTIFICIAL INTELLIGENCE: A GUIDE FOR THINKING HUMANS* 28 (2019) (“Perhaps the most important term in computer science is algorithm, which refers to a ‘recipe’ of steps a computer can take in order to solve a particular problem.”).

³⁰ See Brown, *supra* note 18 (“When companies today deploy artificial intelligence programs, they are most likely using machine learning—so much so that the terms are often used interchangeably.”). For accessible introductions to artificial intelligence, see MITCHELL, *supra* note 29, and David Lehr & Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. DAVIS L. REV. 653 (2017).

³¹ As noted above, an algorithm in its basic form is a set of procedures or processes. Non-digital algorithms include mathematical functions, recipes, and even steps for assembling furniture. See *supra* note 29 and accompanying text.

³² It should be noted that many of the benefits of legal rules, as well as the limitations, can be ascribed to any computerized system that relies on algorithms. Digital algorithms, like the rule of law, can provide consistency and cut down on decision costs. But they can also face the same risks of over- and under-inclusiveness that confront legal decisions based on inflexible application of rules. The creators of digital algorithms, like judges, may be slow to adapt to rapidly shifting trends. Similarly, digital algorithms, like law, could have biases baked into them that make them inappropriate for use in novel situations. Of course, because they depend on data and involve analysis, the problems with digital algorithms may be more easily identified and their errors may be easier to correct on a systemic level.

By contrast, a more complex algorithm might take the form of a traditional statistical model—such as an ordinary least squares regression equation—by which the weights placed on different variables are *not* determined in advance by humans. Humans do select the variables to be included in such conventional analysis, and they make assumptions about the underlying shape of the distribution of these variables in the population.³³ They also preselect the form of the mathematical relationship—such as a linear one—between dependent (or outcome) variables and independent (or explanatory) variables.³⁴ As such, the algorithm’s form can be represented in a single, interpretable equation. Once that equation is specified, a computerized statistical program can be used to analyze a dataset to derive estimates of how much each explanatory variable contributes to the overall outcome.³⁵

A final type of algorithm—one that is commonly referred to as machine learning or AI—is still more complicated and much less easily interpretable. This is because, rather than humans specifying the variables and mathematical relationships between them to include in a statistical model, the machine-learning algorithm is set up to “allow the data themselves to dictate how information contained in *input* variables is put together to forecast the value of an *output* variable.”³⁶ Machine-learning algorithms take many forms—such as random forests and neural networks—but they share in common an automated learning property according to which the algorithm independently selects variables and relationships between them in accordance with the search instructions specified in the algorithm and the objective that the algorithm is told by humans to achieve.³⁷

Machine-learning algorithms have seen an increase in use in recent years because improvements in computing power have enabled them to discern patterns

³³ Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 GEO. L. J. 1147, 1156 (2017).

³⁴ See Rene Y. Choi et al., *Introduction to Machine Learning, Neural Networks, and Deep Learning*, 9 TRANSLATIONAL VISION SCI. TECH. 2020, at 6 (discussing popular forms of regression used in machine-learning, including linear and logistical regression).

³⁵ Because the weight of the explanatory variables is not determined by humans but through a software package, some computer scientists consider traditional parametric regression analysis to be a kind of machine learning. Here we will restrict our use of “machine learning” to non-parametric or learning algorithms.

³⁶ Coglianese & Lehr, *supra* note 33, at 1156–57 (emphasis in original). Sometimes machine learning means that the algorithmic process will choose the number of variables to be included in the analysis and assumptions about population distribution—so-called non-parametric algorithms—whereas other times this will involve even more autonomy in discerning patterns from the data, or what is known as “deep learning.” See Brown, *supra* note 18.

³⁷ See Choi et al., *supra* note 34, at 6–10 (discussing variety of machine-learning forms including neural networks, random forests, and deep learning); Brown, *supra* note 18 (discussing various types of machine-learning). Even the most advanced and autonomous deep learning algorithms that run on computers are still designed and operated by humans—and humans have control at least in deciding whether to automate functions or decisions using these algorithms.

across large quantities of data, which in turn improves the accuracy of their forecasts.³⁸ At least two major cities, for example, now use traffic signaling systems that rely on machine-learning algorithms to determine when street lights turn red and green.³⁹ Rather than just having computers carry out human-specified intervals or follow human-specified weightings of predetermined input variables, these advanced systems rapidly process vast amounts of data fed to them in real time from street sensors throughout the entire city and then autonomously determine when lights should change to meet the algorithms' overarching objective of reducing traffic congestion.

Despite their demonstrated ability to improve forecasting accuracy in many settings, machine-learning algorithms' autonomous nature has generated a set of salient concerns about accountability, transparency, and fairness related to their use.⁴⁰ Because these algorithms identify patterns in data by using mathematical functions selected by a computer rather than a human analyst, machine learning accentuates existing concerns about a lack of accountability between government and members of the public. Legal scholar Karen Yeung even goes so far as to warn that “a wholesale shift towards algorithmic decision-making systems risks eroding the collective moral and cultural fabric upon which democracy and individual freedom rests, thereby undermining the social foundations of liberal democratic political order.”⁴¹

³⁸ See Kim Martineau, *What a Little More Computing Power Can Do*, MIT NEWS (Sept. 16, 2019), <https://news.mit.edu/2019/what-extra-computing-power-can-do-0916> [<https://perma.cc/L49Z-4U94>] (noting that a drawback to AI is its “insatiable need for data and computing power . . . to process all that information”); Kate Saenko, *It Takes a Lot of Energy for Machines to Learn—Here’s Why AI Is So Power Hungry*, THE CONVERSATION (Dec. 14, 2020, 2:41 PM), <https://theconversation.com/it-takes-a-lot-of-energy-for-machines-to-learn-heres-why-ai-is-so-power-hungry-151825> [<https://perma.cc/E739-AGHU>] (noting that computing ability caused AI models to become “much bigger than they need to be”); Choi et al., *supra* note 34, at 10 (discussing the importance of large data sets in improving AI accuracy in the medical field); Brown, *supra* note 18 (“The more data, the better the program.”).

³⁹ Ian Lovett, *To Fight Gridlock, Los Angeles Synchronizes Every Red Light*, N.Y. TIMES (Apr. 1, 2013), <https://www.nytimes.com/2013/04/02/us/to-fight-gridlock-los-angeles-synchronizes-every-red-light.html>; G. WANHOO LEE, IBM CTR. FOR THE BUS. OF GOV'T, *CREATING PUBLIC VALUE USING THE AI-DRIVEN INTERNET OF THINGS* (2021), <https://www.businessofgovernment.org/sites/default/files/Creating%20Public%20Value%20using%20the%20AI-Driven%20Internet%20of%20Things.pdf> (providing case study of Pittsburgh's automated traffic control system).

⁴⁰ See *supra* notes 20–27 and accompanying text; Elizabeth E. Joh, *Artificial Intelligence and Policing: First Questions*, 41 SEATTLE U. L. REV. 1139, 1140 n.5 (2018); Yeung, *supra* note 14, at 517 (expressing “concerns about the implications of the algorithmic turn for the collective values of transparency and accountability”).

⁴¹ Yeung, *supra* note 14, at 505–23; see also Dorothy Roberts, *Digitizing the Carceral State*, 132 HARV. L. REV. 1695, 1722 (2019) (reviewing VIRGINIA EUBANKS, *AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR* (2018))

Exacerbating the problem of accountability can be some distinctive limitations related to the transparency of machine-learning algorithms. The outputs of these algorithms cannot be as readily or intuitively explained compared to other types of statistical algorithms.⁴² They do not afford analysts a basis for making the kinds of causal claims often used to justify governmental decisions.⁴³ As a result of their relative opacity and incomprehensibility, these algorithms are often said to operate in a “black box” fashion⁴⁴—a property that can present acute concerns when they are deployed in governmental settings where transparency has long been desired.

Furthermore, because machine-learning algorithms tend to operate inductively—that is, by searching for patterns within existing data—they run the risk of reinforcing preexisting racial and gender biases that might be contained in the data from which the algorithms “learn.”⁴⁵ For this reason, many scholars and advocates have warned about the disparate impacts that may result from governmental reliance on machine learning.⁴⁶ Digital researcher Kate Crawford, for example, has noted that using machine-learning tools to target “police activity on particular big data-detected ‘hot spots’ runs the danger of reinforcing stigmatized social groups as likely criminals and institutionalizing differential policing as a standard practice.”⁴⁷

Although these concerns about accountability, transparency, and fairness arise acutely in the context of machine-learning algorithms—given the greater inherent

(“Some government decisions simply should not be automated at all because automation itself makes adjudication undemocratic.”).

⁴² Brown, *supra* note 18 (“One area of concern is what some experts call explainability, or the ability to be clear about what the machine learning models are doing and how they make decisions.”). *But cf.* Johan Egbert (Hans) Korteling et al., *Human-versus Artificial Intelligence*, 4 FRONTIERS A.I. 2021, at 7 (warning that “demanding explainability, observability, or transparency may cause artificial intelligent systems to constrain their potential benefit for human society, to what can be understood by humans”).

⁴³ See Korteling et al., *supra* note 42, at 7 (“Based on large quantities of data, the network learns to recognize patterns and links to a high level of accuracy and then connect them to courses of action without knowing the underlying causal links.”).

⁴⁴ See, e.g., PASQUALE, *supra* note 14, at 3 (using the “black box” label to describe “a system whose workings are mysterious; we can observe its inputs and outputs, but we cannot tell how one becomes the other”).

⁴⁵ See Solon Barocas & Andrew D. Selbst, *Big Data’s Disparate Impact*, 104 CAL. L. REV. 671, 680 (2016); Melissa Hamilton, *The Sexist Algorithm*, 37 BEHAV. SCI & L. 145, 146 (2019).

⁴⁶ See generally, e.g., Barocas & Selbst, *supra* note 45; Moy, *supra* note 10 (discussing disparate impacts of using facial recognition in law enforcement); McKenzie Raub, *Bots, Bias, and Big Data: Artificial Intelligence, Algorithmic Bias and Disparate Impact Liability in Hiring Practices*, 71 ARK. L. REV. 529 (2018) (discussing disparate impacts of AI use in hiring practices).

⁴⁷ Kate Crawford, *Think Again: Big Data*, FOREIGN POL’Y (May 9, 2013), http://www.foreignpolicy.com/articles/2013/05/09/think_again_big_data; see also Kate Crawford & Jason Schultz, *Big Data and Due Process: Toward a Framework to Redress Predictive Privacy Harms*, 55 B.C. L. REV. 93 (2014).

challenges in understanding exactly how they arrive at the outputs that they do—critics of digital algorithms have often leveled these same charges against other, simpler types of algorithms, even ones that are not based on machine learning at all.⁴⁸ In short, these various concerns about digital algorithms of any form constitute the foundation for the present-day negative rights orientation toward automation in government.

B. Challenges and Limits

Critics' concerns about governmental use of algorithms have led to proposed prohibitions and limitations framed in terms of constitutional rights.⁴⁹ White House officials in the Biden Administration, for example, have explicitly invoked the Bill of Rights in their call for protections from AI technology:

Soon after ratifying our Constitution, Americans adopted a Bill of Rights to guard against the powerful government we had just created . . . Throughout our history we have had to reinterpret, reaffirm, and periodically expand these rights. In the 21st century, we need a “bill of rights” to guard against the powerful technologies we have created.⁵⁰

Similarly, legal scholar Danielle Citron has argued that governmental use of algorithmic tools “jeopardizes the due process guarantees of meaningful notice and opportunity to be heard.”⁵¹ Others have argued that individuals have an equal protection right to be free from decisions based on algorithms that incorporate racial characteristics as input variables.⁵² Still others have recommended adapting existing constitutional frameworks, creating statutory protections, or even just adopting best

⁴⁸ Cary Coglianese & Lavi M. Ben Dor, *AI in Adjudication and Administration*, 86 BROOK. L. REV. 791, 801–06 (2021) (explaining that controversial risk assessment algorithms used in the criminal law context are not machine-learning algorithms).

⁴⁹ See Huq, *supra* note 9, at 625–27 (noting but not endorsing the view that a right to a human decision—and hence a negative constitutional right to be protected from algorithmic decisions “emerges as an unexpected implication of the Constitution’s protections of the jury trial right and due process”). Such a right to a human decision is expressly provided in European Union law, where Section 22 of the General Data Protection Regulation recognizes a “right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her.”

⁵⁰ Eric Lander & Alondra Nelson, *Americans Need a Bill of Rights for an AI-Powered World*, WIRED (Oct. 8, 2021, 8:00 AM), <https://www.wired.com/story/opinion-bill-of-rights-artificial-intelligence/>.

⁵¹ Danielle Keats Citron, *Technological Due Process*, 85 WASH. L. REV. 1249, 1305 (2008).

⁵² See, e.g., Sonja B. Starr, *Evidence-Based Sentencing and the Scientific Rationalization of Discrimination*, 66 STAN. L. REV. 803, 836–41 (2014); Dawinder S. Sidhu, *Moneyball Sentencing*, 56 B.C. L. REV. 671, 675, 694–99 (2015).

practices as ways to limit the harms from algorithms and protect individuals from these harms.⁵³

All of these calls—whether grounded in constitutional law or other norms—reflect a negative rights posture toward governmental reliance on algorithms. These calls aim to protect people *from* algorithms and their harms.

The negative rights approach has reached its zenith in instances where the use of algorithmic tools has been banned altogether. In the United States, proposed and enacted statutory bans have already been applied to governmental use of facial recognition technology, which relies on machine-learning algorithms.⁵⁴ Opposition to facial recognition technology took on a new dimension after a study revealed that an algorithm used by a number of police departments disproportionately misclassified women and people with darker skin.⁵⁵ Research commissioned by the ACLU subsequently found that a facial recognition algorithm falsely matched twenty-eight congressional representatives with mugshots, again disproportionately misclassifying people of color.⁵⁶ Based on these and other studies,⁵⁷ as well as general privacy concerns, advocates have called for law enforcement agencies to cease their use of

⁵³ See, e.g., Huq, *supra* note 3, at 1948 (outlining “needful regulatory frameworks for promoting a machine-learning state under the rule of law”); Joshua A. Kroll et al., *Accountable Algorithms*, 165 U. PA. L. REV. 633, 699 (2017) (arguing that “lawmakers and policymakers need to recognize and adapt to the changes wrought by algorithmic decisionmaking” and noting “both new opportunities and new challenges for the development of legal regimes governing decisionmaking”); see also Algorithmic Accountability Act, S. 1108, 116th Cong. § 3(b)(1)(A) (2019) (proposed legislation that would require certain private actors to develop “automated decision system impact assessments” related to their use of digital algorithms).

⁵⁴ See, e.g., Kate Conger et al., *San Francisco Bans Facial Recognition Technology*, N.Y. TIMES (May 14, 2019), <https://www.nytimes.com/2019/05/14/us/facial-recognition-ban-san-francisco.html> [<https://perma.cc/5LNM-LKX8>]; Dave Gershgor, *Maine Passes the Strongest State Facial Recognition Ban Yet*, THE VERGE (June 30, 2021, 1:49 PM), <https://www.theverge.com/2021/6/30/22557516/maine-facial-recognition-ban-state-law> [<https://perma.cc/AUD3-5NJD>]; *Facial Recognition Technology Ban Passed by King County Council*, KING COUNTY.GOV (June 1, 2021), <https://kingcounty.gov/council/mainnews/2021/June/6-01-facial-recognition.aspx> [<https://perma.cc/5PAG-2ABB>].

⁵⁵ Joy Buolamwini & Timnit Gebru, *Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification*, 81 PROC. MACH. LEARNING RSCH. 1, 9 (2018).

⁵⁶ Jacob Snow, *Amazon’s Face Recognition Falsely Matched 28 Members of Congress With Mugshots*, ACLU (July 26, 2018, 8:00 AM), <https://www.aclu.org/blog/privacy-tech-technology/surveillance-technologies/amazons-face-recognition-falsely-matched-28> [<https://perma.cc/DKT2-A6Z5>].

⁵⁷ See PATRICK GROTH ET AL., NISTIR 8280 FACE RECOGNITION VENDOR TEST PART 3: DEMOGRAPHIC EFFECTS, NIST 2 (2019), <https://nvlpubs.nist.gov/nistpubs/ir/2019/NIST.IR.8280.pdf> (showing that facial recognition software processing law enforcement data exhibited higher false positive rates for Asian and Black faces); PETE FUSSEY & DARAGH MURRAY, INDEPENDENT REPORT ON THE LONDON METROPOLITAN POLICE SERVICE’S TRIAL OF LIVE FACIAL RECOGNITION TECHNOLOGY 125 (HUM. RTS. DATA PROJECT 2019) (finding that over eighty percent of facial recognition suspects flagged by the London Metropolitan Police were innocent).

facial recognition technology—or at least to adhere to strict standards for its use.⁵⁸ At least seven states and nearly two dozen cities have banned or significantly limited governmental use of facial recognition.⁵⁹ Other legislative bodies at the local, state, and federal levels continue to consider additional limits on the use of facial recognition tools.⁶⁰

Similar proposals have been put forward to limit the use of algorithms in bail and sentencing decisions. A widely used algorithmic tool known as COMPAS came under fire in 2016 when a ProPublica article pointed to racial disparities in its sentencing recommendations.⁶¹ COMPAS, which appears to be a fully human-specified algorithm rather than a machine-learning one,⁶² reportedly flags Black defendants as future criminals at twice the rate of White defendants.⁶³ This finding has spurred a flurry of research papers on both sides of a debate over the use of risk assessments in criminal proceedings.⁶⁴ COMPAS's creator, Northpointe, has responded by arguing that its algorithm is unbiased because both Black and White defendants identified as high risk go on to commit a future crime at the same rate.⁶⁵

From a mathematical standpoint, neither Northpointe nor ProPublica are entirely wrong, but their positions reflect differing ideas about the goal of fairness that should be applied in the use of algorithmic tools.⁶⁶ One goal seeks equality in the rate of false positives across groups, while another seeks equality in the estimated likelihood of recidivism for high-risk defendants.⁶⁷

⁵⁸ Garvie, *supra* note 10.

⁵⁹ Julie Carr Smyth, *States Push Back Against Use of Facial Recognition by Police*, ABC NEWS (May 5, 2021, 5:32 PM), <https://abcnews.go.com/Politics/wireStory/states-push-back-facial-recognition-police-77510175> [<https://perma.cc/W9M2-J49J>].

⁶⁰ Members of Congress, for example, recently introduced the Facial Recognition and Biometric Technology Moratorium Act of 2021, which could prohibit real-time facial recognition and remote surveillance. *See* S. 2052, 117th Cong. (2021).

⁶¹ Angwin et al., *supra* note 14. COMPAS stands for Correctional Offender Management Profiling for Alternative Sanctions. *Id.*

⁶² *See* Coglianese & Lehr, *supra* note 33, at 1205 n.232.

⁶³ *Id.*

⁶⁴ *See, e.g.*, Matias Barenstein, ProPublica's COMPAS Data Revisited (2019) (research paper), ArXiv 1906.04711, <https://arxiv.org/pdf/1906.04711.pdf>; Melissa Hamilton, *The Sexist Algorithm*, 37 BEHAV. SCI & L. 145 (2019); *see generally* Anne Washington, *How to Argue with an Algorithm: Lessons from the COMPAS ProPublica Debate*, 17 COLO. TECH. L.J. 131 (2019) (collecting and analyzing scores of scholarly articles that have cited the ProPublica article).

⁶⁵ WILLIAM DIETRICH ET AL., COMPAS RISK SCALES: DEMONSTRATING ACCURACY, EQUITY, AND PREDICTIVE PARITY 8–9, 13 (Northpointe Inc. Rsch. Dep't 2016).

⁶⁶ For an especially illuminating discussion of different ways of conceptualizing equality in the context of algorithms, see Sandra Mayson, *Bias In, Bias Out*, 128 YALE L.J. 2218, 2238–51 (2019).

⁶⁷ Sam Corbett-Davies et al., *A Computer Program Used for Bail and Sentencing Decisions Was Labeled Biased Against Blacks. It's Actually Not That Clear.*, WASH. POST

The highest court to review COMPAS on the merits—the Wisconsin State Supreme Court—held that judges may legally consider COMPAS when deciding parole or sentencing.⁶⁸ The court did, however, articulate some caveats and suggested some potential limits on how algorithms could be used by judges. In particular, the court seemed to rest its decision in considerable part on the fact that COMPAS only *informed* a human judge’s decision rather than *substituted* for it entirely.⁶⁹ Activists, meanwhile, have taken little solace in such a distinction and have continued to push for an outright ban on the use of algorithmic risk assessment tools by criminal courts.⁷⁰

In addition to calls for banning facial recognition and the use of algorithmic risk assessment tools in criminal law proceedings, the negative rights approach to algorithmic automation can also be found in some state legislatures’ responses to fixed-in-place automated systems designed to enforce traffic laws. Although these systems need not involve any machine-learning algorithms, they do rely on advanced sensor technologies, such as red-light cameras or speed detectors affixed to poles, which connect with larger automated systems. These systems assess compliance with traffic rules and capture images of noncompliant vehicles which are integrated with information from automobile license databases, all of which in some jurisdictions will be reviewed by humans to confirm violations.⁷¹ These systems give states and localities the opportunity not only to detect violations but also to send car owners tickets automatically.⁷² Although legal and constitutional challenges to automated traffic enforcement have generally failed,⁷³ and many city and state

(Oct. 17, 2016), <https://www.washingtonpost.com/news/monkey-cage/wp/2016/10/17/can-an-algorithm-be-racist-our-analysis-is-more-cautious-than-propublicas/> [<https://perma.cc/E6DT-P9FW>]; see generally Mayson, *supra* note 66.

⁶⁸ See generally *State v. Loomis*, 881 N.W.2d 749 (Wis. 2016).

⁶⁹ *Id.* at 769–71.

⁷⁰ See, e.g., *The Use of Pretrial “Risk Assessment” Instruments: A Shared Statement of Civil Rights Concerns*, LEADERSHIP CONF. CIV. & HUM. RTS., <http://civilrightsdocs.info/pdf/criminal-justice/Pretrial-Risk-Assessment-Full.pdf> (“We believe that jurisdictions should not use risk assessment instruments in pretrial decisionmaking, and instead move to end secured money bail and decarcerate most accused people pretrial.”).

⁷¹ See generally *Red Light Running*, INS. INST. FOR HIGHWAY SAFETY, <https://www.iihs.org/topics/red-light-running> (last visited Apr. 26, 2022); Cecilia Wilson et al., *Speed Cameras for the Prevention of Road Traffic Injuries and Deaths (Review)*, 10 THE COCHRANE LIBR. (2010), <https://www.cochranelibrary.com/cdsr/doi/10.1002/14651858.CD004607.pub3/abstract>.

⁷² *Automated Enforcement Overview*, NAT’L CONF. STATE LEGIS. (Jul 21, 2020), <https://www.ncsl.org/research/transportation/automated-enforcement-overview.aspx>.

⁷³ See, e.g., *Knutson v. Village of Lakemoor*, 932 F.3d 572 (7th Cir. 2019) (failure to state a constitutional claim); *Behm v. City of Cedar Rapids*, 922 N.W.2d 524, 534 (Iowa 2019) (holding there was no violation of due process or equal protection); *Jimenez v. State*, 246 So. 3d 219 (Fla. 2018) (holding that state statute authorized local government to contract out review and assessment of red-light camera photos); see generally Matthew S. Maisel,

governments continue to rely on such fixed-in-place automated traffic enforcement tools,⁷⁴ adverse public opinion across the United States has led some state legislatures to consider banning the use of some of these systems.⁷⁵ Today, the laws of at least eleven states explicitly ban at least one kind of fixed-in-place automated traffic enforcement system, such as red-light cameras.⁷⁶

These three examples—facial recognition software, criminal law risk assessments, and red-light cameras—all represent concrete manifestations of a prevailing negative rights posture toward governmental use of digital algorithms. They illustrate that many policymakers, academic commentators, and members of the public today look upon algorithms with suspicion and see individuals as needing legal protection to be free from the ill effects of artificial intelligence.

C. *The Consequences of Negative Rights*

This negative rights view, of course, is far from absolute. Even some of the same scholars and commentators who have warned of the dangers of AI also recognize its potential to improve decision-making.⁷⁷ Nor has the negative rights movement halted the development and use of digital automation in society altogether. On the contrary, AI tools are being widely deployed in the private sector,⁷⁸ and public sector organizations exhibit a growing interest in their use.⁷⁹ One study released in 2020 by researchers from Stanford University and New York University found that federal agencies had developed over 150 distinct uses for algorithmic tools.⁸⁰

Although 150 uses may sound like a lot, the researchers found that the bulk of these uses fell in a category of research and analysis designed to “inform,” rather than to replace or even supplement, human decision-making.⁸¹ Moreover, only about

Slave to the Traffic Light: A Road Map to Red Light Camera Legal Issues, 10 RUTGERS J.L. & PUB. POL’Y 401 (2013).

⁷⁴ See *Automated Enforcement Overview*, *supra* note 72 (discussing how budget constraints lead “many local governments [to] turn[] to automated enforcement” for red-light and speed violations).

⁷⁵ For a state-by-state list of red-light and speeding laws, see *Automated Enforcement Laws*, INS. INST. HIGHWAY SAFETY, <https://www.iihs.org/topics/red-light-running/automated-enforcement-laws> [<https://perma.cc/48S2-9QA2>] (last visited Apr. 26, 2022).

⁷⁶ *Id.*; see also Christine Hauser, *Texas Is Latest State to Pump the Brakes on Red-Light Cameras*, N.Y. TIMES (June 8, 2019), <https://www.nytimes.com/2019/06/08/us/texas-cameras-red-lights.html> [<https://perma.cc/M7QQ-95VB>].

⁷⁷ Citron, *supra* note 51, at 1313 (“Automation has enormous potential to eliminate persistent errors in human-based systems and to produce consistent decisions.”); O’NEIL, *supra* note 22, at 216 (noting that “Big Data, when managed wisely, can provide important insights”).

⁷⁸ See *supra* notes 16–19 and accompanying text.

⁷⁹ Coglianese & Ben Dor, *supra* note 48, at 814–27.

⁸⁰ DAVID FREEMAN ENGSTROM ET AL., GOVERNMENT BY ALGORITHM: ARTIFICIAL INTELLIGENCE IN FEDERAL ADMINISTRATIVE AGENCIES 16 (2020), <https://www-cdn.law.stanford.edu/wp-content/uploads/2020/02/ACUS-AI-Report.pdf>.

⁸¹ *Id.* at 17.

fifty of the projects had been fully deployed.⁸² The researchers concluded that the federal government had “only scratched the surface” of the potential governmental uses for AI tools.⁸³ Similarly, when it comes to use of such tools by federal or state courts, notwithstanding the controversy surrounding criminal courts’ use of risk assessment algorithms, it remains that so far “no machine-learning tool . . . has been adopted in any court in the United States to make an ultimate, fully automated determination on a legal or factual question.”⁸⁴

The relatively slow pace of deployment of AI by governmental institutions compared with the private sector could simply be a function of the sluggish pace of technological development within the public sector in general.⁸⁵ But it may also be affected by the negative rights posture that dominates much discourse related to public use of AI tools. And yet, if a backlash against AI in the public sector is indeed slowing the pace of its development and use, this may not necessarily be best for society—especially if delaying automation merely leaves in place human-based systems that exhibit greater levels of bias, error, and delay.⁸⁶

Without a doubt, AI systems can be designed irresponsibly and can create problems too. But with careful evaluation and validation during the development stage, errors can be caught and mitigated. Indeed, in some instances, it may be far quicker and easier to eliminate errors with an algorithm than to wait for humans to adapt and improve their decision-making.⁸⁷

⁸² *Id.*

⁸³ *Id.* at 20.

⁸⁴ Coglianese & Ben Dor, *supra* note 48, at 798.

⁸⁵ See Tim Hwang, *The Government’s Failure to Keep Up with Technology Is Hurting All of Us*, GOV’T EXEC. (Dec. 6, 2017), <https://www.govexec.com/management/2017/12/governments-failure-keep-technology-hurting-all-us/144345/> [<https://perma.cc/G789-9BM8>]. But see Stuart Bretschneider, *Idea to Retire: Government Lags in Adopting Technology*, BROOKINGS INST. (Apr. 5, 2016), <https://www.brookings.edu/blog/techtank/2016/04/05/idea-to-retire-government-lags-in-adopting-technology/> [<https://perma.cc/F8K3-UY63>] (arguing that “[t]here is a general bias against the public sector” that assumes the government is slow to adapt to new technology).

⁸⁶ See Korteling et al., *supra* note 42, at 8 (noting that the best AI tools “will excel in areas where people are inherently limited,” including areas where cognitive bias and cognitive capacity like human’s limited ability to process large amounts of data quickly are factors); Coglianese & Lai, *supra* note 11, at 1288–1304 (discussing litany of human factors that contribute to poor decision-making); Colson, *supra* note 11 (further discussing human error and cognitive limitations).

⁸⁷ For just a few of many examples of efforts to debias digital algorithms, see generally Tolga Bolukbasi et al., *Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings*, in *ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS* 29 (D. Lee et al. eds., 2016) (examining how gender bias in embedded wording shapes online search results); Alexander Amini et al., *Uncovering and Mitigating Algorithmic Bias through Learned Latent Structure*, 2019 A.I., ETHICS & SOC’Y 289 (proposing a novel algorithm to assess latent variables in AI training data that result in bias); see also *supra* note 12 and accompanying text.

The human alternative to AI tools should hardly be thought of as a gold standard. As mentioned earlier, human-based governmental processes can be themselves opaque and subject to considerable inconsistencies and biases.⁸⁸ For example, notwithstanding the fairness and privacy concerns that have been raised against facial recognition software, the alternative of relying on humans to identify individuals is not without flaws. In fact, eyewitness testimony by humans is considered a leading cause of wrongful convictions today.⁸⁹ Similarly, although automated traffic enforcement systems may be disfavored or prohibited in some parts of the United States, traffic stops by police officers can be incredibly fraught with tensions that escalate to injuries and fatalities.⁹⁰

Human-based adjudicatory processes are prone to delays and inconsistent outcomes. In one analysis of immigration adjudication, for example, two judges denied asylum less than ten percent of the time, while another denied requests more than ninety percent of the time.⁹¹ Similarly, one Miami-based immigration judge denied asylum requests ninety-eight percent of the time, while another in the same office denied them only twenty-two percent of the time.⁹² Another study revealed that outcomes in refugee asylum cases varied depending on a variety of irrelevant factors, such as: “whether a hearing was before lunch or towards the end of the day; the size of the applicant’s family; the weather; the number of recent grants by the court; whether genocide has been in the news; and the date of the decision.”⁹³

These are hardly reassuring findings. Algorithmic decision-making, if done well, could actually reduce the arbitrariness of present-day adjudication and help improve the performance of myriad governmental tasks. Yet a negative right to be free from AI might prevent the responsible development and use of algorithms to complete governmental tasks. Negative rights—motivated by good intentions to protect individuals from harm—could end up only perpetuating harms from human decision-making. The human alternative to AI, after all, is not itself free from error or bias, nor does it guarantee the avoidance of unjust outcomes.⁹⁴

⁸⁸ See Coglianese & Lai, *supra* note 11, at 1288–1304; Colson, *supra* note 11.

⁸⁹ *Eyewitness Misidentification*, KY. DEP’T PUB. ADVOC., <https://dpa.ky.gov/home/about-dpa/who-we-are/kip/causes/misid/> [<https://perma.cc/G55R-ER5A>] (last visited Apr. 26, 2022).

⁹⁰ MALCOLM GLADWELL, *TALKING TO STRANGERS: WHAT WE SHOULD KNOW ABOUT THE PEOPLE WE DON’T KNOW* 1–4, 313–46 (2019); Marco Conner, *Traffic Justice: Achieving Effective and Equitable Traffic Enforcement in the Age of Vision Zero*, 44 *FORDHAM URB. L.J.* 969, 970–71 (2017); David D. Kirkpatrick et al., *Why Many Police Traffic Stops Turn Deadly*, *N.Y. TIMES* (Oct. 31, 2021), <https://www.nytimes.com/2021/10/31/us/police-traffic-stops-killings.html> [<https://perma.cc/G2UZ-JUWG>].

⁹¹ *Asylum Disparities Persist, Regardless of Court Location and Nationality*, TRAC IMMIGRATION (Sept. 24, 2007), <https://trac.syr.edu/immigration/reports/183/> [<https://perma.cc/RXS7-H3C6>].

⁹² *Id.*

⁹³ Daniel L. Chen, *Machine Learning and the Rule of Law*, in *LAW AS DATA 6* (M. Livermore & D. Rockmore eds., 2019).

⁹⁴ See *supra* notes 86–93 and accompanying text.

II. POSITIVE RIGHTS AND THE ACCEPTANCE OF TECHNOLOGY

The adverse consequences from a negative rights approach to AI need not be destined to occur. The current negative rights orientation to digital algorithms may well only be temporary, especially if criticisms of AI and threats of bans serve to provide the impetus for more careful application of AI tools by government. In fact, if the pathways of other previously distrusted technologies provide any guide, opposition to AI could very well dissipate with the passage of time and with the further responsible refinement of AI tools. The paths taken by other technologies and methods of analysis suggest a potential for AI tools to improve governmental decision-making and eventually become widely accepted as a best practice.

Of course, public acceptance and legal approval of new technology is never guaranteed—and the path to acceptance is not always smooth or short.⁹⁵ Yet other technologies that once drew skepticism have sometimes managed to become so accepted by both the courts and the public that they have become woven into the fabric of life and the law. Their use is now simply expected—if not even at times legally required. These technologies have, in effect, earned a positive-right status such that individuals must receive the benefits that they offer instead of being left vulnerable to the vagaries of unaided human decision-making. As a result, each of the three examples of technology that we trace here—namely, DNA analysis, breathalyzers, and radar speed detection—suggest the possibility of a path forward for governmental use of AI from negative to positive algorithm rights.⁹⁶

⁹⁵ See *infra* Sections II.A, II.B, and II.C.

⁹⁶ We do not mean to suggest that all technologies will achieve the status of the technologies and analytic techniques we describe in this Part. Some technologies might be accepted when they should not be, and others might not be accepted when they should be. But the general expectations for use of the technologies described in this Part are so deeply engrained that they have, at least in effect, largely achieved the status of a positive right. And beyond the examples mentioned here, other technological innovations—too numerous to list—have become enmeshed in everyday life, taken for granted and even expected by the public. To mention just one example that relates to individuals' contact with government, consider that the vast majority of drivers on toll roads in eastern states now use an electronic transponder system known as E-ZPass rather than pay with a human toll collector. See, e.g., Larry Higgs, *11% of Highway Drivers Don't Use E-ZPass. State Is Spending \$500K in Ads to Change That*, NJ.COM (Aug. 3, 2021), <https://www.nj.com/news/2021/08/11-of-highway-drivers-don-t-use-e-zpass-state-is-spending-500k-in-ads-to-change-that.html> (reporting approximately 88–89 percent usage rate of E-ZPass on New Jersey Turnpike Authority roads and 87 percent on New Jersey Port Authority roads); Michael Cousineau, *DOT Chief: State Driving Toward Cashless Tolls*, N.H. UNION LEADER (Nov. 15, 2018), https://www.unionleader.com/news/state-driving-toward-fewer-toll-booths-dot-chief/article_9506e009-c99b-5f12-883d-867cd966caeb.html (“About 75 percent of tolls in New Hampshire are paid with E-ZPass.”). The Massachusetts Turnpike eliminated all of its human-staffed toll booths and replaced them with a fully automated, cashless system. Katherine McNerney & Meghna Chakrabarti, *What to Know as the Mass. Pike Switches to All-Electronic Tolling*, WBUR (Oct. 28, 2016),

A. DNA Analysis

DNA was discovered in 1953.⁹⁷ It took another thirty years before government officials started using DNA analysis as a forensic tool in criminal investigations.⁹⁸ As the use of DNA tracing started to be relied upon in criminal prosecutions, it initially became “the subject of bitter disputes” in the courts, with defense lawyers repeatedly challenging its reliability.⁹⁹ A law review comment published in 1989 declared that “DNA print technology threatens to infringe on constitutionally guaranteed rights to procedural due process and individual privacy.”¹⁰⁰ Other legal commentators at the time reportedly took issue with “the sophistication of the technique” used to obtain DNA results.¹⁰¹

In 1992, a *New York Times* article declared that a National Research Council (NRC) report on DNA tracing “says it should not be allowed in court in the future unless a more scientific basis is established.”¹⁰² The NRC panel responded that the *Times* story “seriously misrepresented” its findings¹⁰³—it was not advocating a firm moratorium—but the panel did clearly make a case for recognizing the societal dangers of DNA technology. Moreover, the blue-ribbon scientific panel expressed

<https://www.wbur.org/radioboston/2016/10/26/electronic-tolling>. The public’s acceptance electronic toll collection has occurred notwithstanding expressions of concern about data privacy. See, e.g., Mariko Hirose, *Newly Obtained Records Reveal Extensive Monitoring of E-ZPass Tags Throughout New York*, ACLU (Apr. 24, 2015), <https://www.aclu.org/blog/privacy-technology/location-tracking/newly-obtained-records-reveal-extensive-monitoring-e-zpass>; Kashmir Hill, *E-ZPasses Get Read All Over New York (Not Just at Toll Booths)*, FORBES (Sept. 12, 2013), <http://www.forbes.com/sites/kashmirhill/2013/09/12/e-zpasses-get-read-all-over-new-york-not-just-at-toll-booths/>; Bruce Landis, *Every Time You Pass Through a Toll Booth, A Little Data Is Collected; A Little Bit of Your Privacy Is Lost*, PROVIDENCE J. (June 27, 2013).

⁹⁷ Francis Crick Papers: *The Discovery of the Double Helix, 1951–1953*, NAT’L LIB. MED., <https://profiles.nlm.nih.gov/spotlight/sc/feature/doublehelix> (last visited Apr. 26, 2022).

⁹⁸ The first use of DNA in support of a criminal conviction occurred in 1985 in the United Kingdom. Lauren Beeler & William Wiebe, Comment, *DNA Identification Tests and the Courts*, 63 WASH. L. REV. 903, 908 n.22 (1988).

⁹⁹ Gina Kolata, *U.S. Panel Seeking Restrictions on Use of DNA in Courts*, N.Y. TIMES (Apr. 14, 1992), <https://www.nytimes.com/1992/04/14/us/us-panel-seeking-restriction-on-use-of-dna-in-courts.html>; see also MICHAEL LYNCH ET AL., TRUTH MACHINE: THE CONTENTIOUS HISTORY OF DNA FINGERPRINTING 221 (2019) (noting that “DNA evidence was contested . . . as early as 1987,” even before the emergence of the widely observed “‘DNA wars’ of the early 1990s”).

¹⁰⁰ Anthony Pearsall, *DNA Printing: The Unexpected “Witness” in Criminal Trials*, 77 CAL. L. REV. 665, 676 (1989).

¹⁰¹ John Dougherty, *Beyond People v. Castro: A New Standard of Admissibility for DNA Fingerprinting*, 7 J. CONTEMP. HEALTH L. & POL’Y 269, 271 (1991).

¹⁰² Kolata, *supra* note 99.

¹⁰³ NAT’L RSCH. COUNCIL COMM. DNA TECH. FORENSIC SCI., DNA TECHNOLOGY IN FORENSIC SCIENCE, at x (1992).

its concerns in terms that resonate quite closely with concerns raised today about the use of AI:

The introduction of any new technology is likely to raise concerns about its impact on society. Financial costs, potential harm to the interests of individuals, and threats to liberty or privacy are only a few of the worries typically voiced when a new technology is on the horizon. DNA typing technology has the potential for uncovering and revealing a great deal of information that most people consider to be intensely private. . . . With greater understanding of the human genome, the potential of misuse of DNA samples collected or preserved for purposes of criminal justice will increase. The more databanks are established, the greater the risk of breaches of confidentiality and misuse of the information.¹⁰⁴

Although many courts nevertheless readily admitted DNA evidence into criminal proceedings, other courts did not.¹⁰⁵ In 1989, a New York state trial court conducted a twelve-week proceeding focused solely on providing “an intense and technical examination of DNA identification tests as applied to forensics.”¹⁰⁶ The trial court acknowledged widespread scientific acceptance of DNA, but it ultimately found that the laboratory that processed the DNA evidence put forward by the prosecution had “failed in its responsibility to perform the accepted scientific techniques and experiments in several major respects.”¹⁰⁷ The court, in an effort to protect the negative rights of the accused, denied the admissibility of the DNA evidence.

Much the same outcome followed a decision of the Minnesota Supreme Court, which similarly expressed early reservations about the use of DNA analysis.¹⁰⁸ As with the New York trial court, the Minnesota appellate court held that DNA analysis was inadmissible because of deficiencies in the reliability of underlying laboratory procedures.¹⁰⁹ The court also raised an argument against DNA technology similar to an argument raised today about AI’s potential lack of transparency, noting that

¹⁰⁴ *Id.* at 152.

¹⁰⁵ *See* Dougherty, *supra* note 101, at 270–72 (discussing studies documenting both the admissibility of DNA in many courts but also its inadmissibility or limited admissibility in others).

¹⁰⁶ *People v. Castro*, 545 N.Y.S. 985, 986 (Sup. Ct. 1989).

¹⁰⁷ *Id.* at 974.

¹⁰⁸ *State v. Schwartz*, 447 N.W.2d 422, 427 (Minn. 1989) (“Even if a laboratory has followed reliable procedures to ensure accurate test results, constitutional concerns may prevent the admissibility of such evidence. The fair trial and due process rights are implicated when data relied upon by a laboratory in performing tests are not available to the opposing party for review and cross examination.”).

¹⁰⁹ *Id.* at 428 (“[The] admissibility of specific test results in a particular case hinges on the laboratory’s compliance with appropriate standards and controls.”).

“trade secrets may be at stake for the commercial laboratories.”¹¹⁰ The court insisted that due process required the “availability of their testing data and results.”¹¹¹

Notwithstanding these early concerns about DNA analysis, today state and federal courts routinely treat DNA evidence not only as admissible but as highly reliable.¹¹² Such analysis is effectively considered the gold standard when it comes to evidentiary proof and is both accepted by courts and viewed favorably in the eyes of the public.¹¹³ Any initial skepticism about and resistance to DNA analysis has since evolved into an affirmative insistence that it be used.¹¹⁴

DNA analysis has proven instrumental, for example, in hundreds of exonerations of wrongfully convicted defendants.¹¹⁵ Statutes in all fifty states now effectively provide convicted individuals a positive right to request post-conviction DNA testing.¹¹⁶ The exact wording of these statutory provisions varies from state to state, with many states imposing conditions on the exercise of the right. But these statutes commonly require courts to grant a defendant’s post-conviction request for access to evidence for DNA testing when specified conditions are met, including when the defendant’s identity was an issue at trial, the evidence still exists, and there exists a reasonable probability that the defendant was actually innocent or would have

¹¹⁰ *Id.* at 427.

¹¹¹ *Id.* at 428.

¹¹² *Infra* notes 115–22 and accompanying text.

¹¹³ *See, e.g.,* Michael Lynch, *God’s Signature: DNA Profiling, The New Gold Standard in Forensic Science*, 27 ENDEAVOR 93, 93 (2003) (“Older forms of forensic evidence . . . which rely upon expert judgement and have limited connection to established science, are now called into question in comparison with the new ‘gold standard’ of DNA profiling.”); NAT’L RSCH. COUNCIL COMM. ON IDENTIFYING THE NEEDS OF THE FORENSIC SCI. CMTY., STRENGTHENING FORENSIC SCIENCE IN THE UNITED STATES: A PATH FORWARD 130 (Aug. 2009) (“Although the forensic use of nuclear DNA is barely 20 years old, DNA typing is now universally recognized as the standard against which many other forensic individualization techniques are judged.”).

¹¹⁴ The American Bar Association has adopted standards affirming that, “[c]onsistent with rights of privacy and due process, DNA evidence should be collected, preserved, tested, and used when it may advance the determination of guilt or innocence.” AM. BAR ASS’N, ABA STANDARDS FOR CRIMINAL JUSTICE Standard 1.2(b) (3d ed. 2007).

¹¹⁵ Since 1989, 375 people have been exonerated as a result of DNA evidence, and tens of thousands of people have been dismissed as suspects preconviction when DNA testing proved they were falsely accused. *DNA Exonerations in the United States*, INNOCENCE PROJECT, <https://innocenceproject.org/dna-exonerations-in-the-united-states/> (last visited Apr. 26, 2022).

¹¹⁶ *See* POST-CONVICTION DNA TESTING, NAT’L CONF. STATE LEGIS. (2013), <https://www.ncsl.org/Documents/cj/PostConvictionDNATesting.pdf>, for a state-by-state breakdown of post-conviction DNA testing laws. Although acknowledging that defendants enjoy procedural due process rights to DNA testing after conviction, the U.S. Supreme Court has rejected a freestanding substantive due process claim to post-conviction access to evidence for DNA analysis, relying in part on the fact that “[t]here is no long history of such a right.” *Dist. Att’y’s Off. v. Osborne*, 557 U.S. 52 (2009).

been acquitted based on the evidence from the DNA testing.¹¹⁷ The federal Innocence Protection Act further provides that a court “shall order DNA testing of specific evidence” under a similar set of conditions.¹¹⁸

In Washington, D.C., defendants charged with a violent crime have an additional pretrial right to request DNA testing if it has not already been completed, and they are also entitled to request an independent test if a test has already been completed.¹¹⁹ DNA testing is also now often mandated throughout the country in cases involving paternity disputes.¹²⁰ Its use has been similarly compelled in a variety of jurisdictions for assisting in the adjudication of other kinds of civil disputes.¹²¹

¹¹⁷ See, e.g., D.C. Code Ann. § 22-4133(a); 725 ILL. COMP. STAT. ANN. 5/116-3; KY. REV. STAT. ANN. § 422.285; MD. CODE ANN., CRIM. PROC. § 8-201; 42 PA. CONS. STAT. § 9543.1; TEX. CODE CRIM. PROC. ANN. art. 64.01(a). The last prong of this test, stated above in general terms of a reasonable probability of innocence, is actually more nuanced and applies when:

[T]he result of the testing has the scientific potential to produce new, noncumulative evidence (i) materially relevant to the defendant’s assertion of actual innocence when the defendant’s conviction was the result of a trial, even though the results may not completely exonerate the defendant, or (ii) that would raise a reasonable probability that the defendant would have been acquitted if the results of the evidence to be tested had been available prior to the defendant’s guilty plea and the petitioner had proceeded to trial instead of pleading guilty, even though the results may not completely exonerate the defendant.

725 ILL. COMP. STAT. ANN. 5/116-3.

¹¹⁸ 18 U.S.C. § 3600(a).

¹¹⁹ D.C. Code Ann. § 22-4132(b)(2). Similarly, the American Bar Association affirms that “[a] person charged with or convicted of a crime should be provided reasonable access to relevant DNA evidence and, if it has been tested, to the test results and their interpretation.” AM. BAR ASS’N, *supra* note 114 (Standard 1.2(e)). In addition, of course, the Supreme Court has held that defendants have a general pretrial right to exculpatory evidence, which can include access to DNA test results as well as evidence that can be subjected to DNA analysis. *Brady v. Maryland*, 373 U.S. 83 (1963); *United States v. Agurs*, 427 U.S. 97 (1976). This is not to say that *Brady* rights are sufficiently honored in practice. See, e.g., Daniel S. Medwed, *Brady’s Bunch of Flaws*, 67 WASH. & LEE L. REV. 1533 (2010).

¹²⁰ See, e.g., *Ashby v. Mortimer*, 328 F.R.D. 650, 656 (D. Idaho 2019) (granting motion to compel paternity DNA test when paternity is in controversy and motion is supported by good cause); *Turk v. Mangum*, 268 F. Supp. 3d 928, 939 (S.D. Tex. 2017) (granting motion to compel DNA test due to evidence of previous denial of paternity and failure to legally establish paternity prior to death of child); *In re Emily H. v. Gregory O.*, 68 N.Y.S. 302 (2017) (ordering testing of mother, child, and purported father to ascertain paternity). Such mandatory testing is specifically authorized by statute in some states. See, e.g., 750 ILL. COMP. STAT. 46/401; 23 PA. CONS. STAT. § 4343(c); MISS. CODE ANN. § 93-9-21; OHIO REV. CODE ANN. § 3111.09.

¹²¹ See, e.g., *McGrath v. Nassau Health Care Corp.*, 209 F.R.D. 55, 60–63 (E.D.N.Y. 2002) (holding that a court may order a party to provide a DNA sample during civil discovery when authority for the order exists, the party’s privacy interests are not unduly affected, and there is reasonable possibility of a match); *D’Angelo v. Potter*, 224 F.R.D. 300, 304 (D.

Over time, DNA tracing clearly has traveled a path from negative to positive. Initially confronting contestation and concern in its early years, DNA analysis is now commonplace in the courts and considered such a best practice that in some instances litigants have effectively acquired a right to its use.¹²²

B. Breathalyzers

Breathalyzer technologies have followed a path similar to that of DNA analysis, from initial resistance to general acceptance. The first practical breath alcohol test, called the Drunkometer, was invented in the 1930s (during Prohibition) by Rolla N. Harger, a biochemist at Indiana University.¹²³ After the repeal of Prohibition, a national committee was formed to study motor vehicle accidents,¹²⁴ ultimately drafting a model act that recommended Harger's method and established standards for blood alcohol levels.¹²⁵ This model law was subsequently adopted in some states.¹²⁶

Nevertheless, the Drunkometer was far from immediately accepted by the public or the courts. In 1949, the Michigan Supreme Court ruled against admitting Drunkometer test results, claiming that “[t]here is no testimony in the record that there is general acceptance by the medical profession or general scientific recognition of the results of a Harger Drunkometer test as accurately establishing the alcoholic content

Mass. 2004) (permitting compelled production of DNA sample as part of discovery in civil dispute over nonconsensual sexual contact).

¹²² See, e.g., Kerry Abrams & Brandon L. Garrett, *DNA and Distrust*, 91 NOTRE DAME L. REV. 757, 758 (2015) (“DNA testing has been embraced with enthusiasm by courts, legislatures, and agencies, state and federal, across areas of law ranging from criminal law, employment law, family law, and health law because it is easy to obtain and offers apparent certainty.”) This certainly does not mean that all controversy or concern about genetic analysis has been resolved; indeed, many still worry about the potential abuse of information collected from DNA analysis. See, e.g., *id.* at 813 (suggesting that there may be a need for “a freestanding right to genetic privacy, of the type recognized in other related areas, such as fundamental rights regarding family decisions and reproduction and due process rights concerning privacy and bodily integrity”). Privacy worries over DNA testing have also manifested in federal statutory protections against private actors’ use of genetic testing in making health insurance and employment decisions. See Federal Genetic Information Nondiscrimination Act of 2008, Pub. L. No. 110-233, 122 Stat. 881. For additional discussion, see generally *DNA AND THE CRIMINAL JUSTICE SYSTEM: THE TECHNOLOGY OF JUSTICE* (David Lazer, ed., 2004).

¹²³ Douglas Martin, *Rolla N. Harger Dies; Invented Drunkometer*, N.Y. TIMES (Aug. 10, 1983), <https://www.nytimes.com/1983/08/10/obituaries/rolla-n-harger-dies-invented-drunkometer.html>.

¹²⁴ ADID HANDBOOK: A HISTORY OF THE COMMITTEE ON ALCOHOL AND OTHER DRUGS, NAT’L SAFETY COUNCIL 7 (2004), <https://www.nsc.org/getmedia/6a157e53-a019-4ee6-85a2-428df844deca/nschistoryofcaod.pdf>.

¹²⁵ *Id.* at 8–9.

¹²⁶ *Id.* at 9 (discussing the rapid adoption of the recommended standards in Indiana and Maine).

of a subject's blood and thus the extent of his intoxication."¹²⁷ In the same year, a New Jersey trial court granted a defendant a new trial when evidence of a potential error in the administration of the Drunkometer test came to light.¹²⁸ The court noted that:

[t]he Harger test is rooted in a technology seemingly not fully understood at this time by any except the technicians who developed it and certainly having the flavor of the esoteric to the uninitiated. Even the city physician could perform it only with the aid of a training manual describing the technique and the directions for weighing. Perhaps persons trained in the use of laboratory equipment might be expected to recognize, when laymen might not, the importance of the difference in sensitivity between torsion and analytical balances; still the physician, a competent professional man, seems not to have appreciated the absolute necessity for the use of an analytical balance.¹²⁹

The court viewed the new Drunkometer technology as lacking in the same kind of transparency that currently worries critics of AI.

Despite these concerns, other courts were more deferential to governmental use of the Drunkometer. Even in states where Drunkometer results were not made admissible on their own as a matter of law, courts did begin to allow them to be introduced when accompanied by expert testimony.¹³⁰ Just a few years after the skeptical decision by the New Jersey trial court, for example, a judge in the same court relied on the credibility of the test to reverse a conviction for intoxication, holding that the defendant could not be convicted because the prosecution failed to show that any chemical tests, including the Harger test, had been performed.¹³¹

Chemical testing technology improved when a researcher with the Indiana State Police, Robert Borkenstein, developed a device in 1953 that measured blood alcohol content using chemical oxidation.¹³² This device, known as the Breathalyzer, was reliable enough so that it basically eliminated questions about the admissibility of chemical test results.¹³³ Still, questions remained about how much *deference* to give

¹²⁷ *People v. Morse*, 38 N.W.2d 322, 324 (Mich. 1949).

¹²⁸ *State v. Hunter*, 68 A.2d 274, 277 (N.J. Super. Ct. App. Div. 1949).

¹²⁹ *Id.*

¹³⁰ *See, e.g.*, *People v. Bobczyk*, 99 N.E.2d 567, 570–71 (Ill. App. Ct. 1951); *McKay v. State*, 235 S.W.2d 173 (Tex. Crim. App. 1950), *Lombness v. State*, 243 P.2d 389 (Okla. Crim. App. 1952).

¹³¹ *State v. Matchok*, 82 A.2d 444, 446 (N.J. Super. Ct. App. Div. 1951).

¹³² Douglas Martin, *Robert F. Borkenstein, 89, Inventor of the Breathalyzer*, N.Y. TIMES (Aug. 17, 2002), <https://www.nytimes.com/2002/08/17/us/robert-f-borkenstein-89-inventor-of-the-breathalyzer.html#:~:text=Borkenstein%2C%20who%20revolutionized%20enforcement%20of,being%20tested%20is%20legally%20drunk> [<https://perma.cc/NXE3-VUJ8>].

¹³³ *Id.* (discussing how the National Safety Council deemed the Breathalyzer “sufficiently

these test results. An Oklahoma court, for example, held that the results of a test showing 0.11% blood alcohol content were admissible but not conclusive.¹³⁴ Similarly, in 1967 the Arizona Supreme Court rejected a lower court's instruction that jurors should treat a breathalyzer's results as presumptively valid.¹³⁵

As breathalyzer technology improved further, and even became digitized in 1970, its acceptance increased.¹³⁶ Its use has become so commonplace that its absence in criminal proceedings has come to be viewed with suspicion. Indeed, a Missouri appellate court in 1971 reversed a conviction when the state failed to produce the results of a breathalyzer test.¹³⁷ A year later, a North Carolina court validated a jury instruction declaring a presumption of guilt arising from the results of the breathalyzer test.¹³⁸ The Kentucky Court of Appeals went even further, holding that such an instruction was unnecessary because statutory law creating a presumption of intoxication based on blood alcohol levels created a scientific standard of proof supporting breathalyzer analysis, such that expert testimony was no longer necessary to admit test results into evidence.¹³⁹

This strong acceptance of breathalyzer technology by courts, after initial skepticism and resistance, follows the pattern of DNA analysis. It suggests the possibility that today's mistrust of AI might one day reach a corresponding level of approval.

C. Radar Speed Detection

Yet another example—radar speed detection—presents a similar technological trajectory. Speeding first became a traffic offense in the early 1910s.¹⁴⁰ For decades, police officers predominantly identified speed limit violators using a technique called “pacing,” in which a police car followed a suspected car for a certain distance, matching its speed.¹⁴¹ By the mid-twentieth century, new technologies started to

accura[te] to meet the demands of legal evidence”); *People v. Kovacik*, 128 N.Y.S.2d 492, 506 (Ct. Spec. Sess. 1954) (finding that the Drunkometer was “a scientifically reliable and accurate device” and listing a number of courts across the U.S. that held the same).

¹³⁴ *Armstrong v. State*, 300 P.2d 766, 769 (Okla. Crim. App. 1956).

¹³⁵ *Youngblood v. Austin*, 424 P.2d 824, 826 (Ariz. 1967).

¹³⁶ *Tom Parry Jones*, THE TIMES (Jan. 13, 2013, 12:01 AM), <https://www.thetimes.co.uk/article/tom-parry-jones-97bhjrwqrgc>.

¹³⁷ *State v. Ellsworth*, 468 S.W.2d 722, 724 (Mo. Ct. App. 1971). The court held that when “one of the parties fails to produce evidence which is available to him and which he might be expected to produce, his failure to produce it authorizes a strong presumption that such evidence, if produced, would be adverse to him.” *Id.*

¹³⁸ *State v. Royall*, 188 S.E.2d 50, 53 (N.C. Ct. App. 1972).

¹³⁹ *Marcum v. Commonwealth*, 483 S.W.2d 122, 127–28 (Ky. 1972).

¹⁴⁰ *Bill Loomis, 1900–1930: The Years of Driving Dangerously*, DETROIT NEWS (Apr. 26, 2015, 2:14 PM), <https://www.detroitnews.com/story/news/local/michigan-history/2015/04/26/auto-traffic-history-detroit/26312107/>; *see also, e.g., Commonwealth v. Buxton*, 91 N.E. 128, 128 (Mass. 1910).

¹⁴¹ DAVID K. WHITEFORD, SPEED ENFORCEMENT POLICIES AND PRACTICE 33–36 (1970). For

emerge as alternatives to pacing—the most widely used of which were radar speed meters.¹⁴² These devices, which actually relied on microwaves rather than radar, could be pointed at vehicles and used to identify their speed.¹⁴³ An officer in a police car merely had to point the meter at the target car, obtain a reading, and then pursue the speeding vehicle to make a traffic stop and issue a ticket.

Similar technology now underlies the automated traffic enforcement systems—namely, red-light cameras—that are currently disfavored in some states.¹⁴⁴ Current opposition to these automated systems tends to arise from the steps of photographing license plates and automatically sending tickets to vehicle owners for violations.¹⁴⁵ Back in the 1950s, when speed detection technology was new, it was the mere notion of radar detection itself that generated considerable “sound and fury” over the prospect of an “unseen traffic cop.”¹⁴⁶

At that time, the American Automobile Association (AAA) expressed serious concerns that speed detection technology would be used not for “greater safety but greater harassment of motorists.”¹⁴⁷ An attorney for the Chicago Motor Club charged that “[t]he flagrant misuse of these devices is becoming a serious menace to the entire motoring public.”¹⁴⁸ In a strategy similar to one urged today by activists in connection with AI, motorist advocates pushed for “legislation which would ensure accuracy of the devices and which would require adequate warning signs to alert motorists as to the pre[se]nce of radar.”¹⁴⁹

an illuminating history of traffic regulation in the United States, see SARAH A. SEO, *POLICING THE OPEN ROAD: HOW CARS TRANSFORMED AMERICAN FREEDOM* (2021).

¹⁴² The use of photographic technology to demonstrate speeding was available as early as 1910, but electronic means of speed detection did not get discovered until 1935, with the first serious use not occurring until 1947. William Power Clancey, Jr., *Admissibility of Evidence Obtained by Radar Speed Meter*, 43 CAL. L. REV. 710, 716 (1955).

¹⁴³ NAT’L HIGHWAY TRAFFIC SAFETY ADMIN., *SPEED-MEASURING DEVICE SPECIFICATIONS: DOWN-THE-ROAD RADAR MODULE 2–4* (Apr. 2016).

¹⁴⁴ See generally Maisel, *supra* note 73; see also *supra* notes 71–76 and accompanying text.

¹⁴⁵ For an example of how citizens are pushing back against this technology, see Reuven Blau, *Sneaky Drivers Place Clear Plastic Covers Over License Plates to Foil Traffic Cameras and Evade Tickets*, N.Y. DAILY NEWS (Nov. 28, 2016, 9:36 PM), <https://www.nydailynews.com/new-york/sneaky-drivers-place-clear-plastic-covers-license-plates-article-1.2890577>. For discussion of controversial automatic ticketing, see Irvin Dawid, *Legislation to Ban Traffic Cameras Creates Odd Political Alliances*, PLANETIZEN (Jan. 20, 2018, 9:00 AM), <https://www.planetizen.com/news/2018/01/96800-legislation-ban-traffic-cameras-creates-odd-political-alliances> (discussing how tickets are automatically sent to the owner of the car, not the driver, which leads to inaccuracies).

¹⁴⁶ *Big Brother Is Driving*, TIME (Nov. 23, 1953), <http://content.time.com/time/subscriber/article/0,33009,860106,00.html>.

¹⁴⁷ *Abuses Indicated in Speeder Curbs: A.A.A. Investigating Whether Drivers Are Being Harassed in Use of Highway Radar*, N.Y. TIMES, Sept. 12, 1954, at 127.

¹⁴⁸ Roger D. Greene, *Radar Auto Speed Check Arouses Ire of Motorists*, ATL. J., June 24, 1956, at 13F.

¹⁴⁹ *Id.*; see also Bert Pierce, *Limit Asked on Use of Highway Radar: Auto Clubs Urge*

Much like what transpired in response to the introduction of the Drunkometer, courts initially expressed skepticism to radar. In 1953, for example, a Colorado court held that:

[U]ntil such time as the courts recognize radar equipment as a method of accurately measuring the speed of automobiles in those cases in which the People rely solely upon the speed indicator of the radar equipment, it will be necessary to establish by expert testimony the accuracy of radar for the purpose of measuring speed.¹⁵⁰

It would take a number of years before radar speed detection would start to gain acceptability.

By 1959, a Missouri court was finally willing to declare that “[i]t is now time for the courts . . . to recognize by judicial knowledge . . . that a radar speedmeter is a device which, within a reasonable engineering tolerance, and when properly functioning and properly operated, accurately measures speed in terms of miles per hour.”¹⁵¹ Around that same time, other courts started to allow radar detection to stand on its own, without requiring accompanying expert testimony.¹⁵² By 1968, the use of radar had become so commonplace that a California appellate court held that the trial judge had erred by *not* taking judicial notice of radar evidence.¹⁵³

Although the courts and the public eventually came to accept radar detection of speeding violations, the law still did not affirmatively require radar evidence to justify fines for speeding violations.¹⁵⁴ However, in 1989, shortly after Pennsylvania

Legal Policy on Speed Devices—Scientific Zoning of Traffic Sought, N.Y. TIMES, Sept. 12, 1953, at 17.

¹⁵⁰ *People v. Torpey*, 128 N.Y.S.2d 864, 866 (Monroe Cnty. Ct. 1953); *see also* *People v. Beck*, 130 N.Y.S. 354, 357 (Sup. Ct. 1954).

¹⁵¹ *State v. Graham*, 322 S.W.2d 188, 195 (Mo. Ct. App. 1959).

¹⁵² *See, e.g.,* *Everight v. City of Little Rock*, 326 S.W.2d 796, 797 (Ark. 1959) (“We are of the opinion that the usefulness of radar equipment for testing speed of vehicles has now become so well established that the testimony of an expert to prove the reliability of radar in this respect is not necessary. The courts will take judicial knowledge of such fact.”); *People v. Magri*, 3 147 N.E.2d 728, 730 (N.Y. 1958) (“[T]he time has come when we may recognize the general reliability of the radar speedmeter as a device for measuring the speed of a moving vehicle, and that it will no longer be necessary to require expert testimony in each case as to the nature, function or scientific principles underlying it.”).

¹⁵³ *People v. MacLaird*, 71 Cal. Rptr. 191, 193 (Ct. App. 1968). Of course, although experts were no longer needed to testify to the instrument’s scientific validity, prosecutors still needed to show that the given speedmeter was accurate and that the equipment was used properly.

¹⁵⁴ *See* *State v. Barker*, 490 S.W.2d 263, 273 (Mo. Ct. App. 1973) (holding that an officer’s testimony about pacing the defendant was sufficient to warrant a conviction); *Commonwealth v. Monosky*, 520 A.2d 1192, 1193, 1195 (Pa. Super. Ct. 1987) (holding that an officer’s

enacted comprehensive statutory standards for speed timing devices,¹⁵⁵ a state court held that radar devices were actually *required* for the state to prove speeding violations.¹⁵⁶ Today, uncorroborated officer testimony based on pacing is no longer sufficient to support a conviction for certain traffic offenses in Pennsylvania. The state's statute has effectively granted individuals a positive right to have charges of speeding violations proven by automated technology rather than by relying on the testimony of human police officers.¹⁵⁷

III. TOWARD POSITIVE ALGORITHM RIGHTS

These examples—DNA analysis, breathalyzers, and radar speed detection—illustrate how new technologies that are initially greeted with skepticism or derision can eventually become accepted by the public and the legal system, if not even fully embraced as a substitute for human judgment. The law, after all, is not inherently Luddite. It creates no bar to the reliance on technology rather than humans for important governmental decisions. Quite the contrary, in a number of domains, courts and legislatures affirmatively require the government to rely on advanced technology and analytic techniques, effectively creating a positive right to their use.

In addition to the examples noted in Part II, some states today mandate that the government rely on chemical analysis to sustain convictions for the possession of controlled substances.¹⁵⁸ Outside of the context of criminal law, we see other examples as well. Federal law, for instance, requires that administrative agencies use various kinds of sophisticated analyses as a basis for their regulatory decisions.¹⁵⁹ Consider

testimony that he had to accelerate to fifty-five miles per hour to overtake the defendant was sufficient to show the defendant was speeding).

¹⁵⁵ 75 Pa. C.S.A. § 3368.

¹⁵⁶ *Commonwealth v. Martorano*, 562 A.2d 1229, 1233 (Pa. Super. Ct. 1989).

¹⁵⁷ In a similar vein, although the Supreme Court of Mississippi ultimately upheld a speeding conviction based on a police officer's testimony after pacing the defendant's vehicle, the court also stated that it "strongly encourage[d] the State to properly introduce radar readings in the future." *Freeman v. State*, 121 So. 3d 888 (Miss. 2013).

¹⁵⁸ *See, e.g., State v. Ward*, S.E.2d 738, 747 (2010) ("Unless the State establishes before the trial court that another method of identification is sufficient to establish the identity of the controlled substance beyond a reasonable doubt, some form of scientifically valid chemical analysis is required."); *People v. Hard*, 342 P.3d 572, 580 (Colo. Ct. App. 2014) ("The People were required to prove that the pills were oxycodone, not merely that they appeared to be oxycodone. Without some other confirmatory evidence . . . the Drugs.com evidence was insufficient to prove identity of the pills as oxycodone beyond a reasonable doubt."); *People v. Mocaby*, 882 N.E.2d 1162, 1167–68 (Ill. App. Ct. 2008) (reversing conviction where "there was no chemical analysis of the tablets involved" in alleged crime).

¹⁵⁹ Federal law calls for analysis of costs and benefits before particularly consequential regulations can be adopted. 2 U.S.C. § 1532(a) (requiring a "quantitative assessment of anticipated costs and benefits" before promulgating a "notice of proposed rulemaking" that could likely result in an expenditure of \$1 million or more in a given year). Executive orders have similarly created an institutionalized system for producing and reviewing economic

the U.S. Environmental Protection Agency (EPA), which must base certain decisions on the “best available” scientific analysis.¹⁶⁰ When EPA administrators have failed to rely on statistical analyses of risk but instead have relied on their own expert judgment, judges have rebuked them for ignoring their analytic models.¹⁶¹ Indeed, some administrative officials have even found that both the public and the courts are more receptive to controversial decisions if the administrators claim that their decisions simply follow from scientific analysis rather than from human judgment.¹⁶²

If government officials find that they can bolster their public and legal acceptability of their decisions by claiming that they are based solely on complex, technical analysis, it is far from unthinkable that algorithm-based decision-making might someday earn the status of something akin to a positive right. Notwithstanding the current suspicion and opposition confronting government’s reliance on digital algorithms, AI tools might well in the future come to be the expected, if not even required, basis for certain governmental decisions. Rather than AI being a technology to be resisted, the responsible use of AI might instead follow the path of other technologies and come to constitute a best practice that the public demands and deserves.

analysis of new regulations. *See, e.g.*, Exec. Order 12,291, 46 Fed. Reg. 13,193 (Feb. 17, 1981); Exec. Order 12,866, 58 Fed. Reg. 51,735 (Oct. 4, 1993). The Supreme Court has suggested that a default principle of administrative law requires some kind of benefit-cost analysis to justify regulatory decisions. *See* *Entergy Corp. v. Riverkeeper, Inc.*, 556 U.S. 208, 226 (2009) (upholding EPA’s interpretation of the “best technology available” in the Clean Water Act to encompass the use of benefit-cost analysis); *Michigan v. E.P.A.*, 576 U.S. 743, 761 (2015) (“The Agency must consider cost—including, most importantly cost of compliance—before deciding whether regulation is appropriate and necessary.”).

¹⁶⁰ *See, e.g.*, 42 U.S.C. § 300g-1(B)(3)(A) (“[T]he Administrator shall use the best available, peer-reviewed science and supporting studies conducted in accordance with sound and objective scientific practices; and data collected by accepted methods or best available methods.”).

¹⁶¹ *See generally* *Chlorine Chemistry Council v. E.P.A.*, 206 F.3d 1286 (D.C. Cir. 2000) (holding that an EPA rule setting chloroform levels in drinking water was not sufficiently grounded in best available science).

¹⁶² *See, e.g.*, Cary Coglianese & Gary Marchant, *Shifting Sands: The Limits of Science in Setting Risk Standards*, 152 U. PA. L. REV. 1256, 1263 n.33 (2004); Wendy Wagner, *The Science Charade in Toxic Risk Regulation*, 95 COLUM. L. REV. 1613 (1995). This is not to say that claims to make decisions on the sole basis of science are accurate, nor is it to say that they will always be accepted. During the early months of the COVID-19 pandemic, for example, levels of public confidence in science increased. Daniel Silva Luna et al., *Public Faith in Science in the United States Through the Early Months of the COVID-19 Pandemic*, 2 PUB. HEALTH PRACT. (2021), <https://www.sciencedirect.com/science/article/pii/S2666535221000288>. Nevertheless, this did not immunize the Centers for Disease Control and Prevention (CDC) from public criticism for adopting more relaxed isolation guidance for people who test positive for COVID-19, even though it claimed to be acting on the basis of science. Berkeley Lovelace, Jr. & Teaganne Finn, “*We Must Adapt*”: *CDC Defends New Isolation Guidance Amid Omicron Surge*, NBC NEWS (Dec. 29, 2021), <https://www.msn.com/en-us/news/us/we-must-adapt-cdc-defends-new-isolation-guidance-amid-omicron-surge/ar-AASfnLd?li=BBnb7Kz> (quoting one expert as saying that the CDC’s guidance “has much more to do with societal function than to do with science”).

We cannot, of course, predict the exact role that AI will play in the future of public administration.¹⁶³ Yet we can suggest plausible strategies or preconditions that could at least help some AI tools assume the mantle of a positive right, embraced by both the public and the legal system.¹⁶⁴ In this Part, we point to four broad measures that might make it more likely that both the legal system and the public will eventually demand the use of AI as a best practice or a positive right: (1) standardization; (2) auditing and impact assessment; (3) oversight; and (4) qualification.

In various ways, and to varying degrees, these four measures can be said to be inspired by the paths taken by the technologies discussed in Part II. The acceptance of a new technology will rarely, if ever, come about as a mere property of the technology itself; it will depend on the way it is used and the social processes and practices surrounding that use.¹⁶⁵ The four measures highlighted here are plausible steps that could be readily applied to AI tools to address existing concerns and might help in gliding these tools toward their eventual acceptance and integration into the routine workings of government.

A. Standardization

A technology becomes standardized through the establishment of a set of widely accepted guidance materials and procedures for its proper use. Such standards are designed to help ensure the technology works properly, achieves consistent and reliable results, and avoids potential harms.¹⁶⁶

To be considered valid, for example, DNA analysis must be conducted in conformity with “clear and repeatable standards for analysis, interpretation, and

¹⁶³ Cf. Rodrigo Nieto-Gómez, *No Bad Deed Goes Unrewarded: Cause, Consequence, and Deviance in Emerging Technological Regimes*, in *QUESTIONING CAUSALITY: SCIENTIFIC EXPLORATIONS OF CAUSE AND CONSEQUENCE ACROSS SOCIAL CONTEXTS* 349 (Rom Harre & Fathali M. Moghaddam eds., 2016) (noting the difficulties in forecasting patterns of adoption in and consequences of new technologies).

¹⁶⁴ For suggestions on constructing pathways toward the responsible adoption of technological innovations more generally, see Jack Stilgoe et al., *Developing a Framework for Responsible Innovation*, 42 RES. POL. 1568 (2013).

¹⁶⁵ Technology does not operate in a vacuum but interacts with society and with the law, not infrequently following a pathway from controversy to closure as with the examples noted in Part II. See generally LYNCH ET AL., *supra* note 99; SHEILA JASANOFF, *SCIENCE AT THE BAR: LAW, SCIENCE, AND TECHNOLOGY IN AMERICA* (1995).

¹⁶⁶ Miroslava Mikva et al., *Standardization: One of the Tools of Continuous Improvement*, 149 PROCEDIA ENG'G 329, 330 (2016) (discussing how standardization helps reduce and correct errors, make operational problems readily apparent, and assists with proper training on the use of technology). For an extensive collection of background materials on technology standards, visit *Voluntary Codes and Standards*, PENN PROGRAM ON REGUL., <https://pennreg.org/codes-standards/> (last visited Apr. 26, 2022).

reporting.”¹⁶⁷ DNA laboratories must “meet specific quality guidelines, which include the requirement that [each] laboratory be accredited and that specific procedures be in place and followed.”¹⁶⁸ These procedures must be “well specified and subject to validation and proficiency testing.”¹⁶⁹

Several professional standard-setting organizations have established accreditation and quality assurance guidelines for state DNA laboratories to follow for the purpose of ensuring reliable, accepted results.¹⁷⁰ These standards have played an important role. As much as technical advancements in DNA analysis itself, along with expert testimony about the DNA analytical process, has proven instrumental to this technology’s eventual acceptance in the courts, it is recognized that “equally important were efforts to devise administrative standards for assuring the courts that DNA evidence was correctly handled and analyzed.”¹⁷¹

In much the same way, governments and standard-setting organizations around the world are already beginning a process of standardizing the use of AI.¹⁷² The Organization for Economic Cooperation and Development (OECD) has developed a set of principles to guide member governments in responsible AI use.¹⁷³ Similarly, the European Union (EU) is currently working on an overarching regulatory framework

¹⁶⁷ NAT’L RSCH. COUNCIL COMM. ON IDENTIFYING THE NEEDS OF THE FORENSIC SCI. CMTY., *supra* note 113, at 133.

¹⁶⁸ *Id.* at 131–32.

¹⁶⁹ *Id.* at 133.

¹⁷⁰ *See, e.g., ANAB Accreditation*, ALA. DEP’T FORENSIC SCI., <https://www.adfs.alabama.gov/about/accreditation> (last visited Apr. 26, 2022) (listing Alabama forensic labs accredited through the American Society of Crime Laboratory Directors/Laboratory Accreditation Board); *State Crime Laboratories Recognized as OSAC Standard Implementing System to Continue Providing Advanced, Object Scientific Analysis*, WIS. DEP’T JUST. (July 1, 2021), <https://www.doj.state.wi.us/news-releases/state-crime-laboratories-recognized-osac-standard-implementing-system-continue> (discussing Wisconsin crime lab compliance with Organization of Scientific Area Committees for Forensic Science and National Institute of Standards and Technology recommendations); ARK. STATE CRIME LAB, FORENSIC DNA SECTION QUALITY ASSURANCE MANUAL 5 (2020) (discussing the state’s alignment with DNA Advisory Board Guidelines established by the FBI); *see also* AM. BAR ASS’N, ABA STANDARDS FOR CRIMINAL JUSTICE: DNA EVIDENCE 21 (3rd ed. 2007); FED. BUREAU INVESTIGATION, QUALITY ASSURANCE STANDARDS FOR FORENSIC TESTING LABORATORIES (2020); *About OSAC*, NAT’L INST. STANDARDS & TECH., <https://www.nist.gov/osac> (last visited Apr. 26, 2022).

¹⁷¹ LYNCH ET AL., *supra* note 99, at 45.

¹⁷² There appears to be no shortage of standards and recommendations related to AI. One study found a total of 634 such documents published in English prior to 2020. Carlos Ignacio Gutierrez & Gary E. Marchant, *A Global Perspective of Soft Law Programs for the Governance of Artificial Intelligence* (May 28, 2021) (Report, Center for Law, Science, and Innovation at Sandra Day O’Connor College of Law), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3855171. One challenge with AI standardization may well be to make a more uniform or harmonized set of standards.

¹⁷³ OECD, *OECD AI Principles Overview*, <https://oecd.ai/en/ai-principles> (last visited Apr. 26, 2022).

to set standards for algorithmic decision-making in the private and public sectors.¹⁷⁴ The EU already established a General Data Protection Regulation to address privacy, transparency, and accountability concerns over the data used in AI applications.¹⁷⁵

Numerous nongovernmental efforts are underway to develop standards and accreditation systems in the responsible use of AI.¹⁷⁶ The international organization known as the IEEE Standards Association, for example, has several standards-development initiatives underway, including one that aims to promote responsible use of AI through “governance criteria . . . and process steps for effective implementation, performance auditing, training and compliance in the development or use of artificial intelligence within organizations.”¹⁷⁷

In the United States, the National Institute of Standards and Technology has released a draft risk management framework for the development and use of AI tools by both public and private actors.¹⁷⁸ It has further articulated a set of principles to help promote AI explanation, accuracy, meaningfulness, and an understanding of AI tools’ limitations.¹⁷⁹ In addition, the Administrative Conference of the United States, a federal agency dedicated to issuing good-government recommendations, has issued a statement articulating principles and standards for AI use by other agencies.¹⁸⁰ The U.S. Governmental Accountability Office has also issued an “accountability framework” to guide federal agencies in their use of AI tools.¹⁸¹

¹⁷⁴ See generally *Proposal for a Regulation of the European Parliament and of the Council: Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act) and Amending Certain Union Legislative Acts*, COM (2021) 206 final (Apr. 21, 2021).

¹⁷⁵ Giovanni Sartor & Francesca Lagioia, EU Parliamentary Rsch. Serv., Rep. on the Impact of the General Data Protection Regulation (GDPR) on Artificial Intelligence, at 35–72 (June 2020), [https://www.europarl.europa.eu/RegData/etudes/STUD/2020/641530/EPRS_STU\(2020\)641530_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/STUD/2020/641530/EPRS_STU(2020)641530_EN.pdf).

¹⁷⁶ See *supra* note 172.

¹⁷⁷ P2863: RECOMMENDED PRACTICE FOR ORGANIZATIONAL GOVERNANCE OF ARTIFICIAL INTELLIGENCE, IEEE STANDARDS ASS’N, <https://standards.ieee.org/ieee/2863/10142/> (last visited Apr. 26, 2022). For an overview of IEEE’s efforts related to AI, see *Artificial Intelligence Systems (AIS)*, IEEE STANDARDS ASS’N, <https://standards.ieee.org/initiatives/artificial-intelligence-systems/> (last visited Apr. 26, 2022). See also *infra* note 185.

¹⁷⁸ NAT’L INST. OF STANDARDS & TECH., AI RISK MANAGEMENT FRAMEWORK: INITIAL DRAFT (2022), <https://www.nist.gov/system/files/documents/2022/03/17/AI-RMF-1stdraft.pdf>.

¹⁷⁹ P. JONATHON PHILLIPS ET AL., NISTIR 8312: FOUR PRINCIPLES OF EXPLAINABLE ARTIFICIAL INTELLIGENCE, NAT’L INST. OF STANDARDS & TECH. (Sept. 29, 2021), <https://www.nist.gov/publications/four-principles-explainable-artificial-intelligence>.

¹⁸⁰ *Administrative Conference Statement #20: Agency Use of Artificial Intelligence*, ADMIN. CONF. OF THE U.S. (Dec. 16, 2020), <https://www.acus.gov/sites/default/files/documents/Statement%202020%20Agency%20Use%20of%20Artificial%20Intelligence.pdf>.

¹⁸¹ See generally U.S. GOV’T ACCOUNTABILITY OFF., GAO-21-519SP, ARTIFICIAL INTELLIGENCE: AN ACCOUNTABILITY FRAMEWORK FOR FEDERAL AGENCIES AND OTHER ENTITIES (2021), <https://www.gao.gov/assets/gao-21-519sp.pdf>.

In December 2020, President Donald Trump signed an executive order calling upon federal agencies to use AI tools only when they are reliable, understandable, traceable, monitorable, and transparent.¹⁸² In addition, the Biden Administration's Office of Science and Technology Policy formed an AI-specific task force to help agencies promote fairness, transparency, and risk avoidance when they deploy AI tools.¹⁸³ Some individual agencies have started to develop internal standards or statements of principles for their use of AI tools.¹⁸⁴

Further standardization efforts will likely continue, and over time these standards may become both more uniform and more broadly accepted as sources of operational, if not legal, doctrine governing public sector use of AI tools. With standards and operating procedures in place, it should also become easier to provide oversight of the development of these tools and to verify and validate their use and outcomes.

B. Auditing and Impact Assessment

Another important step in building acceptance of algorithmic tools will likely involve regular and reliable efforts to verify and validate the design and operation of specific AI tools. Verification will entail auditing to see how well a technology meets applicable standards and specifications, while validation will rely on impact assessment to determine how well the technology achieves its overall goals, such as by improving specified outputs or outcomes relative to the status quo.¹⁸⁵

¹⁸² Exec. Order No. 13,960, 85 Fed. Reg. 78,939 (Dec. 3, 2020). The Trump White House also issued a memorandum to agencies on their use of AI. Russell T. Vought, *Guidance for Regulation of Artificial Intelligence Applications*, WHITEHOUSE.GOV (Nov. 17, 2020), <https://www.whitehouse.gov/wp-content/uploads/2020/11/M-21-06.pdf>. To date, the order remains in effect under President Biden.

¹⁸³ Lynn Parker & Rashida Richardson, *OSTP's Continuing Work on AI Technology and Uses That Can Benefit Us All*, WHITEHOUSE.GOV (Feb. 3, 2022), <https://www.whitehouse.gov/ostp/news-updates/2022/02/03/ostps-continuing-work-on-ai-technology-and-uses-that-can-benefit-us-all/>; Press Release, White House, The Biden Administration Launches the National Artificial Intelligence Research Resource Task Force (June 10, 2021), <https://www.whitehouse.gov/ostp/news-updates/2021/06/10/the-biden-administration-launches-the-national-artificial-intelligence-research-resource-task-force/>.

¹⁸⁴ See, e.g., *DOD Adopts Ethical Principles for Artificial Intelligence*, U.S. DEP'T OF DEFENSE (Feb. 24, 2020), <https://www.defense.gov/News/Releases/Release/Article/2091996/dod-adopts-ethical-principles-for-artificial-intelligence/>.

¹⁸⁵ In this respect, we follow Joshua Kroll and his coauthors, who note that “[v]erification typically constitutes a proof that the software object in use matches its specification, but this analysis says nothing about whether the specification is sufficiently detailed, correct, lawful, or socially acceptable, or constitutes good policy.” Kroll et al., *supra* note 53, at 665. Validation aims toward providing assurance of the latter. For discussion of the importance of counterfactual validation of outcomes achieved by public sector use of AI, see Coglianese & Lai, *supra* note 11, at 1329–33. For a comprehensive set of standards for verification and validation of software adopted by a highly regarded standard-setting organization, see *IEEE*

Verification of DNA analysis, for example, has long entailed determining whether proper laboratory procedures have been followed, while validation has involved investigating the degree of accuracy in matching genetic samples.¹⁸⁶ Much the same can be said for breathalyzers, portable speed radar equipment, or any technology. Regular and robust practices of auditing and impact assessment can strengthen societal and legal confidence that a technology is being used properly and achieves accurate results.

Measures to verify and validate governmental use of AI tools may occur at any and all stages of the design and deployment of these tools—and they can take a variety of forms.¹⁸⁷ Examples of such measures include:

- Following checklists and assessing conformity with standards for AI design and operation;
- Completing an impact assessment to determine whether an AI tool improves on current processes and practices;¹⁸⁸
- Testing an algorithm to understand its error rates and the conditions under which it is most likely to fail;¹⁸⁹
- Analyzing the distribution of error across different demographic groups and taking steps to ensure that the algorithm is not subject to higher error rates when processing data related to individuals from a specific population subset; and
- Questioning assumptions embedded in the model and interrogating instances of potential implicit bias and ensuring that the policy employed by the model is an acceptable one.¹⁹⁰

Standard for System, Software, and Hardware Verification and Validation, IEEE STANDARDS ASS'N, <https://standards.ieee.org/standard/1012-2016.html> (last visited Apr. 26, 2022).

¹⁸⁶ See, e.g., NAT'L RSCH. COUNCIL COMM. ON IDENTIFYING THE NEEDS OF THE FORENSIC SCI. CMTY., *supra* note 113, at 133.

¹⁸⁷ For discussion of AI impact assessment and auditing in the governmental context, see generally SUPREME AUDIT INSTS. OF FIN., GER., THE NETH., NOR. & THE U.K., *AUDITING MACHINE LEARNING ALGORITHMS: A WHITE PAPER FOR PUBLIC AUDITORS* (2020); PERS. DATA PROT. COMM'N OF SING., *MODEL ARTIFICIAL INTELLIGENCE GOVERNANCE FRAMEWORK* (2nd ed. 2020) [hereinafter *AUDITING MACHINE LEARNING ALGORITHMS*].

¹⁸⁸ For examples, see Hamsa Bastani et al., *Efficient and Targeted COVID-19 Border Testing Via Reinforcement Learning*, 599 NATURE 108, 111–12 (2021) (reporting results of a study showing how machine learning improved detection of infected travelers); Miyuki Hino et al., *Machine Learning for Environmental Monitoring*, 1 NATURE SUSTAINABILITY 583, 587 (2018) (showing improved detection of water pollution violations through the use of machine-learning algorithms); Jon Kleinberg et al., *Human Decisions and Machine Predictions*, 133 Q.J. ECON. 237 (2017) (showing improved outcomes in bail decisions through use of a machine-learning tool).

¹⁸⁹ Cf. *State v. Loomis*, 881 N.W.2d 749, 769 (Wis. 2016) (affirming the use of an algorithm in criminal sentencing “if used properly with an awareness of the limitations and cautions”).

¹⁹⁰ For related discussion, see Virginia Eubanks, *A Child Abuse Prediction Model Fails*

With robust auditing and impact assessment, officials may be able to mitigate many of the concerns that today surround the use of AI tools by government agencies.¹⁹¹

Already, governments from around the world are paying considerable attention to practices of algorithmic auditing and impact assessment. The leading public auditing bodies of five countries—Finland, Germany, the Netherlands, Norway, and the United Kingdom—have jointly agreed on a framework for auditing AI tools for explainability, fairness, and cybersecurity.¹⁹² The leading federal audit body in the United States—the Government Accountability Office—has issued its own detailed “accountability framework” for auditing AI systems for their governance, data, monitoring, and performance.¹⁹³

In addition, nongovernmental certification programs have begun to emerge that offer a structured basis for checking to make sure AI tools do not create unacceptable or unintended problems. The IEEE Standards Association, for example, has established—and even trademarked—a certification program called IEEE CertifAIED which provides a vehicle for “assessment and independent verification” of an AI system and whether it is operating responsibly.¹⁹⁴ The nonprofit Responsible AI Institute has developed a separate certification program which scores AI systems based on different dimensions, such as explainability, accountability, and fairness, and then yields an overall responsibility score.¹⁹⁵

These efforts to promote AI auditing and assessment by government agencies are, in many respects, akin to a longstanding requirement that agencies consider evidence and rationally justify their decisions. The courts have confirmed that any kind of analysis relied upon by agencies—not just machine learning or AI analysis—must be rationally related to the purpose for which it is used.¹⁹⁶ As early as the mid-1980s,

Poor Families, WIRED (Jan. 15, 2018), <https://www.wired.com/story/excerpt-from-automating-inequality/>.

¹⁹¹ For further discussion of algorithmic impact assessment and auditing, see generally Alex Engler, *Auditing Employment Algorithms for Discrimination*, BROOKINGS INST. (Mar. 12, 2021); Miles Brundage et al., *Toward Trustworthy AI Development: Mechanisms for Supporting Verifiable Claims* (Apr. 2020), <https://arxiv.org/pdf/2004.07213.pdf>; Rachel Courtland, *Bias Detectives: The Researchers Striving to Make Algorithms Fair*, 588 NATURE 357 (2018); Sara Kassir, *Algorithmic Auditing: The Key to Making Machine Learning in the Public Interest*, BUS. GOV’T (2019–2020), <https://www.businessofgovernment.org/sites/default/files/Algorithmic%20Auditing.pdf>; Pauline Kim, *Auditing Algorithms for Discrimination*, 166 U. PA. L. REV. 190 (2017); Kroll et al., *supra* note 53.

¹⁹² AUDITING MACHINE LEARNING ALGORITHMS, *supra* note 187.

¹⁹³ U.S. GOV’T ACCOUNTABILITY OFF., *supra* note 181.

¹⁹⁴ *IEEE CertifAIED: The Mark of AI Ethics*, IEEE STANDARDS ASS’N, <https://engagestandards.ieee.org/ieeecertifaiied.html> (last visited Apr. 26, 2022).

¹⁹⁵ RESPONSIBLE A.I. INST., THE RESPONSIBLE AI CERTIFICATION PROGRAM: WHITE PAPER (June 2022).

¹⁹⁶ See, e.g., *Chem. Mfrs. Ass’n v. E.P.A.*, 28 F.3d 1259, 1265 (D.C. Cir. 1994) (“[W]e must reverse the agency’s application of the generic air dispersion model as arbitrary and capricious if there is simply no rational relationship between the model and the known behavior of the hazardous air pollutant to which it is applied.”). For general discussion, see Thomas McGarity

long before administrative agencies started to use anything close to what today would be considered AI, the D.C. Circuit explained that “[a]n agency may utilize a predictive model so long as it explains the assumptions and methodology it used in preparing the model,” and, “[i]f the model is challenged, the agency must provide a full analytical defense.”¹⁹⁷

More recently, the Wisconsin Supreme Court acknowledged the importance of algorithmic validation in the case of *State v. Loomis*, in which a petitioner raised due process objections to the use of a black-box, human-generated risk assessment algorithm designed to aid in parole evaluations.¹⁹⁸ The court held that the state’s risk assessment algorithm could be used in sentencing, but it further explained that the algorithm’s results needed to be accompanied by a “written advisement listing [their] limitations,” including the fact that “no cross-validation study for a Wisconsin population” had been conducted and that the algorithm “was not developed for use at sentencing, but was intended for use by the Department of Corrections in making determinations regarding treatment, supervision, and parole.”¹⁹⁹ Strikingly, though, the *Loomis* court held that this need for a cautionary “written advisement” could be eliminated if the state sufficiently validated its algorithm.²⁰⁰

Efforts to audit and assess AI—to provide a “full analytical defense” whenever government applies AI tools in consequential ways—can go far to address concerns about their misapplication and misuse.²⁰¹ In this way, these efforts seem likely to facilitate a path toward increased public acceptance and support of governmental reliance on AI.

C. Oversight

Oversight is likely another important step on a path toward public trust in AI. Oversight allows humans to monitor a technology’s results and to challenge or correct them when necessary.²⁰² DNA analysis introduced in a criminal case, for

& Wendy E. Wagner, *Legal Aspects of the Regulatory Use of Environmental Modeling*, 33 ENV’T. L. REP. 10,751 (2003).

¹⁹⁷ *Eagle-Picher Industries, Inc. v. E.P.A.*, 759 F.2d 905, 921 (1985). This does not mean, of course, that the agency’s model must be perfect. *See Alaska v. Lubchenco*, 825 F. Supp. 2d 209, 223 (D.D.C. 2011) (“[E]ven if plaintiffs can poke some holes in the agency’s models, that does not necessarily preclude a conclusion that these models are the best available science. Some degree of predictive error is inherent in the nature of mathematical modeling.”). For general discussion, see Cary Coglianese & David Lehr, *Transparency and Algorithmic Governance*, 71 ADMIN. L. REV. 1, 42–47 (2019).

¹⁹⁸ *State v. Loomis*, 881 N.W.2d 749 (Wis. 2016).

¹⁹⁹ *Id.* at 769–70. The state supreme court approved the trial court’s use of the risk assessment in part because it found that the lower court had been aware of the limitations associated with the use of the COMPAS risk assessment. *Id.* at 770.

²⁰⁰ *Id.* at 770 (“[I]f a cross-validation study for a Wisconsin population is conducted, then flexibility is needed to remove this caution.”).

²⁰¹ *See supra* note 188 and accompanying text.

²⁰² Facebook content moderation is an example of human oversight currently used in the

example, must also be weighed by human decision-makers—namely, members of the jury. The extensive documentation provided with DNA results often gives defense lawyers the ability to critique the methodology when it is put forward to the jury.²⁰³ This documentation must usually include, “at a minimum, a description of the evidence examined, a listing of the loci analyzed, a description of the methodology, results and/or conclusions, and an interpretative statement (either quantitative or qualitative) concerning the inference to be drawn from the analysis.”²⁰⁴

Admittedly, the role for human oversight may seem less obvious in the case of physical machines, such as breathalyzers and speed detectors, because the results of the technology itself can be sufficient to establish a prima facie case. Still, defendants affected by these technologies retain the right to challenge the technology and its results based on improper operation or other errors.²⁰⁵

In the context of AI, some tools may keep humans fully involved, allowing for oversight of individual outcomes generated by the algorithm before any decisions are made.²⁰⁶ Of course, this form of human oversight could merely risk overriding arguably superior algorithmic decision-making with inferior human decision-making, thus defeating the main purpose of deploying algorithmic tools in the first place.²⁰⁷

Another possibility is to implement human oversight at the system level, such as through the processes of auditing and impact assessment discussed above. Having a third party conduct an audit or assessment, or a third-party certification of the government’s own audit or assessment, could instill confidence that a government agency has designed and is using an AI tool in a responsible manner.²⁰⁸ At a minimum,

private sector. Facebook uses AI to manage thousands of posts and flag them for potential content violations, allowing the AI to resolve clear policy violations. However, for less clear-cut cases, human moderators intervene to assess the validity of reports. James Vincent, *Facebook Is Now Using AI to Sort Content for Quicker Moderation*, THE VERGE (Nov. 3, 2020), <https://www.theverge.com/2020/11/13/21562596/facebook-ai-moderation>.

²⁰³ For an in-depth discussion of DNA testing and documentation requirements from collection to post-conviction, see generally ABA STANDARDS FOR CRIMINAL JUSTICE: DNA EVIDENCE, *supra* note 114.

²⁰⁴ See NAT’L RSCH. COUNCIL COMM. ON IDENTIFYING THE NEEDS OF THE FORENSIC SCI. CMTY., *supra* note 113, at 132.

²⁰⁵ See *Denison v. Anchorage*, 630 P.2d 1001, 1003 (Alaska Ct. App. 1981) (holding that the petitioner had the right to introduce a videotape made by police, as well as witness to testify to her sobriety and the amount of alcohol she drank, to prove that the breathalyzer result was wrong).

²⁰⁶ In other words, the results of the AI system would be just an input into the governmental decision, rather than the decision itself or even a default decision. Coglianesse & Lai, *supra* note 11, at 1336–37.

²⁰⁷ See Cary Coglianesse, *Administrative Law in the Automated State*, 150 DÆDALUS 104, 116 (2021) (“If automated decisions turn out increasingly to be more accurate and less biased than human ones, a right to a decision by humans would seem to deny the public of the desirable improvements in governmental performance that algorithms can deliver.”).

²⁰⁸ Conformity with IEEE standards, for example, can be audited by third parties. Jason

details about how the algorithm operates, the data on which it relies, its underlying assumptions, and the results of validation efforts should be reviewed by human officials and made appropriately transparent to the public.²⁰⁹

Taken together, efforts dedicated to standardizing, validating, and overseeing AI tools could boost public support for AI use by the government. Somewhat ironically, the current suspicion of AI tools that underlies the contemporary push for negative algorithm rights may itself provide a form of oversight that helps move toward positive algorithm rights. Contemporary criticism continues to prompt AI researchers and government officials to seek to develop algorithmic tools and processes that can overcome the concerns that underlie the negative rights movement.²¹⁰

To head off public criticism, government agencies should involve the public as early as possible in the design of new AI tools.²¹¹ Any private contractors that agencies use to develop algorithms ought to be involved in any public engagement too.²¹² Public input, of course, must be genuinely valued by government officials, given that symbolic or purely strategic participation efforts may backfire if people feel that their input does not actually matter. Truly meaningful transparency and public participation can produce real legitimating effects and would likely bolster any transition from negative to positive algorithm rights.²¹³

D. Qualification

A trained and thoughtful workforce is a crucial component of the successful development and use of new technology. Having standards for the responsible use of a technology matters little if those using the technology have not been trained in the standards and do not follow them. DNA laboratories, for example, must be

Allnutt, Program Manager, IEEE Standards Ass'n, Presentation on the IEEE Conformity Assessment Program (May 2018), http://site.ieee.org/pes-pscc/files/2018/05/ICAP-Overview_May-2018.pdf. See generally Lesley K. McAllister, *Regulation by Third-Party Verification*, 53 B.C. L. REV. 1 (2012).

²⁰⁹ Coglianesse & Lehr, *supra* note 197, at 47–49.

²¹⁰ The prospect of data scientists developing strategies to make AI more transparent, accountable, and fair is the premise underlying MICHAEL KEARNS & AARON ROTH, *THE ETHICAL ALGORITHM: THE SCIENCE OF SOCIALLY AWARE ALGORITHM DESIGN* (2019); see also Coglianesse & Lehr, *supra* note 197, at 49–55.

²¹¹ See Coglianesse & Lai, *supra* note 11, at 1334–35; Ellen P. Goodman, *Smart Algorithmic Change Requires a Collaborative Political Process*, REGUL. REV. (Feb. 12, 2019), <https://www.theregreview.org/2019/02/12/goodman-smart-algorithmic-change-requires-collaborative-political-process/>.

²¹² See Cary Coglianesse & Erik Lampmann, *Contracting for Algorithmic Accountability*, 6 ADMIN. L. REV. ACCORD 175, 175–99 (2021).

²¹³ See Edmund Malesky & Markus Taussig, *Participation, Government Legitimacy, and Regulatory Compliance in Emerging Economies: A Firm-Level Field Experiment in Vietnam*, 113 AM. POL. SCI. REV. 530, 548–49 (2019); see generally Cary Coglianesse, Heather Kilmartin & Evan Mendelson, *Transparency and Public Participation in the Federal Rulemaking Process*, 77 GEO. WASH. L. REV. 924 (2009).

accredited, and personnel working in these labs must demonstrate their qualification through proficiency tests and education.²¹⁴

Along these same lines, the people who design and operate AI systems should be sufficiently qualified.²¹⁵ They must have the technical competency to design mathematically sound systems free from software bugs and glitches. Equally important, they must be thoughtful and aware of how their biases and assumptions impact the model design and the variables they choose, and how those choices may impact the people affected by the system.²¹⁶ Technology may be an improvement over human decision-making, but because it is itself a product of human decision-making—and the limitations and biases that come with it—it cannot prevent the people who create it from making mistakes in its design and deployment.²¹⁷

It may seem somewhat ironic that the responsible use of AI tools depends on qualified human capital. After all, AI will presumably be used to replace humans at tasks that AI can perform better. But this will not mean that humans will no longer be needed. On the contrary, the need for qualified personnel in government will remain crucial, just in different ways.

Indeed, when looking forward, the size of the government workforce of the future need not necessarily shrink. For one, if automating more administrative tasks frees government workers from drudgery, this will allow employees to shift to tasks that allow them to interact more personally with the public—ultimately improving both governmental efficiency and public satisfaction.²¹⁸ For another, in an era of AI, government agencies will need to recruit and train teams of analysts who possess specific skills and qualifications to use digital algorithms in an effective and trustworthy manner.²¹⁹ Even when agencies rely on private contractors to build AI systems, they will need to ensure that the procurement process results in the hiring of contractors with the needed skills and a suitably public-oriented mindset.²²⁰

²¹⁴ See NAT'L RSCH. COUNCIL COMM. ON IDENTIFYING THE NEEDS OF THE FORENSIC SCI. CMTY., *supra* note 113, at 132.

²¹⁵ Coglianese & Lai, *supra* note 11, at 1323.

²¹⁶ As they do with anything their agency does, analysts need integrity and empathy as well as just technical competence. CARY COGLIANESE, LISTENING, LEARNING, LEADING: A FRAMEWORK FOR REGULATORY EXCELLENCE 23 (2015), https://kleinmanenergy.upenn.edu/wp-content/uploads/2020/08/Listening-Learning-Leading_Coglianese-1.pdf.

²¹⁷ Coglianese & Lai, *supra* note 11, at 1314–18.

²¹⁸ Coglianese, *supra* note 207, at 114–15; P'SHIP FOR PUB. SERV. & IBM CTR. FOR BUS. AND GOV'T, MORE THAN MEETS AI: ASSESSING THE IMPACT OF ARTIFICIAL INTELLIGENCE ON THE WORK OF GOVERNMENT 8 (Feb. 2019), <https://ourpublicservice.org/wp-content/uploads/2019/02/More-Than-Meets-AI.pdf>.

²¹⁹ Cary Coglianese, *Algorithmic Regulation: Machine Learning as Governance Tool*, in THE ALGORITHMIC SOCIETY: POWER, KNOWLEDGE AND TECHNOLOGY IN THE AGE OF ALGORITHMS 35, 49–50 (Marc Schuilenburg & Rik Peeters, eds., 2021); Cary Coglianese, *Optimizing Regulation for an Optimizing Economy*, 4 U. PA. J.L. & PUB. AFF. 1, 10–11 (2018).

²²⁰ For a full range of procurement issues for agencies to consider in their pursuit of responsible design and deployment of AI, see Lavi M. Ben Dor & Cary Coglianese, *Procurement as AI Governance*, 2 IEEE TRANS. TECH. & SOC. 192 (2021), David S. Rubenstein, *Acquiring*

With a well-qualified workforce designing and operating automated systems, AI technology can grow more standardized, validated, overseen, and trustworthy. At the same time, as members of the public grow more accustomed to the use of AI tools in their daily lives in other contexts, they may come to accept increased use of digital algorithms by government too. Indeed, they may well even demand its use. After all, if members of the public can, for example, readily resolve their consumer disputes with online businesses through automated online dispute resolution tools, they may begin to expect, and even demand, the same expedient and satisfactory outcomes from their government.²²¹ If governmental institutions are to keep pace with changing public expectations, they will need to invest in the qualified workforces needed to meet the eventual demand for the use of AI.

CONCLUSION

A vision of the future in which the public demands positive rights to AI may seem naïve, far-fetched, or even foolhardy given current resistance to AI, with its focus on negative consequences from the deployment of ill-designed or poorly tested digital algorithms.²²² From today's vantage point, it may well seem a pipedream to envision a day when members of the public will shift from insisting on a right to a human decision to a right to an AI decision. Yet such a future of positive algorithm rights is not as far-fetched as it might seem.

As we have discussed in this Article, other technologies—such as DNA analysis, breathalyzer testing, and speed radar detection—entered the public scene under a cloud of suspicion and even outright hostility. With time, they became widely accepted and their use is now well embedded in the legal system. Moreover, some of the very same types of claims and dire warnings made today in opposition to AI were made in the past about these other technologies. It is clear that resistance to technological innovations can wane as people become more familiar with new tools, experiencing the benefits they provide and seeing that they do not pose all the dangers initially feared.²²³

Ethical AI, 73 FLA. L. REV. 747, 797–814 (2021), and Coglianese & Lampmann, *supra* note 212, at 184–94.

²²¹ For discussion of the success eBay has reported with its online dispute resolution system, see STEPHANOS BIBAS & BENJAMIN BARTON, *REBOOTING JUSTICE: MORE TECHNOLOGY, FEWER LAWYERS, AND THE FUTURE OF LAW* (2017) and Benjamin Barton, *Rebooting Justice: ODR Is Disrupting the Judicial System*, 44 L. PRAC. 32, 34–36 (2018).

²²² Cf. Huq, *supra* note 9.

²²³ See Daniel Araya & Rodrigo Nieto-Gómez, *Renewing Multilateral Governance in the Age of AI*, CTR. FOR INT'L GOVERNANCE INNOVATION (Nov. 9, 2020), <https://www.cigionline.org/articles/renewing-multilateral-governance-age-ai/> (noting “the truism that ‘technology is often the stuff that doesn’t work yet’” and arguing that, once it does work, AI becomes “just” a well-accepted feature of life—“becoming everyday ‘stuff that works’” that “simply ‘disappear[s]’ into the furniture”).

More importantly, criticism of a new technology can serve as a catalyst to the development of standards for its responsible use. The qualifications of professionals using the technology can improve. Efforts at auditing, validation, and oversight can help confirm the technology's safety and soundness and provide ongoing incentives for its ethical and reliable use.²²⁴ Along the way, as new technology demonstrates its value and becomes part of standard practice, its use can gain recognition as a positive right.

This may be the future direction for AI. Today's criticisms may eventually dissipate as AI tools and the data science underlying them advance. And given the error- and bias-prone nature of human decision-making, AI tools that deliver positive value and avoid unintended consequences may well end up markedly improving governmental performance along a range of dimensions.²²⁵ If such improvements come to pass, society will be justified in assigning a positive right to governmental use of AI.

²²⁴ We should be clear that, by itself, no technology can eliminate any underlying fundamental unfairness in the legal rules and governmental institutions within which the technology is applied. *Cf.* Roberts, *supra* note 41; Mayson, *supra* note 66. It is conceivable, though, that thoughtful use of AI tools, with their inherent reliance on large quantities of data that can be used to assess the overall fairness of governmental systems and processes, may more readily expose the status quo's inequities and potentially make them easier to redress.

²²⁵ Coglianese & Lai, *supra* note 11, at 1304–14.