DIGGING INTO ALGORITHMS: LEGAL ETHICS AND LEGAL ACCESS

Carla L. Reyes* & Jeff Ward**§

The current discussions around algorithms, legal ethics, and expanding legal access through technological tools gravitate around two themes: (1) protection of the integrity of the legal profession and (2) a desire to ensure greater access to legal services. The hype cycle often pits the desire to protect the integrity of the legal profession against the ability to use algorithms to provide greater access to legal services, as though they are mutually exclusive. In reality, the arguments around protecting the profession from the threats posed by algorithms represent an over-fit in relation to what algorithms can actually achieve, while the visions of employing algorithms for access to justice initiatives represent an under-fit in relation to what algorithms could provide. A lack of precision about algorithms results in blunt protections of professional integrity leaving little room for the potential benefits of algorithmic tools. In other words, this incongruence persists because of imprecise understandings and unrealistic characterizations of the algorithmic technologies and how they fit within the broader technology of law itself. This Article provides an initial set of tools for empowering lawyers with a better understanding of, and critical engagement with, algorithms.

With the goal of encouraging a more nuanced discussion around the ethical dimensions of using algorithms in legal technology—a discussion that better fits technological reality—the Article argues for lawyers and non-technologists to shift away from evaluating legal technology through a lens of mere algorithms—as though they can be evaluated outside of a specific context—to a focus on understanding algorithmic systems as technology created, manipulated, and used in a particular context. To make this argument, this Article first reviews the current use of algorithms in legal settings, both criminal and civil, reviewing the related literature and regulatory responses. This Article then uses the shortcomings of legal technology lamented by the current literature and the related regulatory responses to demonstrate the importance of shifting our collective paradigm from a consideration of law and algorithms to law and algorithmic systems. Finally, this Article offers a framework for use in assessing algorithmic systems and applies the framework to algorithmic systems employed in the legal context to demonstrate its usefulness in accurately separating true tensions from those that merely reverberate through the hype cycle. In using the framework to reveal areas at the intersection of law and algorithms truly most ripe for progress, this Article concludes with a call to action for more careful design of both legal systems and algorithmic ones.

TABLE OF CONTENTS

INTRODUCTION

Dramatically and suddenly, algorithms are becoming tools for administering justice, displacing lawyers, and transforming how governments deliver services. The situation is chaotic. Take, for example, attempts to use algorithms to improve the accuracy and efficiency of the criminal justice system. In an attempt to eliminate human bias and error from the sentencing process in criminal proceedings, courts increasingly adopt technology tools for conducting recidivism risk assessments.[1] However, commentators question the neutrality of the technology.[2] Concerns of embedded bias in algorithmic assessments used to determine sentencing become particularly acute when defendants face obstacles to meaningfully challenge the technology.[3] For example, Eric Loomis challenged the predictive computer system that labeled him a high risk for recidivism and led to a six-year prison sentence on grounds that included the impermissible consideration of gender in making the prediction.[4] The Wisconsin Supreme Court denied Loomis' challenge on a variety of grounds, without allowing Loomis full access to the algorithm, which was protected by trade se-

---

* Assistant Professor of Law, Southern Methodist University Dedman School of Law; Affiliated Faculty, Indiana University Bloomington Ostrom Workshop Program on Cybersecurity and Internet Governance; Research Associate, University College London Center for Blockchain Technology.

** Associate Dean for Technology & Innovation; Clinical Professor of Law & Director of the Center on Law & Technology, Duke University School of Law; Faculty Associate, Berkman Klein Center for Internet & Society at Harvard University.

§ The authors would like to thank the participants in the 2020 AALS Section on Professional Responsibility Works in Progress Session, especially Jayanth Krishnan, for helpful feedback, as well as Casandra Laskowski, Charlie Giattino, Jeffery Ritter and Kelli Raker. The authors would also like to thank Kirsten Albers-Fielder, Rohit Jayawardhan, Victoria R. Nelson, and Hadar Tanne for excellent research assistance.

[1] *See, e.g.*, Mirko Bagaric & Gabrielle Wolf, *Sentencing by Computer: Enhancing Sentencing Transparency and Predictability, and (Possibly) Bridging the Gap Between Sentencing Knowledge and Practice*, 25 GEO. MASON L. REV. 653, 654 (2018) ("This Article concludes that [alleged bias] problems can be overcome and that computers could determine sentences more effectively and fairly than human judges. The application of a properly designed algorithm that incorporates all relevant sentencing variables and confers appropriate weight on sentencing objectives and considerations could lead to sentences that are transparent and fair.").

[2] *See, e.g.*, Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CALIF. L. REV. 671 (2016); Harry Surden, *Ethics of AI in Law: Basic Questions*, *in* THE OXFORD HANDBOOK OF ETHICS OF AI 719 (Markus D. Dubber et al. eds., 2020); Rebecca Wexler, *Life, Liberty, and Trade Secrets: Intellectual Property in the Criminal Justice System*, 70 STAN. L. REV. 1343 (2018); Amanda Levendowski, *How Copyright Law Can Fix Artificial Intelligence's Implicit Bias Problem*, 93 WASH. L. REV. 579 (2018); Sonia K. Katyal, *Private Accountability in the Age of Artificial Intelligence*, 66 UCLA L. REV. 54 (2019).

[3] Wexler, *supra* note 2, at 1346 ("A death penalty defendant in Pennsylvania state court was denied access to the source code for a forensic software program that generated the critical evidence against him; the program's commercial vendor argued that the code is a trade secret. In a federal court in Texas, the federal government claimed that trade secret interests should shield details about how a cybercrime investigative software program operates, even though the information was necessary to determine whether warrantless use of the tool had violated the Fourth Amendment. And in a Wisconsin case, the state supreme court rejected a defendant's claim that he had a right to scrutinize alleged trade secrets in an algorithmic risk assessment instrument used to sentence him. The court reasoned that no due process violation had occurred in part because the judge's own access to the secrets was equally limited." (footnotes omitted) (citing Petition for Review Filed by Defendant Michael Robinson at 4, Robinson v. Commonwealth, No. 25 WDM 2016 (Pa. Super. Ct. Mar. 7, 2016); United States v. Ocasio, No. 3:11-cr-02728, slip op. at 1–2, 11–12 (W.D. Tex. May 28, 2013); State v. Loomis, 881 N.W.2d 749, 760–61 (Wis. 2016), *cert. denied*, 137 S. Ct. 2290 (2017))).

[4] *Id.* at 1369 (citing *Loomis*, 881 N.W.2d, at 755, 756 n.18).

cret law.[5] Despite the Supreme Court's decision, concern remains that denying access to the process by which sentencing and other impactful determinations are made represents a due process problem in and of itself.[6] Those engaged in debates at the intersection of law and algorithms employ Loomis' experience and the court's response as a rallying cry for technologies' potential to inject additional inequity into the criminal justice system, rather than less.[7] These concerns amplify as state and federal government institutions adopt technological tools in an increasing number of government-citizen interactions.[8]

Meanwhile, in the context of a seemingly innocuous case about overtime pay for contract lawyers, the United States Court of Appeals for the Second Circuit fanned the flame of a core fear related to the implications of algorithms for the legal services industry.[9] David Lola challenged what he described as the legal services industry's exploitation of recent law graduates by refusing to pay overtime for grueling hours spent on "document review projects that do not in

---

5 *Id.* at 1369–70.

6 Katyal, *supra* note 2, at 105–06 ("While automation dramatically lowers the cost of decisionmaking, it also raises significant due process concerns, involving lack of notice and the opportunity to challenge the decision.").

7 *See, e.g.*, *id.* at 87; Wexler, *supra* note 2, at 1346; *Criminal Law—Sentencing Guidelines—Wisconsin Supreme Court Requires Warning Before Use of Algorithmic Risk Assessments in Sentencing*—State v. Loomis, *881 N.W.2d 749 (Wis. 2016)*, 130 HARV. L. REV. 1530, 1530–37 (2017) [hereinafter *Loomis Note*].

8 For detailed discussions of a variety of government-citizen interactions to which state and federal governmental institutions apply algorithms and other methods of artificial intelligence, see, for example, Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249, 1252, 1259 (2008) (examining the use of technology in administrative law); Andrea Roth, *Trial by Machine*, 104 GEO. L. J. 1245, 1296–98 (2016) (exploring use of technology in criminal adjudication); Margaret Hu, *Algorithmic Jim Crow*, 86 FORDHAM L. REV. 633, 637–38, 672, 679, 682–84 (2017) (examining immigration and national security contexts); and Wexler, *supra* note 2, at 1346–48 (exploring the automation of the criminal justice system).

We also note that private actors also increasingly adopt advanced technological tools, including algorithms, in a variety of business-to-consumer contexts. Similar to the adoption of algorithms in the administration of law, which we use as the focal point of this Article, the goal of adopting such technology in business-to-consumer transactions ostensibly include increasing efficiency and reducing bias. However, a wide body of literature points out the ways that, like their government counterparts, private entities using algorithms may be interjecting more bias into their decisions, rather than less. *See generally, e.g.*, Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 4–5, 13–14 (2014); Kristin Johnson et al., *Artificial Intelligence, Machine Learning, and Bias in Finance: Toward Responsible Innovation*, 88 FORDHAM L. REV. 499, 500–01, 504–05 (2019); Kristin N. Johnson, *Automating the Risk of Bias*, 87 GEO. WASH. L. REV. 1214, 1215, 1220 (2019); Matthew Adam Bruckner, *The Promise and Perils of Algorithmic Lenders' Use of Big Data*, 93 CHI.-KENT L. REV. 3, 5–6, 25–26 (2018); Matthew Adam Bruckner, *Preventing Predation & Encouraging Innovation in Fintech Lending*, 72 CONSUMER FIN. L. Q. REP. 370, 377–80 (2018).

9 *See* Lola v. Skadden, Arps, Slate, Meagher & Flom LLP, 620 F. App'x 37, 45 (2d Cir. 2015).

any way resemble the practice of law."[10] Although the case seemed unlikely to succeed—indeed, Mr. Lola initially lost[11]—on appeal, the Second Circuit ultimately ruled in his favor.[12] The Second Circuit rested the decision on the fact that "an individual who, in the course of reviewing discovery documents, undertakes tasks that could otherwise be performed entirely by a machine cannot be said to engage in the practice of law."[13] This understanding that lawyering requires some measure of reasoning attainable only by humans, such that whatever a computer can do, it cannot be lawyering, directly feeds another common refrain around algorithms and the delivery of legal services. Namely, arguments that legal technology may actually enable the unlicensed or inadequate practice of law by non-lawyers and threaten to undermine quality across the entire industry.[14]

The *Loomis* and *Lola* cases touch on themes that sit at the heart of debates around the integration of technology into all service models, including governmental and legal services. Can technology live up to the hopes of reducing human error and bias?[15] Or will technology simply compound and reinforce historically entrenched biases and inequalities?[16] Can technology be used to improve society[17] or simply enable new ways for those in power to extort value from those who are not?[18] How many workers will experience technological job displacement?[19] If those that retain employment must use technological

---

[10] Compl. ¶¶ 20–21, Lola v. Skadden, Arps, Slate, Meagher & Flom LLP, No. 13-cv-5008, 2014 WL 4626228 (S.D.N.Y. Sept. 16, 2014).

[11] Michael Simon et al., Lola v. Skadden *and the Automation of the Legal Profession*, 20 YALE J. L. & TECH. 234, 243 (2018).

[12] *Lola*, 620 F. App'x at 45.

[13] *Id.*

[14] *See, e.g.*, Sherley E. Cruz, *Coding for Cultural Competency: Expanding Access to Justice with Technology*, 86 TENN. L. REV. 347, 350 (2019) ("Without culturally competent design considerations, does technology provide all individuals with meaningful and quality user experiences? Worse yet, what if the technology places the user's privacy at risk or promotes implicit biases because the design did not consider the diversity of end users or the stakeholders?"); Michele DeStefano, *Compliance and Claim Funding: Testing the Borders of Lawyers' Monopoly and the Unauthorized Practice of Law*, 82 FORDHAM L. REV. 2961, 2961 (2014) ("The complexity of commerce in today's globalized era and the rise of technology have sparked new developments in the debate surrounding unauthorized practice of law (UPL) statutes. Proponents of UPL statutes argue that these rules protect consumers from the incompetency of nonlawyers.").

[15] Bagaric & Wolf, *supra* note 1, at 654.

[16] *See generally, e.g.*, DAVID BARNHIZER & DANIEL BARNHIZER, THE ARTIFICIAL INTELLIGENCE CONTAGION: CAN DEMOCRACY WITHSTAND THE IMMINENT TRANSFORMATION OF WORK, WEALTH AND THE SOCIAL ORDER? (2019).

[17] John O. McGinnis & Russell G. Pearce, *The Great Disruption: How Machine Intelligence Will Transform the Role of Lawyers in the Delivery of Legal Services*, 82 FORDHAM L. REV. 3041, 3064 (2014).

[18] *See, e.g.*, SHOSHANA ZUBOFF, THE AGE OF SURVEILLANCE CAPITALISM: THE FIGHT FOR A HUMAN FUTURE AT THE NEW FRONTIER OF POWER (2019).

[19] Deborah Jones Merritt, *What Happened to the Class of 2010? Empirical Evidence of Structural Change in the Legal Profession*, 2015 MICH. ST. L. REV. 1043, 1106 (2015) ("Three-fifths of law firm managing partners acknowledge that their firms have increased

tools to keep pace, how will the pressures of increased production affect the quality of work?[20] These important themes, discussed in interdisciplinary settings, require a commonly accessible paradigm that encourages more nuanced discussion and policy decisions.

Indeed, the themes at the heart of the *Loomis* and *Lola* cases will only rise in importance as service providers across a variety of industries increasingly turn to the potential use of a variety of computational techniques,[21] together often referred to as artificial intelligence or "AI,"[22] to improve efficiency, eliminate human error and bias, and make service delivery altogether more responsive. The legal services industry is not immune.[23] Lawyers presently use AI, or more specifically, machine learning tools that are perhaps the most prominent approach to AI today,[24] to improve due diligence, e-discovery and document review, predict litigation outcomes, draft documents using language models, and employ other efficiency-enhancing tools.[25] Meanwhile, judges and other

---

efficiency by substituting technology for human workers. An even higher percentage (84.3%) agree that '[t]echnology replacing human resources' is a permanent trend in law practice. Although technology enriches the work of experienced lawyers, it reduces the need for lower skilled attorneys." (footnotes omitted)).

[20] McGinnis & Pearce, *supra* note 17, at 3042 ("These new technologies will substantially shake up the legal profession, harming the economic prospects of many lawyers, but providing advantages to some others. Machines may actually aid two kinds of lawyers in particular. First, superstars in the profession will be more identifiable and will use technology to extend their reach. Second, lawyers who can change their practice or organization to take advantage of lower cost inputs made available by machines will be able to serve an expanding market of legal services for middle-class individuals and small businesses, meeting previously unfulfilled legal needs.").

[21] Harry Surden, *Artificial Intelligence and Law: An Overview*, 35 GA. ST. U. L. REV. 1305, 1310 (2019) [hereinafter Surden, *AI Overview*] ("At a high level, AI is generally considered a subfield of computer science. However, AI is truly an interdisciplinary enterprise that incorporates ideas, techniques, and researchers from multiple fields, including statistics, linguistics, robotics, electrical engineering, mathematics, neuroscience, economics, logic, and philosophy, to name just a few. Moving one level lower, AI can be thought of as a collection of technologies that have emerged from academic and private-sector research." (footnotes omitted)).

[22] Many misunderstand artificial intelligence because, at least in part, of the lack of a generally agreed upon definition. Ryan Calo, *Artificial Intelligence Policy: A Primer and Roadmap*, 51 U.C. DAVIS L. REV. 399, 403 (2017); Matthew U. Scherer, *Regulating Artificial Intelligence Systems: Risks, Challenges, Competencies, and Strategies*, 29 HARV. J. L. & TECH. 353, 362 (2016) ("'[A]rtificial intelligence' refers to machines that are capable of performing tasks that, if performed by a human, would be said to require intelligence.").

[23] McGinnis & Pearce, *supra* note 17, at 3041 (declaring "[t]he disruption has already begun"); Simon et al., *supra* note 11, at 237 ("Technological advances will also usher in a new era of legal services, among others.").

[24] Surden, *AI Overview*, *supra* note 21, at 1311 (explaining that machine learning is actually "a family of AI techniques that share some common characteristics," and that it "is not one approach but rather refers to a broad category of computer techniques that share these features . . . includ[ing] neural networks/deep learning, naive Bayes classifier, logistic regression, and random forests.").

[25] Cruz, *supra* note 14, at 349 ("Technology is expanding access to justice by helping individuals spot legal issues using mobile applications. These applications facilitate the ex-

government officials employ algorithms—specific sets of instructions used to calculate an outcome—to predict the likelihood of recidivism, set bail amounts, determine parole eligibility, distribute social welfare benefits, and help decide a whole host of other decisions that sit at the core of key issues around life and liberty.[26] Such uses of algorithms in legal technology lead to heated discussions around algorithms, legal ethics, and expanding legal access through technological tools.

Two key themes feature prominently in these law and technology discussions: (1) protection of the integrity of the legal profession and legal institutions such as the criminal justice system, and (2) a desire to ensure greater access to legal services.[27] The hype cycle often pits the desire to protect the integrity of the legal profession against the ability to use algorithms to provide greater access to legal services, as though they are mutually exclusive. In reality, the arguments around protecting the profession from the threats posed by algorithms represent an over-fit in relation to what algorithms can actually achieve, while the visions of employing algorithms for access to justice initiatives represent an under-fit in relation to what algorithms could provide. To encourage a discussion around the ethical dimensions of using algorithms in legal technology that better fits technological reality, this Article argues for a fundamental shift away from evaluating legal technology through a lens of mere algorithms—as though they can be evaluated outside of a specific context—to a focus on understanding algorithmic systems—as technology created, manipulated, and used in a particular context.

To make this argument while also providing an initial set of analytical tools to empower lawyers with a better understanding of, and critical engagement with, algorithms, this Article proceeds in three parts. First, this Article will review the current use of algorithms in two legal settings: criminal proceedings and civil legal services, reviewing the related literature and regulatory responses. This Article then will use the concerns raised in current literature and related regulatory responses to demonstrate the importance of shifting our collective paradigm from a consideration of law and algorithms to law and algorithmic systems. Finally, this Article will offer a framework for use in assessing algorithmic systems and applies the framework to algorithmic systems employed in the legal context to demonstrate its usefulness in accurately separating true tensions from those that merely reverberate through hype-driven debates. In using the framework to reveal areas at the intersection of law and algorithms truly most ripe for progress, this Article concludes with a call to action for more careful design of both legal systems and algorithmic ones.

change of information and documents through virtual client portals, assist self-represented individuals with the drafting of legal documents using chatbots, and allow for virtual interviews guided by artificial intelligence. Lawyers are using technology to make the practice of law more efficient, more affordable, and more accessible." (footnotes omitted)).

[26] *See, e.g.*, Citron, *supra* note 8, at 1267, 1279; Roth, *supra* note 8, at 1248; Hu, *supra* note 8, at 636, 642; and Wexler, *supra* note 2, at 1349.

[27] For further discussion of these themes, *see infra* Sections I.B–C.

I. TENDING TOWARD EXTREMES AT A DISSERVICE TO ALL: THE DEBATE ABOUT LAW AND ALGORITHMS

As illustrated by the *Loomis* and *Lola* cases, discussion at the intersection of law, algorithms, and artificial intelligence more broadly, often unthinkingly separates into two streams: the use of algorithms in criminal proceedings and the use of algorithms in civil legal proceedings.[28] This simple packaging of the issues at the intersection of law and algorithms into two separate spheres actually reflects implicit assumptions that lie at the heart of the debates in both areas. To begin to reveal these assumptions and shed light on how they detrimentally affect our ability to accurately discuss pressing issues of due process and access to justice, this Part begins with an overview of the issues and leading themes. By drawing out the hidden values interwoven into the fabric of the law in the context of both criminal and civil legal proceedings, this Part demonstrates the need for a paradigm shift from thinking about algorithms standing alone—outside of the context in which they are employed—to thinking about algorithmic systems more holistically.

A. *Defining Algorithms, AI, and Machine Learning*

The computational techniques and machine technologies that make up the science and study of artificial intelligence ("AI") had their beginnings in the 1950s, but several recent societal developments enable greater use of such technologies in a wider variety of industries now than ever before.[29] When speaking in the most general terms, experts explain AI as "a set of techniques aimed at approximating some aspect of human or animal cognition using machines."[30] Beyond such broad statements, a generally agreed-upon definition of AI remains elusive.[31] Popularly today, when many people speak of AI, they

---

[28] Lauren Sudeall, *Integrating the Access to Justice Movement*, 87 FORDHAM L. REV. ONLINE 172, 172 (2019) ("One important preliminary question we tackled was how [the access to justice movement] would define 'justice,' and whether it would apply only to the civil justice system. Although the phrase 'access to justice' is not exclusively civil in nature, more often than not it is taken to have that connotation. Lost in that interpretation is an opportunity to engage in a broader, more holistic conversation about what justice entails and what is required to gain access to it." (footnote omitted)).

[29] Klaus Schwab, *The Fourth Industrial Revolution: What it Means, How to Respond*, WORLD ECON. F. (Jan. 14, 2016), https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/ [https://perma.cc/L263-X32A]; *see also* PWC/CB INSIGHTS, MONEYTREE REPORT Q1 2018 (2018), https://www.pwc.com/us/en/technology/assets/MoneyTree_Report_2018_Q1_FINAL.pdf [https://perma.cc/XT7F-XD3D] (revealing that the first quarter of 2018 saw the highest total investments in artificial intelligence ever recorded with funding exceeding $1.9 billion).

[30] Calo, *supra* note 22, at 404.

[31] Scherer, *supra* note 22, at 359 ("Unfortunately, there does not yet appear to be any widely accepted definition of artificial intelligence even among experts in the field, much less a useful working definition for the purposes of regulation.").

have machine learning in mind.[32] Increased interest in machine learning techniques—by which computers crunch data[33] using an algorithm to perform its assigned objective function,[34] make predictions,[35] and automate certain tasks[36]—stems in large part from recent advances in computer processing speed, some advances in algorithms, and the rise of big data.[37] Many believe that the advances in machine learning and other sophisticated emerging technologies "ha[ve] the potential to help address some of the biggest challenges that society faces."[38] However, along with that potential comes the challenge of ensuring equitable development of the technology and the uses to which it is put.[39] The use of machine learning and other forms of AI to assist in the adjudication of criminal proceedings represents one context in which questions of equity and fairness receive heightened attention.

---

[32] Levendowski, *supra* note 2, at 590 ("When journalists, researchers, and even engineers say 'AI,' they tend to be talking about machine learning, a field that blends mathematics, statistics, and computer science to create computer programs with the ability to improve through experience automatically.").

[33] Simon et al., *supra* note 11, at 254 ("Machine learning can take place in a number of ways. These include 'supervised learning,' where the learning algorithm is given inputs and desired outputs with the goal of learning which rules lead to the desired outputs; 'unsupervised learning,' where the learning algorithm is left on its own to determine the relationships within a dataset; and 'reinforcement learning,' where the algorithm is provided feedback on its performance as it navigates a data set." (citing STUART J. RUSSELL & PETER NORVIG, ARTIFICIAL INTELLIGENCE: A MODERN APPROACH 650 (2d ed. 2009))).

[34] An objective function is an algorithm's performance criterion, by which computers crunch data using an algorithm—through many iterations—to learn to meet some criterion of success, such as accurately predicting case outcomes or likelihood of recidivism. *See* Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 GEO. L.J. 1147, 1157 (2017) (explaining that machine learning algorithms " 'optimize a performance criterion using example data or past experience.' In other words, these algorithms make repeated passes through data sets, progressively modifying or averaging their predictions to optimize specified criteria." (footnote omitted) (quoting ETHEM ALPAYDIN, INTRODUCTION TO MACHINE LEARNING 3 (2d ed. 2010))).

[35] Levendowski, *supra* note 2, at 590–91 ("Most AI systems are trained using vast amounts of data and, over time, hone the ability to suss out patterns that can help humans identify anomalies or make predictions." Most AI needs lots of data exposure to automatically perform a task).

[36] Calo, *supra* note 22, at 405 ("Machine learning ("ML") refers to the capacity of a system to improve its performance at a task over time."); *see also* Harry Surden, *Machine Learning and Law*, 89 WASH. L. REV. 87, 88 (2014) [hereinafter Surden, *Machine Learning*] ("Broadly speaking, machine learning involves computer algorithms that have the ability to 'learn' or improve in performance over time on some task." (citing PETER FLACH, MACHINE LEARNING: THE ART AND SCIENCE OF ALGORITHMS THAT MAKE SENSE OF DATA 3 (2012))).

[37] Calo, *supra* note 22, at 405.

[38] EXEC. OFF. OF THE PRESIDENT NAT'L SCI. AND TECH. COUNCIL COMM. ON TECH., PREPARING FOR THE FUTURE OF ARTIFICIAL INTELLIGENCE 5 (2016).

[39] STAN. U., ARTIFICIAL INTELLIGENCE AND LIFE IN 2030: ONE HUNDRED YEAR STUDY ON ARTIFICIAL INTELLIGENCE 10 (2016), https://ai100.stanford.edu/sites/default/files/ai_100_report_0831fnl.pdf [perma.cc/4JX5-34ZB].

B. Due Process in Criminal Proceedings

Law enforcement, prosecutors, and judicial decision-makers increasingly employ algorithms and tools based on such algorithms in the criminal justice process. In the context of criminal investigations, law enforcement employs algorithms to, among other things, analyze DNA, assess and capture Internet traffic, identify neighborhoods for increased police presence, analyze forensic evidence, and flag individuals for further investigation.[40] Judges and parole boards use algorithms for risk assessments in setting bail, determining sentencing, and assessing parole eligibility.[41] At least two general themes drive the deepening integration of algorithmic tools into criminal justice decision-making: (1) the potential for reducing or even removing human bias and error from decisions with deep impact on the life and liberty of defendants, and (2) an ever-increasing need for efficiency and cost-savings in the judicial system.[42]

Although reduction of bias and increased efficiency represent worthy goals for criminal justice system reform, critics increasingly raise concerns about the pervasive and indiscriminate use of algorithms for these purposes.[43] In particular, commentators point to concerns that when algorithms rely on data from the criminal justice system, that data already likely reflects a history of bias and discrimination, which is then merely reinforced by the computational processes of the algorithm.[44] Because of the potential for algorithms to reinforce bias and discrimination rather than eliminate it, many argue that the capacity to chal-

---

[40] Wexler, *supra* note 2, at 1346–48; Andrew D. Selbst, *Disparate Impact in Big Data Policing*, 52 GA. L. REV. 109, 113 (2017) (examining the use of data mining in policing); Andrew Guthrie Ferguson, *Policing Predictive Policing*, 94 WASH. U. L. REV. 1109, 1112–13 (2017); Elizabeth E. Joh, *Policing by Numbers: Big Data and the Fourth Amendment*, 89 WASH. L. REV. 35, 35 (2014); Elizabeth E. Joh, *The Consequences of Automating and Deskilling the Police*, UCLA L. REV. DISCOURSE 134, 136–37 (2019).

[41] Wexler, *supra* note 2, at 1347–48; *see* Sandra G. Mayson, *Bias In, Bias Out*, 128 YALE L.J. 2218, 2222 (2019); Megan Stevenson, *Assessing Risk Assessment in Action*, 103 MINN. L. REV. 303, 307 (2018) (pre-trial risk assessment); Erin Collins, *Punishing Risk*, 107 GEO. L.J. 57, 59–60 (2018) (actuarial sentencing); Jessica M. Eaglin, *Constructing Recidivism Risk*, 67 EMORY L.J. 59, 61(2017).

[42] *See* Ric Simmons, *Big Data, Machine Judges, and the Legitimacy of the Criminal Justice System*, 52 U.C. DAVIS L. REV. 1067, 1072 (2018).

[43] *See, e.g.*, *id.* at 1074–77; *see* Rashida Richardson et al., *Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice*, 94 N.Y.U. L. REV. ONLINE 15, 46, 48 (2019); Joshua A. Kroll et al., *Accountable Algorithms*, 165 U. PA. L. REV. 633, 636, 680, 692 (2017).

[44] *See, e.g.*, Simmons, *supra* note 42, at 1074; Selbst, *supra* note 40, at 115, 120 (quoting Barocas & Selbst, *supra* note 2, at 674); ANDREW GUTHRIE FERGUSON, THE RISE OF BIG DATA POLICING 47–48 (2017); Sonja B. Starr, *Evidence-Based Sentencing and the Scientific Rationalization of Discrimination*, 66 STAN. L. REV. 803, 806 (2014); Barocas & Selbst, *supra* note 2, at 671; Mayson, *supra* note 41, at 2224 ("Given the nature of prediction, a racially unequal past will necessarily produce racially unequal outputs. To adapt a computer-science idiom, 'bias in, bias out.' "); Frank McIntyre & Shima Baradaran, *Race, Prediction, and Pretrial Detention*, 10 J. EMPIRICAL LEGAL STUD. 741, 759 (2013); Jennifer L. Skeem & Christopher T. Lowenkamp, *Risk, Race and Recidivism: Predictive Bias and Disparate Impact*, 54 CRIMINOLOGY 680, 683–84, 704–05 (2016).

lenge the algorithm is a due process right that requires algorithmic explainability and transparency.[45] Others query whether a right to explanation, or requirements of transparency into the "black box" of algorithmic computation will provide meaningful insight to defendants who ultimately seek a fair process in the adjudication of the charges against them.[46] These debates pit equally important social policy goals against each other as though they are mutually exclusive: reducing bias, increasing efficiency, and enhancing fair process. Ultimately, the debate often creates a menu of false choices. A more nuanced analysis of the computational and contextual components of a particular algorithm often reveals that the algorithm and its use are more explainable than the general debate over the intersection of law and technology suggests.[47] What is needed, then, is a framework that helps adopters and users of algorithms undertake a more nuanced assessment of whether any particular algorithm is the appropriate tool for the use at hand. Indeed, such a framework would be useful not just in the context of ensuring due process in criminal proceedings, but also in the fight to expand access to justice for low- and moderate-income individuals in civil proceedings.

C. Access to Justice in Civil Proceedings

Virtually everyone agrees that the United States' legal system suffers from an acute and persistent access-to-justice crisis.[48] The resulting "justice gap—the difference between the unmet need for civil legal services and the resources

---

[45] *See, e.g.*, Ashley Deeks, *The Judicial Demand for Explainable Artificial Intelligence*, 119 COLUM. L. REV. 1829, 1844–45 (2019); Simmons, *supra* note 42, at 1070; Kiel Brennan-Marquez, "*Plausible Cause": Explanatory Standards in the Age of Powerful Machines*, 70 VAND. L. REV. 1249, 1251, 1256 (2017).

[46] *See, e.g.*, Lillian Edwards & Michael Veale, *Slave to the Algorithm? Why a 'Right to an Explanation' is Probably Not the Remedy You Are Looking For*, 16 DUKE L. & TECH. REV. 18, 67 (2017).

[47] *See* Andrew D. Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085, 1088–90, 1138 (2018).

[48] *See, e.g.*, Drew Simshaw, *Ethical Issues in Robo-Lawyering: The Need for Guidance on Developing and Using Artificial Intelligence in the Practice of Law*, 70 HASTINGS L.J. 173, 179 (2018) ("The United States is in the midst of an access to justice crisis. Too many people lack access to the legal services they need, usually because they cannot afford them."); *See* Jessica Frank, *A2J Author, Legal Aid Organizations, and Courts: Bridging the Civil Justice Gap Using Document Assembly*, 39 W. NEW ENG. L. REV. 251, 251 (2017). For detailed accounts, see generally LEGAL SERVS. CORP., THE JUSTICE GAP: MEASURING THE UNMET CIVIL LEGAL NEEDS OF LOW-INCOME AMERICANS 30 (2017), https://www.lsc.gov/sites/default/files/images/TheJusticeGap-FullReport.pdf [perma.cc/XRK5-86YP] [hereinafter JUSTICE GAP REPORT]; ABA COMM'N ON THE FUTURE OF LEGAL SERVS., REPORT ON THE FUTURE OF LEGAL SERVICES IN THE UNITED STATES (2016), https://www.americanbar.org/content/dam/aba/images/abanews/2016FLSReport_FNL_WEB.pdf [https://perma.cc/V5W5-9KU3] [hereinafter FUTURE OF LEGAL SERVICES REPORT]; CTR. FOR AM. PROGRESS, CLOSING THE JUSTICE GAP: HOW INNOVATION AND EVIDENCE CAN BRING LEGAL SERVICES TO MORE AMERICANS (2011), https://cdn.americanprogress.org/wp-content/uploads/issues/2011/06/pdf/prose_all.pdf [https://perma.cc/K7BH-LUNK] [hereinafter, CLOSING THE JUSTICE GAP].

available to meet that need"[49]—largely affects low- and middle-income individuals and spans a large set of diverse civil legal needs related to property protection, family matters, and other basic needs for advancing individual livelihood.[50] Many predict that technology, while insufficient on its own to fully bridge the justice gap, represents an important piece of the solution.[51] Indeed, prior advances in technology, such as the Internet, helped link underserved clients with new service options,[52] improved access to dispute resolution systems,[53] and increased efficiencies in many legal services contexts.[54] Many hope that algorithms, and artificial intelligence more broadly, will offer tools to drive the next wave of innovation in meeting unmet legal needs.[55] However, fears that artificially intelligent legal technology may ultimately displace lawyers drives strenuous objections to such innovation. This Section unpacks the access-to-justice problem and examines the debate between those that hope technology can close the justice gap[56] and those that fear technology will either take their jobs[57] or undermine the provision of quality legal services.[58]

---

[49] LEGAL SERVS. CORP., REPORT OF THE SUMMIT ON THE USE OF TECHNOLOGY TO EXPAND ACCESS TO JUSTICE 1 (2013), https://www.lsc.gov/media-center/publications/report-summit-use-technology-expand-access-justice [perma.cc/5P7C-KRQE] [hereinafter TECHNOLOGY SUMMIT REPORT].

[50] CLOSING THE JUSTICE GAP, *supra* note 48.

[51] *See* Raymond H. Brescia et al., *Embracing Disruption: How Technological Change in the Delivery of Legal Services Can Improve Access to Justice*, 78 ALB. L. REV. 553, 554 (2015); Cruz, *supra* note 14, at 357 ("The legal profession is increasingly using technology to assist individuals with their legal needs."); Ronald W. Staudt & Andrew P. Medeiros, *Access to Justice and Technology Clinics: A 4% Solution*, 88 CHI.-KENT L. REV. 695, 708–10 (2013) (discussing the potential of A2J Author and similar tools to advance access to justice).

[52] Brescia et al., *supra* note 51, at 597 (discussing the development of online tools for increasing access to pro bono services).

[53] Michael J. Wolf, *Collaborative Technology Improves Access to Justice*, 15 N.Y.U. J. LEGIS. & PUB. POL'Y 759, 762 (2012) (discussing how technology improved access to dispute resolution forums); Anjanette H. Raymond & Scott J. Shackelford, *Technology, Ethics, and Access to Justice: Should an Algorithm be Deciding Your Case?*, 35 MICH. J. INT'L L. 485, 491 (2014) (noting that online dispute resolution systems have increased access to justice).

[54] Simshaw, *supra* note 48, at 192–95 (discussing document review, e-discovery, legal research, and outcome prediction); *see also* Joseph M. Green, Legaltech and the Future of Startup Lawyering (Mar. 15, 2019) (unpublished manuscript), https://ssrn.com/abstract=3360174 [perma.cc/CNS2-W2DJ].

[55] *See, e.g.*, Simshaw, *supra* note 48, at 180 ("AI will be an even more impactful force than previous tools, and has the potential to magnify and transform benefits of existing technologies."); Raymond & Shackelford, *supra* note 53, at 491–92, 511, 514, 516, 524; Benjamin H. Barton & Deborah L. Rhode, *Access to Justice and Routine Legal Services: New Technologies Meet Bar Regulators*, 70 HASTINGS L.J. 955, 959–62 (2019).

[56] *See, e.g.*, Brescia et al., *supra* note 51, at 554, 595–97; Cruz, *supra* note 14, at 349; Staudt & Medeiros, *supra* note 51, at 698; Frank, *supra* note 48, at 260–61.

[57] RICHARD SUSSKIND & DANIEL SUSSKIND, THE FUTURE OF THE PROFESSIONS: HOW TECHNOLOGY WILL TRANSFORM THE WORK OF HUMAN EXPERTS 68–71 (2015) (predicting that artificial intelligence will replace a host of professions, including lawyers, by providing the same service at much lower (or no) cost).

[58] Cruz, *supra* note 14; DeStefano, *supra* note 14, at 2961–62, 2970, 2989–90.

Traditionally, the U.S. legal system relies upon Legal Services Corporation (LSC)-funded organizations and volunteer pro bono attorneys to provide civil legal services to low-income individuals.[59] Unfortunately, studies estimate that approximately 85 to 97 percent of civil legal issues go unaddressed by LSC-funded organizations due to insufficient resources.[60] In other terms, only a minuscule percentage of low-income individuals in the United States enjoy access to legal services[61] for issues related to such basic human needs as housing, employment, and access to healthcare.[62] Notably, the discussion often centers on providing legal services to low-income individuals because doing so tracks LSC's mandate.[63] However, individuals considered "middle-income" often also experience difficulty accessing legal services.[64] This chronic access-to-justice crisis experienced by millions of low- and middle-income Americans results in a civil justice system overwhelmed by self-represented and untrained litigants, which, in turn, places further stress on the system.

Obtaining accurate data regarding the number of *pro se* litigants nationwide proves persistently difficult due to diffuse data and the lack of interoperability of court systems.[65] Nevertheless, anecdotal evidence overwhelmingly points to an alarmingly high number of litigants representing themselves in matters of significant personal and financial import.[66] For example, in 2016,

---

[59] Lisa R. Pruitt & Bradley E. Showman, *Law Stretched Thin: Access to Justice in Rural America*, 59 S.D. L. REV. 466, 503 (2014); Lisa R. Pruitt et al., *Legal Deserts: A Multi-State Perspective on Rural Access to Justice*, 13 HARV. L. & POL'Y REV. 15, 35, 79 (2018).

[60] Pruitt & Showman, *supra* note 59, at 503; *see also* JUSTICE GAP REPORT, *supra* note 48, at 8.

[61] JUSTICE GAP REPORT, *supra* note 48, at 30.

[62] Rebecca L. Sandefur, *What We Know and Need to Know About the Legal Needs of the Public*, 67 S.C. L. REV. 443, 443–46 (2016).

[63] Pruitt & Showman, *supra* note 59, at 503 ("To be eligible for LSC services, an individual or family's gross income must be below 125 percent of the federal poverty line, a very restrictive threshold that nevertheless leaves one in five Americans eligible." (footnote omitted) (citing Deborah L. Rhode, *Whatever Happened to Access to Justice?*, 42 LOY. L.A. L. REV. 869, 879 (2009); Legal Services Corp. Regulations, 45 C.F.R. § 1611.3(c)(1) (2019); LEGAL SERVICES CORP., 2012 FACT BOOK 7 (2013), https://www.lsc.gov/sites/default/files/Grants/RIN/Grantee_Data/2012Fact%20Book_FINAL.pdf [perma.cc/7NFV-6GBC])).

[64] Rebecca L. Sandefur, *Money Isn't Everything: Understanding Moderate Income Households' Use of Lawyers' Services*, *in* MIDDLE INCOME ACCESS TO JUSTICE 222, 244 (Michael Trebilcock et al. eds., 2012); Victoria J. Haneman, *Bridging the Justice Gap with a (Purposeful) Restructuring of Small Claims Courts*, 39 W. NEW ENG. L. REV. 457, 457 (2017) ("[Access to justice] is a problem that reaches not only the poor, but also working-class and middle-income individuals unable to afford standard attorney rates." (citing Tiffany Buxton, *Foreign Solutions to the U.S. Pro Se Phenomenon*, 34 CASE W. RES. J. INT'L L. 103, 105 (2002))).

[65] NAT'L CTR. STATE CTS., DEVELOPING STANDARDIZED DEFINITIONS AND COUNTING RULES FOR CASES WITH SELF-REPRESENTED LITIGANTS 3 (2013), https://cdm16501.contentdm.oclc.org/digital/collection/accessfair/id/335 [perma.cc/4WE6-TSQZ].

[66] *Id.* ("Despite longstanding anecdotal reports of an 'explosion' in self-represented litigants and a resulting increase in workload, there is not a standard method for state courts to use when counting cases in which one or more of the litigants is self-represented.").

81.6 percent of all civil cases in Minnesota involved self-represented litigants;[67] in Massachusetts, a 2014 report found that civil legal aid programs lacked sufficient resources to assist 64 percent of those who sought help;[68] a report issued that same year in Colorado determined that at least one in every two eligible legal aid applications are denied because of inadequate resources;[69] and in Ohio, a 2015 task force of the Supreme Court concluded that legal aid organizations only enjoy sufficient resources to help one in every four who seek assistance.[70]

Why are the high numbers of self-represented litigants alarming? *Pro se* litigants consistently experience less satisfactory legal outcomes than represented parties.[71] Even with the proliferation of self-help tools,[72] and even when the law favors their position, those representing themselves face significant obstacles to prevailing.[73] Consider, for example, the nature of the legal system, which depends on complex and highly formalized processes.[74] Even assuming that self-represented litigants can determine the appropriate form for use in their proceedings, studies show that self-represented litigants find the forms less than intuitive and highly intimidating.[75] Ultimately, even the smallest of errors in completing a form can have serious consequences for *pro se* litigants.[76] Thus, when the literature speaks of a "justice gap" resulting from a lack

---

[67] Pruitt et al., *supra* note 59, at 89.

[68] BOSTON BAR ASS'N STATE TASK FORCE, INVESTING IN JUSTICE: A ROADMAP TO COST-EFFECTIVE FUNDING OF CIVIL LEGAL AID IN MASSACHUSETTS 3 (2014), http://www.bostonbar.org/docs/default-document-library/statewide-task-force-to-expand-civil-legal-aid-in-ma---investing-in-justice.pdf [perma.cc/Q2YZ-NDM9].

[69] COLORADO BAR ASS'N, JUSTICE CRISIS IN COLORADO 2014: REPORT ON CIVIL LEGAL NEEDS IN COLORADO 1 (2014), http://www.coloradojustice.org/portals/16/repository/ATJHearingFullReport.pdf [perma.cc/94TK-2HK5].

[70] THE SUP. CT. OF OHIO, REPORT & RECOMMENDATIONS OF THE TASK FORCE ON ACCESS TO JUSTICE 5 (2015), http://www.sc.ohio.gov/Publications/accessJustice/finalReport.pdf [perma.cc/CZ9C-QCEE].

[71] *See, e.g.*, Carroll Seron et al., *The Impact of Legal Counsel on Outcomes for Poor Tenants in New York City's Housing Court: Results of a Randomized Experiment*, 35 LAW & SOC'Y REV. 419, 426–27 (2001) (represented tenants more likely to prevail than self-represented tenants); D. James Greiner et al., *The Limits of Unbundled Legal Assistance: A Randomized Study in a Massachusetts District Court and Prospects for the Future*, 126 HARV. L. REV. 901, 927 (2013) (representation improves likelihood of success). *See generally* Rebecca L. Sandefur, *The Impact of Counsel: An Analysis of Empirical Evidence*, 9 SEATTLE J. SOC. JUST. 51 (2010) (evaluating effects of representation).

[72] *See, e.g.*, LAWHELP, https://www.lawhelp.org/ [perma.cc/JLA7-6CMS].

[73] *See* Elizabeth L. MacDowell, *Reimagining Access to Justice in the Poor People's Courts*, 22 GEO. J. ON POVERTY L. & POL'Y 473, 507 (2015) ("Like providing attorneys in the absence of sufficient resources and procedural protections, these services can work to legitimize an unjust legal system without rendering it more effective.").

[74] Latonia Haney Keith, *The Structural Underpinnings of Access to Justice: Building a Solid Pro Bono Infrastructure*, 45 MITCHELL HAMLINE L. REV. 116, 117–18 (2019) ("Because the civil legal system is designed to require an attorney in most, if not all, legal situations . . . ").

[75] *See* James E. Cabral et. al., *Using Technology to Enhance Access to Justice*, 26 HARV. J. L. & TECH. 241, 256 (2012).

[76] Frank, *supra* note 48, at 254.

of access to lawyers, it refers to very real negative legal outcomes for millions of individuals. But the individual litigants forced to proceed *pro se* are not the only ones adversely affected by the justice gap.

Rather, when potential litigants do not pursue meaningful claims, and when litigants proceed on a *pro se* basis, broader impacts to the justice system and other governmental institutions ripple outward from the lack of meaningful access to legal representation.[77] "Self-represented litigants tend to be disorganized, confused, and take up a lot of clerk time."[78] Court proceedings involving *pro se* litigants also often involve a high number of errors and rejected pleadings, leading to delayed resolution and court congestion.[79] Further contributing to the congestion of the civil legal system, approximately 50 percent of all appeals are conducted *pro se*.[80] Because civil legal problems often involve basic human needs such as housing, employment, and access to healthcare, failure to pursue remedies, or ineffectively pursuing available remedies, frequently leads to other problems including stress-related illness, verbal and physical abuse, and alcohol and drug problems.[81] Ultimately, the lack of meaningfully available remedies leads many to believe their claims simply are not justiciable, and individuals entitled to remedies simply do not view the legal system as an institution available to assist them.[82] Thus, the access-to-justice crisis represents a compounding problem that threatens to undermine the public's faith in the legitimacy of the justice system. In light of the seriousness of the access-to-justice crisis and its implications, a variety of actors and institutions have worked relentlessly to bridge the justice gap, with new contributors to the work generally always welcome. Increasingly, however, one new contributor to the fight to decrease the justice gap, an emerging "legal technology" industry, seems to cause just as much controversy as it engenders hope for new solutions.[83]

---

[77] Haneman, *supra* note 64, at 457 ("As the need for affordable legal services far outstrips access, the rising number of self-represented individuals burdens the system.").

[78] Frank, *supra* note 48, at 258 (citing Rochelle Klempner, *The Case for Court-Based Document Assembly Programs: A Review of the New York State Court System's "DIY" Forms*, 41 FORDHAM URB. L.J. 1189, 1215 (2014)).

[79] *See id.*

[80] Judith Resnik, *A2J/A2K: Access to Justice, Access to Knowledge, and Economic Inequalities in Open Courts and Arbitrations*, 96 N.C. L. REV. 605, 607–08 (2018) (citing U.S. COURTS, U.S. COURTS OF APPEALS—PRO SE CASES COMMENCED AND TERMINATED BY CIRCUIT AND NATURE OF PROCEEDING, DURING THE 12-MONTH PERIOD ENDING SEPTEMBER 30, 2016, http://www.uscourts.gov/sites/default/files/data_tables/jb_b9_0930.2016.pdf [perma.cc/R5XZ-XRHM]).

[81] REBECCA L. SANDEFUR, ACCESSING JUSTICE IN THE CONTEMPORARY USA: FINDINGS FROM THE COMMUNITY NEED AND SERVICES STUDY 9–10 (2014).

[82] *See* Rebecca L. Sandefur, *The Fulcrum Point of Equal Access to Justice: Legal & Nonlegal Institutions of Remedy*, 42 LOY. L.A. L. REV. 949, 950 (2009).

[83] *See generally* Daniel Martin Katz, *Quantitative Legal Prediction—or—How I Learned to Stop Worrying and Start Preparing for the Data-Driven Future of the Legal Services Industry*, 62 EMORY L.J. 909 (2013).

Despite the potential benefits of using new legal technology tools to narrow the justice gap, an increasingly loud chorus of objections to the use of algorithms and other forms of artificial intelligence in law continues to grow around themes of quality assurance,[84] preventing the unauthorized practice of law,[85] and a general, nebulous fear of compounding the job market constriction experienced by lawyers in recent years.[86] Two rules often invoked by those that object to the growth of legal technology include the requirement that lawyers be technologically competent and that only lawyers may practice law. Both rules seek to ensure the provision of quality legal services to consumers. Attorneys have long been charged with a duty of competence—to ensure they stay "abreast of changes in the law and its practice."[87] This duty recently expanded, in at least thirty-eight states and in the American Bar Association Model Rules of Professional Conduct, to include knowledge of the benefits and risks associated with technology.[88] As such, one objection raised to the use of advanced and emerging technologies in the practice of law centers on the alleged inability of lawyers to fully assess the technology tools at issue.[89] In particular, some argue that because the algorithms used in the technology tools are protected by trade secrets, attorneys will never be able to fully assess the range of benefits and risks associated with any particular tool's use.[90] Others go further and argue that even if attorneys were granted unfettered access inside the "black boxes" of how an algorithm works, doing so may mean little to those not steeped in computational sciences.[91]

Meanwhile, still other objectors to the use of algorithms in legal practice cite professional rules that prohibit the unauthorized practice of law (UPL).

---

84 Cruz, *supra* note 14, at 366–67 ("Without intentional consideration of end users and their needs, limits, and preferences, technology can lead to end user frustration, perpetuate implicit biases, compromise users' privacy, and create additional barriers that will prevent access to legal services. Recent studies and reviews of the newest legal technology have, in some cases, uncovered unintentional consequences that expose end users to such harms, risks, and difficulties.").

85 *See* DeStefano, *supra* note 14, at 2971–72; McGinnis & Pearce, *supra* note 17, at 3057; Larry E. Ribstein, *The Death of Big Law*, 2010 WIS. L. REV. 749, 807–08 (2010); Simon et. al., *supra* note 11, at 260.

86 Staudt & Medeiros, *supra* note 51, at 695.

87 MODEL RULES OF PRO. CONDUCT r. 1.1 cmt. (AM. BAR ASS'N 2020).

88 *Id.*; Robert Ambrogi, *Tech Competence*, LAWSITES, https://www.lawsitesblog.com/tech-competence [perma.cc/JGZ9-B7VT].

89 David Lat, *The Ethical Implications of Artificial Intelligence*, ABOVE THE LAW (2020), https://abovethelaw.com/law2020/the-ethical-implications-of-artificial-intelligence [perma.cc/6VSB-XM94].

90 Meghan J. Ryan, *Secret Conviction Programs*, 77 WASH. & LEE L. REV. 269, 270 (2020) ("Across the country, judges and juries are convicting defendants based on secret evidence. . . . That is because much of this complicated, 'scientific' evidence is generated by computer programs—'conviction programs'—built on secret algorithms and source codes developed in many instances by for-profit companies.").

91 Mike Ananny & Kate Crawford, *Seeing Without Knowing: Limitations of the Transparency Ideal & Its Application to Algorithmic Accountability*, 20 NEW MEDIA & SOC'Y 973, 982 (2018).

State regulation of UPL aims to "protect the public from bad legal advice and representation and from inferior legal or law-related services."[92] Ostensibly, UPL regulations achieve this, at least in part, by requiring that legal services be provided only by "those who have been found by an investigation to be properly prepared to do so."[93] With bar passage as its primary metric, UPL measures only who delivers services rather than measuring the effectiveness or equity of legal service delivery. The result of a focus on the role of licensed lawyers is a limited role for technology. Some state bars object to technology offerings designed to help self-represented litigants draft documents and court pleadings on the grounds that such software violates the prohibition on the practice of law by laypeople.[94] Indeed, some courts have ruled that such software violates unauthorized practice of law rules,[95] while others have required various ad-hoc consumer protections without rethinking regulatory approaches more broadly.[96] Model Rule 5.4's prohibition against nonlawyers owning or controlling interests in law firms presents similar hurdles to more innovative and technology-driven access to services.[97] As with UPL, Rule 5.4 focuses on the roles of those owning and controlling legal entities rather than on the effectiveness and equity of services those entities deliver and might further stifle technological innovation in service delivery.[98] Regulatory frameworks and court decisions that pro-

---

[92] DeStefano, *supra* note 14, at 2969.

[93] *See, e.g.*, Janson v. Legalzoom.com, 802 F. Supp. 2d 1053, 1059, 1064 (W.D. Mo. 2011) (quoting Hulse v. Cringer, 247 S.W. 2d 855, 858 (Mo. 1952)); Lucas Subway Midmo, Inc. v. Mandatory Poster Agency, 524 S.W.3d 116, 122 (Mo. App. W.D. 2017). *But see* TEX. GOV'T. CODE ANN. § 81.101(c) (West 2019) (excluding products, including those on Internet websites, from the definition of the "practice of law" if a clear and conspicuous statement is made providing that the product is not a "substitute for the advice of an attorney").

[94] Mary Juetten, *Unauthorized Practice of Law Claims Threaten Access to Justice*, FORBES (May 8, 2018, 7:15 AM), https://www.forbes.com/sites/maryjuetten/2018/05/08/unauthorized-practice-of-law-claims-threaten-access-to-justice/#2f58cdf467a5 [perma.cc/2PH8-C33T].

[95] *Janson*, 802 F. Supp. 2d at 1064–65; *In re* Lazarus, No. 05-80274C-7D, 2005 WL 1287634, at *5 (Bankr. M.D.N.C. 2005) (finding UPL where "the evidence reflected that the Debtor had no understanding [of the matters such as priority claims, executory contracts, codebtor, or exemptions] and that [the preparer] advised the Debtor regarding such matters," including making a determination of what information would be included in the forms).

[96] LegalZoom.com, Inc. v. N.C. State Bar, No. 11 CVS 15111, 2014 NCBC LEXIS 9, at **19 (N.C. Super. Ct. Mar. 24, 2014); LegalZoom.com, Inc. v. N.C. State Bar, No. 11 CVS 2015, 2015 NCBC LEXIS 100, at **2–3 (N.C. Super. Ct., Oct. 22, 2015).

[97] *See* MODEL RULES OF PRO. CONDUCT r. 5.4 (AM. BAR ASS'N 2020).

[98] A growing set of regulatory reform efforts respond to concerns that Model Rule 5.4's prohibitions against nonlawyer ownership prevent the outside investment and expertise that might spawn innovation and technology tools to help close the access to justice gap. As a primary example, a report of the Utah Work Group on Regulatory Reform saw "elimination or substantial relaxation of Rule 5.4 as key to allowing lawyers to fully and comfortably participate in the technological revolution. Without such a change, lawyers will be at risk of not being able to engage with entrepreneurs across a wide swath of platforms." UTAH WORK GRP. ON REGUL. REFORM, NARROWING THE ACCESS-TO-JUSTICE GAP BY REIMAGINING REGULATION 15 (2019), https://www.utahbar.org/wp-content/uploads/2019/08/FINAL-Task-Force-Report.pdf [perma.cc/453L-4G72]. In boldly taking action in light of the report, the Utah Supreme Court authorized the creation of an Implementation Task Force on Regulatory

tect the legal services industry by preventing the public from accessing legal technology or by allowing such access only under very limited circumstances implicitly impose a dichotomous choice on low- and middle-income individuals: find a way to pay high prices for legal services or go without legal services entirely.

These arguments clearly pit the desire to protect the integrity of the legal profession against the ability to use algorithms to provide greater access to legal services, as though they are mutually exclusive. In reality, the arguments around protecting the profession from the threats posed by algorithms represent an over-fit in relation to what algorithms can actually achieve, while the visions of employing algorithms for access to justice initiatives represent an under-fit in relation to what algorithms could provide. A lack of precision about algorithms results in blunt protections of professional integrity leaving little room for the potential benefits of algorithmic tools to decrease the justice gap. Rather than actively contribute to keeping low- and moderate-income individuals from some measure of legal assistance because of the profession's fears built solely on technology's hype-cycle, we propose shifting the debate's focus from the algorithm standing alone, as though the context for its use is unimportant, to algorithmic systems. Such a paradigm shift would enable consideration of both the human and non-human actors that touch legal technology in both the criminal and civil legal contexts. Doing so not only enables more precise and robust discussions about the appropriate design and use of algorithms in legal contexts but also takes a step toward integrating the access to justice discussions beyond their current criminal and civil law silos.

II. FROM ALGORITHMS TO ALGORITHMIC SYSTEMS

Of the many underlying causes of this tension around the use of algorithms in law, dominant conceptions of algorithms and their function are fundamental. We speak of algorithms—or increasingly of the almost all-encompassing "AI" tools driven by algorithms—in ways that might not serve us well. The goal here is to encourage a shift toward a more fruitful conception, not of acontextual algorithms or standalone algorithm-driven tools, but rather of algorithmic systems—i.e. of meaningful social contexts in which our algorithm-driven tools have significant effects. Doing so will enable the more precise and robust discussions about the appropriate design and use of algorithms in legal contexts that the law requires. This Part begins by describing the popular misconception

---

Reform in the fall of 2019, which designed the Office of Legal Services Innovation, now a division of the Utah Supreme Court. *See generally* THE OFFICE OF LEGAL SERVS. INNOVATION, https://sandbox.utcourts.gov [perma.cc/8WR5-LA4S]. The Office of Legal Services Innovation oversees the Utah legal Sandbox, which aims to license, oversee, and, as necessary, enforce against, new legal providers and services—including those legal service providers that fee-share with nonlawyers, allow nonlawyer ownership investment, and fee-split among lawyers in the same office. UTAH IMPLEMENTATION TASK FORCE ON REGULATORY REFORM, UTAH REG. REFORM FREQUENTLY ASKED QUESTIONS, https://www.utahbar.org/wp-content/uploads/2020/05/Utah-FAQs-FINAL.pdf [perma.cc/4K97-TWWE].

of an algorithm as a technology that sits apart from its social use. The Part then argues that properly conceiving of algorithms as a socio-technical system—an algorithmic system—enables deeper and more robust engagement around key design and policy questions. To do so, this Part introduces the two core elements of an algorithmic system: the computational components, and the contextual components.

A. Misconception of Algorithms as Artifacts Set Apart

With every emerging technology, we can expect a struggle to find the appropriate analogies, metaphors, and conceptions to allow meaningful human engagement and effective management.[99] In the case of the growing use of algorithms among our human systems of decision-making and resource delivery, several common but overly narrow conceptions impede our success. Most prominently, we tend to conceive of algorithms as technologies set apart—the invisible life-blood of machines operating all on their own. This is unsurprising. After all, our common cultural visions of a modern, algorithm-driven world often derive from movies with machines invading against our will or moving about the world with a human-like agency.[100] People commonly perceive AI to be a sort of magic,[101] further distancing the perceived levers of human control. And even where reality reigns over rhetoric, modern machine tools are often quite complex,[102] driven by overwhelming data that is transformed unrecognizably amid the layers of deep-learning systems,[103] and some-

---

[99] *See, e.g.*, Ryan Calo, *Robots as Legal Metaphors*, 30 HARV. J. L. & TECH. 209, 209 (2016) (explaining the various ways in which conceptions and misconceptions about robots shape and mis-shape resulting law and policy); Madeleine Clare Elish, *Moral Crumple Zones: Cautionary Tales in Human-Robot Interaction*, 5 ENGAGING SCI., TECH., AND SOC'Y 40, 52 (2019) (explaining that "[e]specially in the context of emerging technologies, social norms and expectations play a significant role in the legal integration of a technology into existing frameworks. For instance, perceptions of new technologies become condensed in the metaphors used to describe technology and its effects. These metaphors influence the outcome of legal interpretations of new technology." (citing A. Michael Froomkin, *The Metaphor is the Key: Cryptography, the Clipper Chip, and the Constitution*, 143 U. PA. L. REV. 709 (1995)); Ryan Calo, *Robots in American Law* (U. of Wash. Sch. L., Research Paper No. 2016-04, Feb. 2016)).

[100] Jeff Ward, *10 Things Judges Should Know About AI*, JUDICATURE, Spring 2019, at 13 (noting that "they are nowhere near the general and broad intelligences that we know from movies and literature").

[101] M.C. Elish, *Don't Call AI 'Magic,'* DATA & SOC'Y: POINTS (Jan. 17, 2018), https://points.datasociety.net/dont-call-ai-magic-142da16db408 [perma.cc/C4L2-R32S].

[102] *See, e.g.*, Martin Giles, *The GANfather: The Man Who's Given Machines the Gift of Imagination*, 121 MIT TECH. REV. 48, 51 (2018); CHIHEB TRABELSI ET AL., DEEP COMPLEX NETWORKS 2 (2018) https://openreview.net/pdf?id=H1T2hmZAb [perma.cc/26P9-MEQX] (offering a formulation to help "exploit the advantages offered by complex representations" of neural network).

[103] Paul B. de Laat, *Algorithmic Decision-Making Based on Machine Learning from Big Data: Can Transparency Restore Accountability?*, 31 PHIL. & TECH. 525, 526 (2018) (explaining that "ever more data are becoming available for analysis (big data). This abundance subsequently enables ever more powerful machine learning . . . ."); Yavar Bathaee, *The*

times even capable of super-human performance[104] (albeit in narrowly constrained areas), serving to intimidate all but the most sophisticated technologists.

While good for theater, marketing, or bolstering the egos of technologists, this conception of machines operating independently from human constraints is—at least for the foreseeable future—quite misguided. In truth, humans maintain control. We design these tools for our specified ends. We choose when and how such machines are deployed. And all such tools are effective in only narrow applications of our selection.[105] Beyond misguided, this conception of algorithms as independent and set apart is also harmful, most immediately because it undermines the recognition of our abilities and responsibilities to govern machine tools and the effects they have on the communities lawyers are meant to serve.[106] We might underestimate their potential and fail to offer guidance as they shape legal practice or overestimate their potential and fail to invite their potential to better the law. Therefore, to enable engagement with and the more competent management of algorithms—both generally in decision making and resource delivery and specifically in ways that both protect the integrity of legal practice and expand access to legal resources—we need to move toward a fuller conception of algorithmic systems.

B. The Reality of Algorithms as Sociotechnical Systems: Algorithmic Systems

Engagement by a broad range of stakeholders—not merely by technologists—is essential to "control how technology will define humanity's common future."[107] With bourgeoning technologies of the kind at issue here, this engagement begins with the recognition that no algorithm stands alone. Rather, like any technology, an algorithm is a social technology, set within and interacting with humans in a social context. And this recognition is necessary to

---

Artificial Intelligence Black Box and the Failure of Intent and Causation, 31 HARV. J. L. & TECH. 889, 891 (2018) ("It may be impossible to tell how an AI that has internalized massive amounts of data is making its decisions. For example, AI that relies on machine-learning algorithms, such as deep neural networks, can be as difficult to understand as the human brain." (citing Davide Castelvecchi, *Can We Open the Black Box of AI?*, 538 NATURE 20, 22 (2016))).

[104] *See, e.g.*, Abhimanyu S. Ahuja, *The Impact of Artificial Intelligence in Medicine on the Future Role of the Physician*, 7 PEER J. 1, 4 (2019), https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6779111/ [perma.cc/RKP7-UZTE] (citing Abby Norman, *Your Future Doctor May Not be Human. This Is the Rise of AI in Medicine*, FUTURISM (Jan. 31, 2018), https://futurism.com/ai-medicine-doctor [perma.cc/FY6G-EXEY]) (noting the existence already of many examples where "AI is already just as capable as (if not more than capable than) doctors in diagnosing patients.").

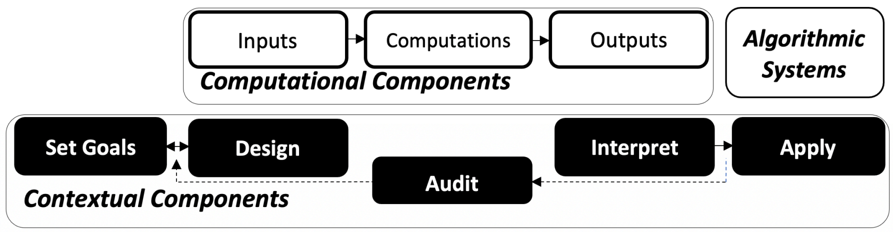
[105] Erik Brynjolfsson & Tom Mitchell, *What Can Machine Learning Do? Workforce Implications*, 358 SCI. 1530 (2017) (noting the task algorithms are most suited for).

[106] Tom Simonite, *A Health Care Algorithm Offered Less Care to Black Patients*, WIRED (Oct. 24, 2019, 2:00 PM), https://www.wired.com/story/how-algorithm-favored-whites-over-blacks-health-care [perma.cc/4Q62-8XPQ].

[107] SHEILA JASANOFF, THE ETHICS OF INVENTION: TECHNOLOGY AND THE HUMAN FUTURE 10 (2016).

achieve control and accountability of algorithm-enabled systems. As Mike Ananny and Kate Crawford state, "we . . . hold systems accountable by looking *across* them—seeing them as sociotechnical systems that do not *contain* complexity but *enact* complexity by connecting to and intertwining with assemblages of humans and non-humans."[108]

DIAGRAM 1: ALGORITHMIC SYSTEM SCHEMATIC



To illuminate this complexity and interaction in an accessible way that enhances engagement, rather than referring to algorithms as computational instructions standing alone, we refer to "algorithmic systems"[109] and intend that term to refer to an algorithm[110] taken together with the social context in which the algorithm is used. In other words, we envision these algorithmic systems as two overlapping spheres: a system's (1) computational components and (2) contextual components (Diagram 1).

At a theoretical level, this simple division provides a schematic with which to map our required instruments of control and accountability. Science and technology experts like Sheila Jasanoff remind us not only that "technology functions as an instrument of governance" but further that "technological systems rival legal constitutions in their power to order and govern society."[111] As such, this division helps us to move outward from the computational components to contextual components, considering the influence technology has on the communities where it takes shape. Still, others remind us that the social context will place inward demands on the technology. In speaking of Internet governance, Lawrence Lessig notes that "[s]ome architectures of cyberspace are more regulable than others; some architectures enable better control than others" and that "the architectures that render space less regulable can themselves be changed to make the space more regulable."[112] Captured in this schematic, then, is the recursive and interactive dialogue that takes place between

---

108 Ananny & Crawford, *supra* note 91, at 974.

109 Mike Ananny, *Toward an Ethics of Algorithms: Convening, Observation, Probability, and Timeliness*, 41 SCI., TECH., & HUM. VALUES 93, 94 (2016) (referring to "algorithmic assemblage" as being "a mix of computational code, design assumptions, institutional contexts, folk theories, [and] user models").

110 Or, more often, a *set* of algorithms.

111 JASANOFF, *supra* note 107, at 8–9.

112 LAWRENCE LESSIG, CODE: AND OTHER LAWS OF CYBERSPACE, VERSION 2.0, 24 (2d rev. ed. 2006).

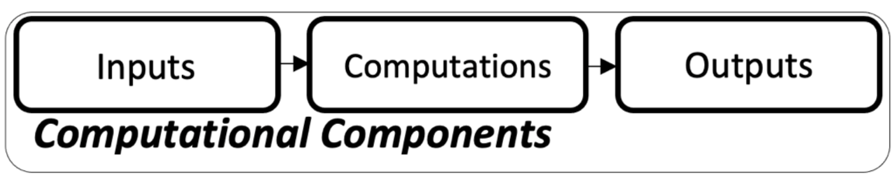
the computational components and contextual components of a technology system or, more specifically here, an algorithmic system.

Ideally, then, this simple conceptual framework of an algorithmic system with overlapping spheres of computational and contextual components should foster at least two conclusions, both of which serve as invitations to engage. First, the contextual components of an algorithmic system are already very much the domain of social thinkers like lawyers. No degree is required in computer science or electrical and computer engineering to engage immediately and critically with the social goals or intended uses of applied algorithms. Lawyers understand well the demands that the criminal justice system, for example, places inwardly on the machine tools that serve it and are prepared to interact critically with the outputs of such tools even prior to any specific technological training. Second, even the computational components can be accessible to non-technologists like lawyers; "[o]ne does not need to be able to describe in detail the workings of multilayer perceptrons and convolutional neural networks, for example, to engage with AI on an intuitive level."[113] The taxonomies and frameworks we provide later in Part III are examples of methods we might use to bolster our abilities to engage with these computational components even without any hyper-technical understanding.

1. Computational Components of Algorithmic Systems

In essence, algorithm-driven tools function in three steps referred to as the "computational components" of Algorithmic Systems: "(1) inputs of data, (2) computations on that data, and (3) outputs of information derived from that data" (Diagram 2).[114]

DIAGRAM 2: COMPUTATIONAL COMPONENTS OF ALGORITHMIC SYSTEMS



To be sure, common conceptions of algorithms focus on the central step of computations—i.e. the specific set of instructions used for calculating a function, much like the recipe that is used to direct preparation of a meal.[115] This is often appropriate and will be our starting point. We will aim to highlight not only the steps that serve as the computations, however, but also the inputs of data and the outputs of information in order to emphasize links between the

---

[113] Lyria Bennett Moses & Anna Collyer, *When and How Should We Invite Artificial Intelligence Tools to Assist with the Administration of Law? A Note from America*, 93 AUSTRALIAN. L. J. 176, 179 (2019).
[114] *Id.* at 179 (emphasis omitted); *see also* Surden, *AI Overview*, *supra* note 21, at 1311–15.
[115] *See, e.g.*, CATHY O'NEIL, WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY 213 (2017).

computational and contextual components of the broader algorithmic system. In doing so, we recognize that entire books, degree programs, and careers are built upon the mastery of these computations—the mathematics, the syntax, the programming, etc. We aim not to engage with such details here, but rather, with a brief discussion that presages the simple taxonomy of algorithmic characteristics we provide in Part III, we aim to provide a brief background and some related examples overviewing the primary types of algorithm-driven tools that are entering important law-related contexts. Critical to the values and demands of many of the social systems in which these algorithms rest is whether they are (1) handcrafted algorithms or (2) machine learning algorithms.

Some computations are handcrafted. They are modeled on human logic and rules, replicating our analytical processes to produce expert systems that might look familiar to us. Expert systems use algorithms to reach conclusions based on knowledge and rules that are derived from accumulated human expertise.[116] These systems make use of specialized knowledge to solve problems that require the intelligence and expertise of a human expert—a lawyer, for example—and present specific tasks as "a structured dialogue with the user."[117] Even here, various types of systems exist, sometimes employing more sophisticated approaches such as artificial neural networks that implement software simulations,[118] but most often taking shape as rule-based systems—preprogrammed *if/then* systems that mimic human logic to analyze information and recommend possible solutions in keeping with human expertise.

For example, in the context of criminal sentencing, such algorithms might largely replicate or approximate human mental calculations regarding an appropriate criminal sentence: "if it was a violent crime, then was it the defendant's first or a repeat offense? If it was not a repeat offense, then did the defendant use a weapon? Therefore, the defendant's sentence should fall within a range of *x* to *y* months."[119] This kind of decision-making should be familiar to us; it is not only intuitive, but it is the kind of stepwise logic prominent in the law in, say, the Federal Sentencing Guidelines.[120]

---

116 *See* Benjamin L. W. Sobel, *Artificial Intelligence's Fair Use Crisis*, 41 COLUM. J. L. & ARTS 45, 58 (2017); EXEC. OFF. OF THE PRESIDENT NAT'L SCI. AND TECH. COUNCIL COMM. ON TECH., *supra* note 38, at 8.

117 Dana Remus & Frank Levy, Can Robots be Lawyers?: Computers, Lawyers, and the Practice of Law 31 (Nov. 27, 2016) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2701092 [perma.cc/3LC6-XUU2]; T. Gonciarz, *An Expert System for Supporting the Design and Selection of Mechanical Equipment for Recreational Crafts*, 8 INT'L J. ON MARINE NAVIGATION & SAFETY OF SEA TRANSP. 275, 275 (2014).

118 Mohamed Radhouene Aniba et al., *Knowledge-Based Expert Systems and a Proof-of-Concept Case Study for Multiple Sequence Alignment Construction and Analysis*, 10 BRIEFINGS BIOINFORMATICS 11, 14 (2008).

119 Bennett Moses & Collyer, *supra* note 113, at 179.

120 *See* U.S. SENT'G GUIDELINES MANUAL §§ 3D1.1, 4A1.1, (U.S. SENT'G COMM'N 2018), https://www.ussc.gov/sites/default/files/pdf/guidelines-manual/2018/GLMFull.pdf [perma.cc/SBN5-H5WG].

Machine learning algorithms are different in several ways from these handcrafted algorithms. To start, modern successes in AI applications derive largely from tools built upon these algorithms, which might explain our tendency to conflate AI with machine learning.[121] These powerful tools "fuse various statistical techniques with oftentimes enormous amounts of input data to 'learn' directly from the data itself rather than from stepwise human instruction."[122] In other words, these systems do not replicate the step-by-step logic and rules that are intuitive to us. Instead, they discern patterns from massive sets of examples—often isolating relevant features that are not obvious to human observers—to produce increasingly accurate predictions or probabilistic determinations about the phenomena at hand.[123]

For example, in the context of criminal sentencing, machine learning algorithms might learn to predict the likelihood that any newly convicted criminal would recidivate based not on if/then logic structures or any criteria preprogrammed by humans but rather by reviewing vast amount of data that might be available on past criminals. In a supervised machine learning process, the algorithm would attempt to use various mathematical descriptions and relationships based on historical criminal recidivism data (the "training data") in order to make predictions about new input—e.g., whether the person at issue is at high risk or low risk to recidivate.[124] During training, the algorithm "learns" by seeking classifications that are based on mathematical descriptions yielding the lowest error rates, such as limiting the error of making classifications as high risk for the subject who did not actually recidivate, and vice versa.[125]

This is, of course, a simplified bifurcation. Of the innumerable ways to classify algorithmic computations, why focus here on the distinctions between handcrafted and machine learning approaches? In short, this distinction is salient to our systemic goals noted above of reducing bias, increasing efficiency, and enhancing fair process, as there are advantages and disadvantages to both approaches, especially insofar as demands for accuracy and transparency can be in tension.[126]

With handcrafted computations, achieving high levels of predictive accuracy can be difficult. After all, the world and especially human behavior is complex and not easily captured by such systems. On the other hand, even though we might struggle to shape these algorithms in ways that capture real-world complexity, we might nonetheless feel reasonably comfortable about our abili-

---

[121] Karen Hao, *What is Machine Learning?*, MIT TECH. REV. (Nov. 17, 2018), https://www.technologyreview.com/2018/11/17/103781/what-is-machine-learning-we-drew-you-another-flowchart/ [perma.cc/S723-C5L5] (noting that "[m]achine learning algorithms are responsible for the vast majority of the artificial intelligence advancements and applications you hear about").

[122] Bennett Moses & Collyer, *supra* note 113, at 179.

[123] Surden, *Machine Learning*, *supra* note 36, at 89; FLACH, *supra* note 36, at 3.

[124] *See* Coglianese & Lehr, *supra* note 34, at 1158; Sobel, *supra* note 116 at 58–59.

[125] *See* Coglianese & Lehr, *supra* note 34, at 1158.

[126] *See* discussion *supra* notes 40–47 and accompanying text.

ties to understand them and the ways they produce the outputs that inform our decisions.

Conversely, machine learning algorithms might achieve greater accuracy, though at the costs of transparency and intuitive explainability. Of course, all kinds of computations—even the most simple of handcrafted algorithms—might lack transparency where, as in the *Loomis* case noted earlier, the algorithms are protected by trade secret.[127] Had the computational mathematics of Northpoint Consulting's COMPAS product not been maintained as a trade secret, an answer to whether Eric Loomis's gender was considered as a "criminogenic factor" or statistical "norming" factor would not have been difficult to attain and an explanation of his maximum sentence might have been provided in keeping with expectations of fairness.[128] Even so, potential obscurity is a particularly prominent concern with machine learning algorithms, as "[t]he route from inputted data to outputted information is determined by the system itself."[129] Especially where the computational structures are "deep," involving many hidden layers and transformations of the input data that discern latent features of the phenomena at hand, these systems can remain obscure to any human observer no matter how expert, achieving a level of obscurity that is often referred to as a "black box."[130] As such, despite their potential to meet our demands for increased accuracy, consistency, and predictability, their opaque structures can challenge our needs to ensure fairness or meet due process demands. This simple taxonomy, then, allows us to navigate more precisely a common line of criticism of algorithms in law and to engage more robustly in the kinds of design and discourse around value balancing described in Part III.

2. *Contextual Components of Algorithmic Systems*

A primary benefit of this conceptual map of algorithmic systems is that it makes explicit the obvious but often overlooked fact that algorithms do not appear from thin air.[131] Rather, the development of their computational components is an act of intention, subject to innumerable human choices and demands

---

[127] State v. Loomis, 881 N.W.2d 749, 761 (Wis. 2016); Wexler, *supra* note 2, at 1358.

[128] *Loomis*, 881 N.W.2d at 765 ("Due to the proprietary nature of COMPAS, the parties dispute the specific method by which COMPAS considers gender. Loomis asserts that it is unknown exactly how COMPAS uses gender, but contends that COMPAS considers gender as a criminogenic factor. The State disagrees, contending that the DOC uses the same COMPAS risk assessment on both men and women, but then compares each offender to a 'norming' group of his or her own gender.").

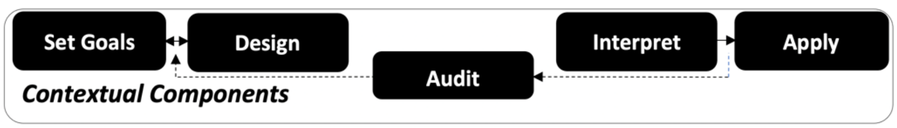
[129] Bennett Moses & Collyer, *supra* note 113, at 179.

[130] CHRISTOPH MOLNAR, INTERPRETABLE MACHINE LEARNING : A GUIDE FOR MAKING BLACK BOX MODELS EXPLAINABLE § 1.3 (2019), https://christophm.github.io/interpretable-ml-book [perma.cc/4GQH-6CUE] ("A Black Box Model is a system that does not reveal its internal mechanisms. In machine learning, 'black box' describes models that cannot be understood by looking at their parameters (e.g. a neural network).").

[131] *See* Karen Hao, *This is How AI Bias Really Happens—and Why It's So Hard to Fix*, MIT TECH REV (Feb. 4, 2019), https://www.technologyreview.com/s/612876/this-is-how-ai-bias-really-happensand-why-its-so-hard-to-fix/ [perma.cc/S7KR-KGTA].

based on relevant contextual components. As noted, much of the resistance to algorithm-driven tools in law stems from an admirable commitment to safeguard the values of the legal system.[132] Where algorithms that might not adequately maintain these values intrude upon our human systems, the logic goes, we ought to erect substantial barriers. Here, the vocabulary of computational and contextual components of algorithmic systems and the concomitant recognition that the development of any algorithm is an act of intention subject to levers of human control can help us to choose our barriers more selectively. A conception of algorithmic systems highlights that goal setting and system design are elements of the system that rest squarely in the domain of lawyers and social thinkers and offer productive levers of control and modes of necessary accountability.

DIAGRAM 3: CONTEXTUAL COMPONENTS OF ALGORITHMIC SYSTEMS



In the context of criminal sentencing, for example, a tool might aim to *predict the likelihood that a criminal will commit another crime*, a prediction of obvious social value if accurate. In keeping with our goal to consider the full algorithmic system, we will probe the interactions among this social goal, the design of the system, and especially the data that feeds the computational components. Data inputs and information outputs are linked inextricably no matter the domain of application.[133] To continue the sentencing example, a lawyer might then ask: what data does the tool use to know if a person commits another crime? If a response is that the training data (in the case of a machine learning system) includes information on subsequent arrests or convictions, then one might object that the tool does not *predict the likelihood that a criminal will commit another crime*, but rather that the tool will predict the likelihood that a criminal will be *caught committing* another crime.

This is a significant distinction, and it serves to highlight two intended takeaways of this conception of algorithmic systems. First, even non-technologist lawyers and other social thinkers are already well-prepared to engage in this kind of inquiry. After all, the distinction between committing crimes or being caught committing crimes and a careful analysis of the concomitant evidentiary requirements necessary to draw such conclusions are the very essence of lawyering skills. Second, one can understand any complex algorithmic system only through a consideration of the interactions between its computational and contextual components. It should be evident, for instance,

[132] *See* discussion *supra* notes 84–98 and accompanying text.

[133] *See, e.g.*, Ziad Obermeyer et al., *Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations*, 366 SCIENCE 447, 453 (2019) (choice to determine health risk based on future cost lead to racially biased outcomes). It is common parlance in computer programming circles to refer to this phenomenon as GIGO (garbage in, garbage out).

that both the underlying input data and the resulting predictions of likelihood to be caught committing a crime are inextricably linked to policy and law enforcement decisions around targeted criminal activities and neighborhood policing.[134] That is, scrutiny of the algorithmic tool might not only point out the insufficiencies of criminal arrest data for training computational components meant to predict all criminal action (even that which evades arrest), but it might also sharpen focus on contextual components that had evaded full public scrutiny. So integrated are the spheres of algorithmic systems that the very act of shaping computational components to predict recidivism might offer less value in its successful computational function or informational outputs than in its ability to highlight these larger contextual issues.[135]

Once the computational components of any algorithmic system produce information outputs, it remains incumbent upon human actors and institutions to interpret and perhaps (if satisfactory in the social context) to apply these outputs as part of a complex and ongoing discourse between contextual demands and computational capacities. This process is once again laden with challenges. Interpretation must occur cautiously, consistent with the goals of the algorithmic system as a whole, and users must apply output information in appropriate domains in light of systemic understandings. To illustrate, once again, we can look to examples from the context of criminal sentencing, where it is made apparent that even the most concrete computational outputs produce more social questions than answers.

Imagine that an algorithm-driven tool used in a pre-sentencing investigative report assesses a particular convicted person to pose a "high risk" of recidivism. What does this mean? A sentencing judge will likely have many choices in how to interpret and apply the predictive output.[136] Does the high-risk classification denote mere possibility, substantial likelihood, or near certainty? Does a sentencing judge have the ability to probe the computations—whether based

---

134 *See* O'NEIL, *supra* note 115, at 25–26; *see also* Richardson et al., *supra* note 43, at 41 (2019).

135 To expand on this notion of technology as a lens through which we scrutinize larger social systems, let's consider a recent interaction on Twitter that captures succinctly this socio-technical phenomenon. Highlighting important concerns regarding emerging insights gained from genetic testing, the MIT Technology Review (@techreview) tweeted: "Ready for a world in which a $50 DNA test can predict your odds of earning a PhD or forecast which toddler gets into a selective preschool?" MIT Technology Review (@techreview), TWITTER (Apr. 2, 2018, 4:07 PM), https://twitter.com/techreview/status/980944730841403392 [perma.cc/R5V4-MGGL]. To which Twitter user @nfinitefreetime replied: "You can do this already with a ZIP code." @nfinitefreetime, TWITTER (Apr. 5, 2018, 5:19 AM), https://twitter.com/nfinitefreetime/status/981868863880089600?lang=en [perma.cc/STZ5-87DV]. With a pithiness only modern online interactions of this sort can offer, this conversation highlights the way in which scrutiny of technological systems might add urgency to our scrutiny of existing social systems. In the early years of AI applications, this same pattern has often emerged: algorithms are applied in some context, the computational components are shown to be biased, and criticism of these new algorithmic biases are recognized to reflect existing social biases.

136 *Loomis Note*, *supra* note 7 at 1530–31.

on handcrafted algorithms, machine learning algorithms or otherwise—to better understand the findings? What additional information is considered? What weight or significance is given to the output of the algorithm-driven tool? What training is offered to the judge to guide the application of this tool? Where judges are elected, what political pressures might deter a judge from granting less than the maximum sentence for an individual rated "high risk" who might yet re-offend? Rooted in the particular shape of computational outputs, might such a "high risk" classification, then, lead to an overall heightening of criminal sentences across the social system?

Such queries demonstrate just how inextricable the computational components and contextual components of algorithmic systems can be. Even if a 100 percent accurate prediction of recidivism were possible, how should such information be used within the broader contexts of our criminal justice, public safety, and public health systems? Here, an undue focus on computational components will lead us astray. After all, a fixation on acontextual computational components might see 100 percent predictive accuracy as a success. Those aware of the full algorithmic system, on the other hand, should recognize the limitations of even a perfectly predictive tool. Even the most accurate prediction of recidivism might offer no information at all about urgent systemic issues we care about—e.g., appropriate interventions such as mental health services to reduce criminal behavior,[137] policy decisions around predictions of future behavior applied to heighten culpability,[138] or the broader social structures that contribute to such criminal propensities in the first place.[139]

In light of these complex and recursive interactions between the computational components and contextual components of algorithmic systems, appropriate stakeholders must continue to audit any algorithm-driven tool. Algorithmic systems require ongoing stewardship, even long after they might be perceived to operate successfully, in order to ensure that dynamic systems con-

---

[137] *See* Starr, *supra* note 44, at 855–56. Also note that *Loomis* court left open a wide range of applications, many of which seemingly extend beyond the information output offered. The court permits expressly that, "[a]lthough it cannot be determinative, a sentencing court may use a COMPAS risk assessment as a relevant factor for such matters as: (1) diverting low-risk prison-bound offenders to a non-prison alternative; (2) assessing whether an offender can be supervised safely and effectively in the community; and (3) imposing terms and conditions of probation, supervision, and responses to violations." State v. Loomis, 881 N.W.2d 749, 767 (Wis. 2016).

[138] Thomas Mathiesen, *Selective Incapacitation Revisited*, 22 L. & HUM. BEHAV. 455, 461 (1998).

[139] *See, e.g.*, *id.* at 468 (providing an example of this phenomena in research about predictive criminal justice tools for selective incapacitation, noting that "[r]ather than continuing the effort at increasing prediction accuracy by 2%, or rejoicing when the correlation coefficient increases from 0.34 to 0.36, and rather than seeing such increases as major scientific victories, penal researchers should now turn to the really critical issues: the enormous growth in the use of prisons, with the United States in the lead with 1.7 million prisoners, or 650 prisoners per 100,000 inhabitants, the horrendously inhumane conditions under which prisoners live, and so on.").

tinue to meet evolving social needs.[140] The need for such stewardship in the context of legal systems demands again that legal practitioners engage thoroughly with algorithmic systems. Part III offers a framework for this engagement.

III. ASSESSING ALGORITHMIC SYSTEMS

It is one thing to identify the problems inherent in attempting to assess algorithms outside of the social context in which they are used, and another thing altogether to find a workable solution to the problem. We do not claim to offer a full solution in this one law review article. In this Part, we do, however, hope to offer a tool—an analysis framework—that moves the collective discussion toward a space in which solutions can flourish, rather than be drowned out by over-hyped arguments about professional ethics and the difficulties posed by the black box that encases the computational components of algorithms. To begin that journey this Part first develops a framework for evaluating algorithmic systems, which we call "Algorithmic Systems Query" or "ASQ." ASQ can be applied to any algorithmic system—any algorithm used within a specific social context. This Part then demonstrates ASQ's utility by applying it to the social context at issue in this Article: the law. Using ASQ to assess the use of algorithms in the criminal justice system and in the quest to reduce the justice gap demonstrates the potential for a debate better tailored to technological reality and less rooted in broad value statements, misunderstandings, and general fear.

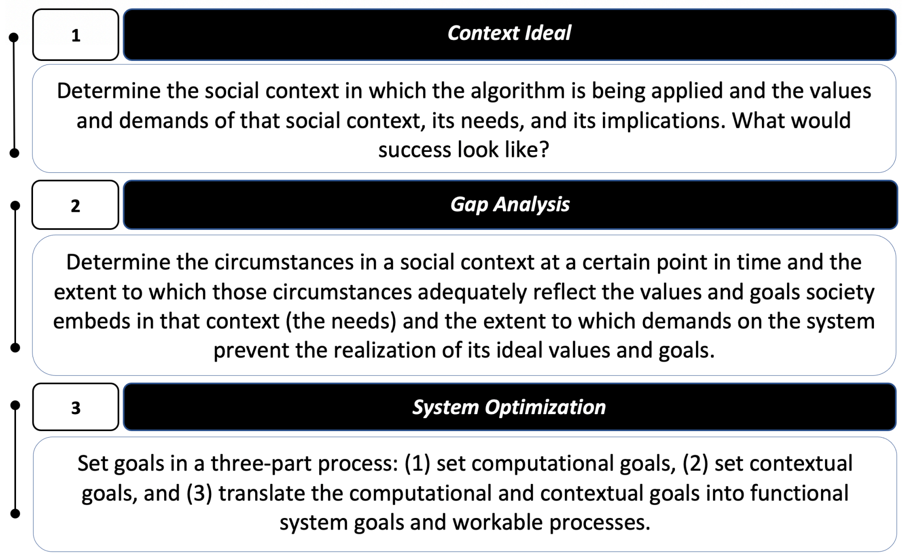
A. *Framework for Evaluation*

We root ASQ in three key steps: (1) a needs assessment, (2) a gap analysis, and (3) a process of system optimization. The first two steps focus on the contextual components and set the stage for assessing the computational design. The third step takes a holistic approach, first requiring separate evaluation of the contextual and conceptual components of an algorithmic system, and then translating the results into functional goals relating to the earlier needs and gap assessments. In this way, ASQ intrinsically builds the feedback loops necessary for responsible and ethical design and the use of algorithmic systems. We detail each element of the framework below.

---

[140] *See, e.g.*, James Guszcza et. al., *Why We Need to Audit Algorithms*, HARVARD BUS. REV. (Nov. 28, 2018), https://hbr.org/2018/11/why-we-need-to-audit-algorithms [perma.cc/97RW-PMQT].

DIAGRAM 4: ALGORITHMIC SYSTEMS QUERY



1. Context Ideal: Identify the Social Context, Its Needs, and Its Implications

Currently, computational components sit as a common starting point for assessing algorithms.[141] The tendency to begin with the computation rests on the assumption that the process of creating an algorithm's code is purely technical and strictly rational, based on math and objectivity.[142] ASQ turns this assumption on its head. ASQ starts from the premise that all technologies, including algorithms, are social technologies.[143] That is, algorithms are always used

[141] Rob Kitchin, *Thinking Critically About and Researching Algorithms* 2 (THE PROGRAMMABLE CITY, WORKING PAPER NO. 5, 2014), (citing Matthew Fuller, *Introduction* to SOFTWARE STUDIES: A LEXICON (Mathew Fuller ed., 2008); WENDY HUI KYONG CHUN, PROGRAMMED VISIONS: SOFTWARE AND MEMORY (2011); LEV MANOVICH, SOFTWARE TAKES COMMAND (2013); ROB KITCHIN & MARTIN DODGE, CODE/SPACE: SOFTWARE AND EVERYDAY LIFE (2011)).

[142] *Id.* at 6–7 (citing Andrew Goffey, *Algorithm*, *in* SOFTWARE STUDIES: A LEXICON, *supra* note 141, at 16; Nick Seaver, *Knowing Algorithms*, 1–2 (Media in Transition 8, Working Paper, rev. Feb. 2014), http://nickseaver.net/papers/seaverMiT8.pdf [perma.cc/ZR8V-2PVL]).

[143] Paul M. Leonardi, *Materiality, Sociomateriality, and Socio-Technical Systems: What Do These Terms Mean? How are They Different? Do We Need Them?*, *in* MATERIALITY AND ORGANIZING: SOCIAL INTERACTION IN A TECHNOLOGICAL WORLD 25, 38 (Paul M. Leonardi et al. eds., 2012) (citing Jos Benders et al., *First Organise, Then Automate: A Modern Socio-Technical View on ERP Systems and Teamworking*, 21 NEW TECH., WORK & EMP. 242 (2006); Robert P. Bostrom & J. Stephen Heinen, *MIS Problems and Failures: A Socio-Technical Perspective Part II: The Application of Socio-Technical Theory*, 1 MGMT. INFO. SYS. Q. 11, 11 (1977)).

in a specific social context.[144] Understanding how an algorithm will behave, and predicting the implications and repercussions of that behavior depends on first understanding the social context in which it will be deployed.[145] Thus, ASQ begins with an exploration of the context ideal,[146] asking the following: What is the social context in which the algorithm is being applied? What are the values and demands of that social context?

Identifying the social context requires more than merely naming a context. A social context is composed of a variety of stakeholders, processes, rules, and other institutional forces (such as roles, statuses, hierarchies, power relations, and communication networks).[147] Fully identifying a social context in a way useful for designing and using algorithmic systems requires understanding each of these components of the social system and the linkages between them.[148] The exploration of context ideal begins by identifying the desired or required state.[149] Doing so requires asking questions like "What results should be accomplished at the societal, organizational, and individual levels?" and "How

---

[144] Leonardi, *supra* note 143, at 25 ("Others argue that a basic term like 'technology' is too simplistic because its use creates the illusion that there is some object, device, or artifact out there doing things and it ignores the empirical reality that those objects, devices, and artifacts only come to have meaning and effects when they are enrolled in social practice." (citing LUCY A. SUCHMAN, HUMAN-MACHINE RECONFIGURATIONS (2006))).

[145] *Id.* at 42 (defining socio-technical system as "[r]ecognition of a recursive (not simultaneous) shaping of abstract social constructs and a technical infrastructure that includes technology's materiality and people's localized responses to it.").

[146] James W. Altschuld & Ryan Watkins, *A Primer on Needs Assessment: More Than 40 Years of Research and Practice*, NEW DIRECTIONS FOR EVALUATION, NEEDS ASSESSMENT: TRENDS AND A VIEW TOWARD THE FUTURE, Winter 2014, at 5, 6 ("A need in the simplest sense is a measurable gap between two conditions—what currently is and what should be . . . .This requires ascertaining what the circumstances are at a point in time, what is to be desired in the future, and a comparison of the two. Needs assessment also includes making judgments with regard to needs and putting them into prioritized order to guide decisions about what to do next.").

[147] Leonardi, *supra* note 143, at 43.

[148] FILIPPO A. RASO ET AL., BERKMAN KLEIN CTR., ARTIFICIAL INTELLIGENCE & HUMAN RIGHTS: OPPORTUNITIES & RISKS 1, 14 (2018), https://cyber.harvard.edu/publication/2018/artificial-intelligence-human-rights [perma.cc/G7VS-YDSR] ("It is only by embracing a comparative approach, that accounts for background conditions from the pre-AI world, that we can properly understand the human rights impacts of introducing AI into the criminal justice system or any other human institution. Unless the human rights implications, both positive and negative, of pre-existing institutional structures are identified and accounted for, the human rights impacts of introducing AI will be conflated with the ongoing impacts of whatever was there before.").

[149] This differs from the starting point of a continual process improvement approach, in which benchmarking starts with comparison to similar operations, usually the leaders among a group of entities viewed as competitors. *See* Andrej Stefanik et al., *Tools for Continual Process Improvement—Simulation and Benchmarking*, 3 PROC. INT'L CONF. "BUS. SYS. MGMT. – UPS 2004" 223, 223 (2003). In the case of an algorithmic system, this article advocates for considering a context ideal over merely the approach of competing technological tools, in order to get at the heart of what needs to be achieved in the specific socio-technical context at issue.

should we think about diverse needs in terms of importance?"[150] The danger in exploring the context ideal lies in jumping to the identification of potential solutions, rather than needs.[151] Identifying needs before moving to the next step in ASQ can help guide analysis in the next step, and decisions about how to proceed at the end of the analysis.[152]

2. *Current State Gap Analysis: Assess the Current State of the Social Context*

After identifying the social context, its subparts, institutional forces, and its needs, ASQ directs the evaluation to a gap analysis. A gap analysis focuses on the current state of the social context, asking the following: What are the current realities of the extent to which the identified values and demands are achieved in the social context? What are the gaps between the ideal of the values and reality? In considering the current realities of the social context, an inventory of assets and problem areas can often serve as a helpful starting point.[153] Essentially, the goal is to determine the circumstances in a social context at a certain point in time and the extent to which those circumstances adequately reflect the values and goals society embeds in that context (the needs). Equally important, the gap analysis considers the extent to which demands on the system prevents the realization of its ideal values and goals.

What is the difference between the exploration of context ideal in step one and the gap analysis in step two of ASQ? In the first step, ASQ evaluates the desired outcomes in a particular identified social context, and in step two, ASQ analyzes the current performance of the system in comparison.[154] As with the exploration of context ideal, more components to a gap analysis exist than may

---

[150] Altschuld & Watkins, *supra* note 146, at 7.

[151] Ryan Watkins & Jolanta Kavale, *Needs: Defining What You are Assessing*, NEW DIRECTIONS FOR EVALUATION, NEEDS ASSESSMENT: TRENDS AND A VIEW TOWARD THE FUTURE, Winter 2014, at 19, 19, 24.

[152] *Id.* at 27.

[153] Altschuld & Watkins, *supra* note 146, at 6.

[154] Maurya West Meiers et al., *International Perspectives: Similarities and Differences Around the Globe*, NEW DIRECTIONS FOR EVALUATION, NEEDS ASSESSMENT: TRENDS AND A VIEW TOWARD THE FUTURE, Winter 2014, at 75, 75, 78. Again, this differs significantly from the continual process improvement model which cautions not to assume an optimal set of indicators from the outset. Kerstin Gerke et al., *Optimization of Service Delivery Through Continual Process Improvement: A Case Study*, *in* INFORMATIK: BUSINESS PROCESS AND SERVICE SCIENCE–PROCEEDINGS OF ISSS AND BPSC 94, 95 (2010). Rather, because law, like an abstract computer system, is a normative system (in the technical meaning of that term), it is appropriate to compare the current state to the context ideal rather than the current state of some perceived competitor (like one U.S. state legal system compared to another, or the U.S. legal system compared to that of the EU). Andrew J.I. Jones & Marek Sergot, *On the Characterisation of Law and Computer Systems: The Normative Systems Perspective*, *in* DEONTIC LOGIC IN COMPUTER SCIENCE: NORMATIVE SYSTEM SPECIFICATION 275, 276 (1993) ("The general position which we here develop and illustrate is that—at the appropriate level of abstraction—law, computer systems, and many other kinds of organisational structure may be viewed as instances of normative systems.").

appear to be involved at first glance. In particular, the second step of ASQ requires the evaluator to consider the root causes of the gap between the values of the system and its current realities.[155] Only by identifying the root causes can the evaluator later consider all possible solutions.[156] ASQ also requires that the evaluator strip away any assumptions about which gap represents a priority for resolution.[157] Rather, prioritizing which gaps to address comes later in the ASQ framework. Furthermore, ASQ rejects the notion that priority setting constitutes a single step in the analysis. Rather, ASQ invites an iterative approach to evaluating gaps, the payoffs from their resolution, and the broader impacts of those payoffs on the larger social system at issue. Such iteration is required because the social context and the demands placed on it do not remain static.[158] Rather, the social context, its needs, and the demands placed on it change over time, and ASQ must be a framework flexible enough to change with them.

3. *Algorithmic System Optimization: Set Functional Goals Based on System Components*

Having explored the context ideal and identified the gap between meeting that context ideal and the current circumstances, ASQ next engages in a goal-setting phase, broken into three parts: (1) setting computational goals, (2) setting contextual goals, and (3) translating the computational and contextual goals into functional system goals and workable processes. At this point, ASQ moves beyond what might be considered a traditional needs-assessment paradigm in the organizational and development literature and creates a new tool for assessing algorithmic systems. Only by clearly delineating how goals fit separately within the computational and contextual goals of an algorithmic system can those adopting an algorithmic system adequately design workable system processes that ensure the algorithm achieves the desired function within the social context in which it is employed.

a. *Set Computational Goals*

When we refer to "computational goals," we refer to goals related to the computational components of an algorithmic system.[159] As discussed at length above, the computational components of an algorithmic system include data inputs, computation, and outputs.[160] The nature and scope of appropriate computational goals will vary by the nature of data and computation used, and by the nature of the outputs produced. To help set parameters on the scope of appropriate computational goals, we offer a generalized taxonomy of algorithms that begins the process of unpacking the nature of the data, computation, and

---

155 Meiers et al., *supra* note 154, at 78.
156 *Id.*
157 *Id.* at 78–79.
158 *Id.*
159 *See supra* notes 108–21 and accompanying text.
160 *See supra* notes 108–11 and accompanying text.

outputs involved. As noted in our prior discussion about moving towards a conception of algorithmic systems, we rely on two key categories: hand-crafted algorithms and machine learning algorithms. For the purposes of ASQ, we break the category of machine learning algorithms into two sub-categories to consider three types of algorithms:[161] hand-crafted algorithms, "adjustable" machine learning algorithms, and "black-box machine" learning algorithms. We note here that we find that the most compelling distinction between algorithms lies between hand-crafted and machine learning algorithms.[162] However, for the purposes of ASQ, we further distinguish between two types of machine learning algorithms to hint at, albeit in a brief and short-hand fashion, the fact that machine learning algorithms can vary widely in their computational sophistication. Indeed, as discussed above in Section II.B, we view machine learning as encompassing a broad spectrum of algorithms, with the two categories we name here standing as mere entry points to either end of that spectrum.[163] To unpack the potential impact on computational goal setting, we expand here on the brief technical introduction to each type of algorithm provided in Part II above, focusing on characteristics of each category important to ASQ.[164]

---

[161] We recognize that there are other ways to categorize algorithms, and we do not claim to offer the best categories for all purposes. However, we think that the three categories presented here offer the clearest opportunity to probe at the issues necessary for creating clear and meaningful computational goals for algorithmic systems using ASQ.

[162] Andrew Tutt, *An FDA for Algorithms*, 69 ADMIN. L. REV. 83, 94 (2017) ("[Algorithms that learn] go by many names, but the most common are 'Machine Learning,' 'Predictive Analytics,' and 'Artificial Intelligence,' although the use of 'intelligent' and its variants can be misleading because it is more important to distinguish between algorithms that learn and algorithms that do not, than it is to distinguish between algorithms that appear intelligent and those that do not." (footnotes omitted)).

[163] We cannot over-emphasize the extent to which we view the technology in each of our three general categories as a spectrum. We do not intend to suggest, by creating three categories of algorithms, that all algorithms within each category are monolithic. We recognize the diverse range of implementations that might be designed within any given category, and that some implementations might cross categories or exist at the margins of one of the categories named here. We do not think this undermines our taxonomy or the ASQ framework. Rather, it highlights the importance of ASQ as a flexible and robust framework that can be used across a wide array of potential algorithmic systems.

[164] We recognize that many of our categories and characteristics do not fall squarely along the lines of technological distinctions. For example, as Zachary Lipton points out, even what we call handcrafted algorithms can be extremely complex and mathematically difficult. Zachary C. Lipton, *The Mythos of Model Interpretability*, 61 COMMC'NS ACM 36, 40 (2016) ("[N]either linear models, rule-based systems, nor decision trees are intrinsically interpretable. Sufficiently high-dimensional models, unwieldy rule lists, and deep decision trees could all be considered less transparent than comparatively compact neural networks."). Nonetheless, our focus here is on general distinctions of socio-legal significance that can jumpstart engagement and conversation among legal practitioners and technologists. As such, we hope that specific technological objections will indeed arise, but preferably in conversations with a broad set of stakeholders with no undue focus on algorithms themselves but instead with a full view of algorithmic systems in mind.

Hand-crafted algorithms, often referred to as "expert systems,"[165] are built with rules and instructions designed to mimic the type of reasoning a human subject-matter expert would undertake to decide within their area of expertise.[166] Creating a hand-crafted algorithm requires deep involvement of human subject-matter experts who use their knowledge to develop the rules or other logical sequence that will achieve a pre-determined goal.[167] Notably, for the purposes of ASQ, because the algorithm design is predefined and all the questions answered with certainty, hand-crafted algorithms are deterministic and might be adjusted as necessary.[168]

By way of reminder, machine learning, a term thought to have been originally coined in 1959,[169] generally refers to the science of programming computers to enable them to learn from data.[170] Different machine learning algorithms use different approaches to learning from data.[171] In broad strokes, some machine learning algorithms use supervised learning,[172] while others learn in an unsupervised manner,[173] and still, others use a form of learning somewhere in

---

[165] Dorothy Leonard-Barton & John J. Sviokla, *Putting Expert Systems to Work*, HARV. BUS. REV., Mar.-Apr. 1988, at 91, 91.

[166] Tutt, *supra* note 162, at 92–93 ("Most algorithms are extremely straightforward. The instructions are relatively basic and the outcomes relatively deterministic. The algorithm responds to specific inputs with specific outputs that the programmer anticipated in advance." (footnote omitted)).

[167] Leonard-Barton & Sviokla, *supra* note 165, at 93. For example, a decision tree is a hierarchical algorithm that asks a series of if-then statements which lead to a conclusion. MOLNAR, *supra* note 130, § 4.4 ("Tree based models split the data multiple times according to certain cutoff values in the features."). Note that a decision tree can be created via a hand-crafted algorithm, where experts determine the cutoff values in the features, or via machine learning models, where algorithms predict the outcome of a decision tree analysis given certain input data. *Id*. Other rules-based algorithms assign weights to different variables, creating a numeric output that reflects the values of the variables. Tutt, *supra* note 162, at 93 (describing Google's "PageRank Algorithm").

[168] Tutt, *supra* note 162, at 93 ("If something goes wrong, the programmer can go back through the program's instructions to find out why the error occurred and correct it.").

[169] Warren E. Agin, *A History of Artificial Intelligence*, *in* THE LAW OF ARTIFICIAL INTELLIGENCE AND SMART MACHINES: UNDERSTANDING A.I. AND THE LEGAL IMPACT 3, 8 (Theodore F. Claypoole ed., 2019) ("Arthur Samuel of IBM supposedly coined the term 'machine learning' for the first time in a 1959 article describing his checker playing programs and the techniques used.").

[170] AURÉLIEN GÉRON, HANDS-ON MACHINE LEARNING WITH SCIKIT-LEARN & TENSORFLOW: CONCEPTS, TOOLS AND TECHNIQUES TO BUILD INTELLIGENT SYSTEMS 4 (Nicole Tache ed., 1st ed. 2017).

[171] *Id*. at 7–8.

[172] *Id*. at 8–9 ("In *supervised learning*, the training data you feed to the algorithm includes the desired solutions, called labels . . . . Here are some of the most important supervised learning algorithms (covered in this book): k-Nearest Neighbors, Linear Regression, Logistic Regression, Support Vector Machines, Decision Trees and Random Forests, Neural networks." (internal parentheticals removed and list edited for clarity)).

[173] *Id*. at 10 ("In *unsupervised learning*, as you might guess, the training data is unlabeled. The system tries to learn without a teacher. Here are some of the most important unsupervised learning algorithms . . . [c]lustering (k-Means, Hierarchal Cluster Analysis, Expectation Maximization), Visualization and dimensionality reduction (Principal Component

between those two extremes (including via semi-supervised[174] and reinforcement learning[175]).[176] Some machine learning algorithms improve incrementally, while other machine learning algorithms improve continuously while operating.[177] These general characteristics, and many others not described in detail here,[178] can be implemented in a variety of combinations—too many to consider individually for the purposes of ASQ. Instead, we propose two very broad categories divided by level of complexity, irrespective of the precise combination of machine learning techniques used: "adjustable" machine learning algorithms and "black-box" machine learning algorithms.

Adjustable machine learning algorithms include those algorithms in which the parameters learned by the algorithm can be manipulated easily by intentional design choices. For example, although the algorithm creator does not pre-determine the weights of variables, the creator provides the algorithm with variables from which the algorithm finds patterns for use in making probabilistic predictions.[179] In adjustable machine learning algorithms, the algorithm creator may still influence the trajectory of the algorithm through training data selection, or by adjusting features like dropout, learning rate, and other parameters.[180]

We distinguish black-box machine learning algorithms from adjustable machine learning algorithms by their level of complexity.[181] The high level of

---

Analysis, Kernel PCA, Locally-Linear Embedding, t-distributed Stochastic Neighbor Embedding), Association rule learning (Apriori, Eclat)." (internal parentheticals removed and list edited for clarity)).

[174] *Id.* at 13 ("Some algorithms can deal with partially labeled training data, usually a lot of unlabeled data and a little bit of labeled data. This is called *semisupervised learning*.").

[175] *Id.* ("Reinforcement learning is a very different beast. The learning system, called an agent in this context, can observe the environment, select and perform actions, and get rewards in return (or penalties in the form of negative rewards . . .). It must then learn by itself what is the best strategy, called a policy, to get the most reward over time. A policy defines what action the agent should choose when it is in a given situation." (emphasis omitted)).

[176] *Id.* at 7.

[177] *Id.* (describing the difference between online learning and batch learning).

[178] For more detailed information on potential characteristics of machine learning algorithms, see generally PEDRO DOMINGOS, THE MASTER ALGORITHM: HOW THE QUEST FOR THE ULTIMATE LEARNING MACHINE WILL REMAKE OUR WORLD (2015).

[179] Barocas & Selbst, *supra* note 2, at 677 ("In contrast to those traditional forms of data analysis that simply return records or summary statistics in response to a specific query, data mining attempts to locate statistical relationships in a dataset. In particular, it automates the process of discovering useful patterns, revealing regularities upon which subsequent decision making can rely." (footnote omitted)).

[180] Anastassia Lauterbach, *Introduction to Artificial Intelligence and Machine Learning*, *in* THE LAW OF ARTIFICIAL INTELLIGENCE AND SMART MACHINES: UNDERSTANDING A.I. AND THE LEGAL IMPACT, *supra* note 169, at 29, 35–36 ("Learning can come in various forms. In the simplest cases it is little more than data accumulation and aggregation (e.g., the k-nearest neighbors algorithm (KNN)). In slightly more advanced cases the instantiated model parameters (such as connection weights or decision trees) are modified during learning, but the algorithm (the learning rules and their implementation) stays fixed.").

[181] As commonly discussed, "[a] Black Box Model is a system that does not reveal its internal mechanisms. In machine learning, 'black box' describes models that cannot be under-

complexity necessary to create a black-box machine learning algorithm makes it more difficult to interpret the relationship between input variables and outcomes,[182] and thereby decreases the ease with which humans can explain, adjust, or otherwise influence the algorithm's parameters.[183] "Even if we can fully describe what makes them work, the actual mechanisms by which they implement their solutions are likely to remain opaque: difficult to predict and sometimes difficult to explain."[184]

The type of algorithm selected—hand-crafted, adjustable machine learning, or black-box machine learning—influences the scope of the computational goals that might be achieved by an algorithmic system.[185] As discussed at some length above, and summarized in Table 1 below, the choice of an algorithm from one of these three categories influences the nature of the available computational parameters, the need for domain experts in creating the algorithm, the level of computational explainability achievable by identifying the relationship between inputs and outputs, the algorithm's accuracy, the extent to which the algorithm can be adjusted, and whether the computation is probabilistic or deterministic in nature.[186] Each of these categories represents a spectrum along which algorithmic system designers might make an intentional design choice, beginning at the choice of algorithm type.

stood by looking at their parameters (e.g. a neural network)." MOLNAR, *supra* note 130, § 1.3 (emphasis omitted). Again, we note that our broad categorizations, including this definition of "a black box model" will not fit neatly with all potential permutations of the technology. We anticipate fleshing out the technical differences in later work, and encourage others to contribute to the conversation by doing the same. It is our contention, however, that the ASQ framework is adaptable and robust enough to accommodate both the more generalized descriptions our word count permits in this Article, and the more technical details that should unquestionably be considered in any specific algorithmic system.

182 Tutt, *supra* note 162, at 99 ("The outputs of machine-learning algorithms that engage in their own feature extraction are sometimes almost indistinguishable from magic.").

183 *Id.* at 101–02 ("An algorithm's predictability is a measure of how difficult its outputs are to predict, while its explainability is a measure of how difficult its outputs are to explain."). Such algorithms include random forests, neural networks, and deep neural networks.

184 *Id.* at 102.

185 For example, "What we know, and what can be known, about how an algorithm works will play vital roles in determining whether it is dangerous or discriminatory." *Id.* at 104.

186 *See* discussion *supra* notes 159–84 and accompanying text.

TABLE 1: ALGORITHMIC CHARACTERISTICS TO CONSIDER WHEN SETTING COMPUTATIONAL GOALS[187]

TYPE	FEATURES	EXPLAINABILITY	ACCURACY	PROBABILISTIC	COMPLEXITY	DEVELOPMENT
Hand-Crafted	Explicitly defined and rigid features created using domain expertise	Can always explain the steps taken to reach an output for a given input.	Only as accurate as the humans that created the if-then statements.	Not probabilistic. Results occur with certainty—deterministic.	As simple or complex as the parameters created for it.	Not mathematically difficult. Easy to adjust.
Adjustable Machine Learning	Learned by connecting inputs to known, mapped outputs.	Somewhat explainable, depending on the complexity of the computation.	Somewhat accurate, depending upon training data and any given parameters.	Probabilistic. Results are given with a degree of probabilistic confidence.	Can be simple machine learning algorithms like an ordinary least square regression.	Mathematically sophisticated. But can still be adjusted with some reasonable level of effort.
Black-Box Machine Learning	Learned by finding patterns in unstructured data.	Least explainable. Difficult to fully explain the steps taken to create the output, given specific inputs.	High levels of accuracy. May find relationships in data that humans cannot find.	Probabilistic. Results are given with a degree of probabilistic confidence.	Can be fairly complex, like a neural network architecture.	Mathematically advanced. Difficult to adjust.

[187] We acknowledge that this Table 1 inherently uses broad strokes in identifying types of algorithms and their characteristics. For example, in the context of whether algorithms are probabilistic, we are aware our use of that term refers only to one meaning of "probabilistic" when it comes to machine learning. We are aware that algorithms that learn black-boxy features to do classification, for example, are not probabilistic in this way. Indeed, some support vector machines generate non-probabilistic outputs while retaining features that are difficult to explain. It is not our intention to shortchange the technical issues with this chart. Rather, it is our goal to offer a starting point for non-technologists to engage some aspects of technical considerations involved in algorithmic design. We hope to further expand our thoughts and the robustness of the tool in later work.

b. Set Contextual Goals

Having set computational goals for the algorithmic system and having identified the resulting implications for the type of algorithm the system might reasonably employ to achieve those computational goals, ASQ now turns to contextual goal setting. When we refer to contextual goals, we intend to refer to the values embedded in the interpretation of, and the demands on the application of, an algorithms' output in order to make them useful for the social context of the algorithmic system.[188] At this stage of ASQ, contextual goal setting requires reflection on the earlier context ideal and gap analysis conducted in the first two steps of the framework. What type of output does the algorithmic system need to produce, and what framework for the interpretation of that output must be created in order to reduce the gaps between ideal and reality in the social context in which the outputs of the algorithmic system will be applied? Can that type of output be realistically obtained, given the computational goals previously set? Can processes for interpretation of the output or its application make-up for any shortcomings in the output or the computation? Only by considering these and related questions that naturally arise when applying ASQ to a specific social context can the designer of the algorithmic system set realistic contextual goals.

c. Translate Computational and Contextual Goals into Functional System Goals and Workable Processes

Although setting computational and contextual goals may constitute an end in themselves, the goals and the process of defining them also serve as a feedback mechanism for initially outlining, and then continuously refining, the overall goals of the algorithmic system, the design of the algorithmic system, and the creation of audit mechanisms to ensure that the algorithmic system achieves its goals to the greatest possible extent. To formalize this feedback mechanism, ASQ's final step requires the algorithmic system designer to set the computational and contextual goals for the system side-by-side, in order to consider how they relate to one another. Indeed, even if the computational goals use the same or similar words to the contextual goals, those words may not mean the same thing in the computational setting as in the contextual setting.[189] Thus, a type of translation exercise is required, whereby the designers of the algorithmic system consider the contextual and computational goals together and consider what functional goals the two have in common. Those common functional goals should form the basis of the goals for the algorithmic system as a whole and should drive the design of the computational compo-

---

[188] *See supra* notes 131–40 and accompanying text.

[189] *See, e.g.*, Deirdre K. Mulligan et al., *This Thing Called Fairness: Disciplinary Confusion Realizing a Value in Technology*, PROCEEDINGS ACM ON HUM.-COMPUT. INTERACTION, Nov. 2019, at 119, 119:6 (discussing the difficulty in finding common meaning across disciplines with regard to the term "fairness" as it relates to algorithms and the use of algorithms).

nents (inputs, computation, and outputs) as well as the contextual components (interpretation and application of the outputs). Finally, the algorithmic system should be audited for the extent to which it achieves these functional goals, as opposed to specific computational or contextual goals standing alone. When algorithms are placed within and used as a tool in a social context, the social context impacts the performance of the algorithm, and the performance of the algorithm impacts the social context in a two-way relationship. Functional goals identified by translating across the computational and contextual domains better reflect the capacity of the algorithmic system to achieve any given outcome because they sit at the algorithmic system level, accounting for both components, rather than focusing on one to the exclusion of the other.

B. When the Social Context is Law: Assessing Legal Algorithmic Systems

To illustrate our approach to evaluating algorithmic systems, this Section applies ASQ to the debates that surround the use of algorithms in the legal context. We first use the values and demands that often permeate the policy and academic debates related to using algorithmic systems to advance legal outcomes to develop a values taxonomy that identifies the ideal needs of the legal system. Next, we critically evaluate the current ability of the legal system to meet those needs, identifying the gaps where algorithmic tools may enhance and support values. We then illustrate how using ASQ forces a dialogue between those focused on the technological aspects of an algorithmic system and those focused on the contextual aspects. The dialogue, in turn, enables a joint functional design approach to the algorithmic system that focuses on workable solutions and avoids the problems of under-fit and over-fit that currently plague the legal technology field.

1. Exploration of Context Ideal: Due Process and Access as Two Key Value Arenas for Algorithmic Systems in the Legal Context

Applying ASQ to the legal context, we begin by asking: what are the core values and demands of a successful legal system? This is a profound line of inquiry and one we cannot presume to cover fully here. Among other complexities, the sources of legal values and demands are multifarious and the applications to specific legal contexts are nuanced; thus, a full context ideal is certain to be correspondingly various. Nonetheless, even in this brief article, we can discern a core set of demands and values to facilitate the application of ASQ in this context.

For purposes of applying ASQ to law, we limit our inquiry in at least two ways. First, as with this article as a whole, we spotlight the integrity of legal decision-making and access to legal resources, broad categories themselves but a significant narrowing of the whole of a legal system. As touchpoints, we continue to use criminal sentencing and access to civil legal services.[190] Second, we

---

[190] *See* discussion *supra* Sections I.B–C.

aim to identify only a core set of salient values and demands rather than a comprehensive set. The intention is not to oversimplify; we recognize that such discussions of values and demands are ongoing, complex, and central to the social discourse that constitutes the very fabric of our legal and political systems. Such discourse will continue. In the midst of these ongoing discussions, this context ideal highlights a set of values that are among the most widely shared and salient—for legal decision making and access to legal services, respectively—to demonstrate the ASQ methodology and place our assessments of algorithmic systems and law on more solid foundations.

What, then, are the desired and required states of legal decision-making and access to legal services? To start, several core values emerge by looking to the expectations the legal system places upon its primary actors: lawyers and judges. Aligned with a primary expectation of all consumers of legal services, the model rules of professional responsibility begin with expectations of performance, captured in Rule 1.1's requirements of competency.[191] After all, people employ legal services to help solve problems and gain opportunities and expect "the highest standards of legal acumen"[192] Intrinsic in this expectation of accurate advice and competent services—and made express throughout the rules of professional responsibility—are related demands for careful, diligent services;[193] independent and unbiased judgment;[194] and transparent and open communication such that clients can not only understand legal consequences and processes[195] but also participate actively in legal choices.[196] To realize these demands for open communication in situations—endemic to legal issues—where information might for many reasons be sensitive, the system places great emphasis on candor and the flow of information,[197] especially prizing confidentiality and privacy where required.[198]

The performance expectations of those who seek solutions to their problems are manifest not only at the doors of the law office, but also at the doors of the courthouse, demanding that judges, judicial processes, and legal institutions be efficient[199] as well as fair, unbiased, consistent, and predictable.[200] Such values and demands are seminal and rather universal, echoed in aspirations of le-

---

[191] MODEL RULES OF PRO. CONDUCT r. 1.1 (AM. BAR ASS'N 2020).
[192] LEXMUNDI, LEX MUNDI AND PROFESSIONALISM: A STATEMENT OF SHARED FUNDAMENTAL VALUES 2 (2013).
[193] MODEL RULES OF PRO. CONDUCT r. 1.3 (AM. BAR ASS'N 2020).
[194] *Id*. at r. 1.7–1.8.
[195] *Id*. at r. 1.4.
[196] *Id*. at r. 1.2.
[197] *Id*. at r. 3.3.
[198] *Id*. at r. 1.6.
[199] MODEL CODE OF JUD. CONDUCT Canon 2 (AM. BAR ASS'N 2020) [hereinafter MODEL JUDICIAL CODE].
[200] MODEL RULES OF PRO. CONDUCT r. 8.2 (AM. BAR ASS'N 2020); MODEL JUDICIAL CODE, *supra* note 199, at Canons 1–4.

gal/judicial system reform efforts domestically[201] and rule of law expectations internationally.[202]

Beyond what any individual client or petitioner demands of legal practitioners and institutions, there are collective demands on the legal system as an institutional backbone of a democratic society. Foremost among these values are demands for fairness and equity—founding pillars of our democratic political system, constituent legal institutions, and cultural expectations. After all, enshrined on architrave above the entry doors to the Supreme Court of the United States is the command of "Equal Justice Under Law."[203] The foundational conception of equal justice here speaks both to the fair and impartial treatment of all who come before the court[204] and an overarching "responsibility for the adequate distribution of legal services."[205] Fair treatment by and equitable access to the law comprise the foundations of our ideal legal system.

It is from the vantage of these values that we consider our demands for law and algorithmic systems. These values and demands echo in recent literature and academic debates related to using algorithmic systems, both in general discussions of algorithms and decision-making and resource allocation and in specific assessments of algorithms and legal solutions and access.

In assessing the potential of algorithm-driven tools to improve the legal system,[206] the literature focuses on efficiency and costs,[207] access to services,[208] and the potential to mitigate human biases.[209] Demands for accurate, predictable, and consistent performance of algorithms are central to technological literature, which, of course, takes an ever-improving performance of the computa-

---

201 *See generally, e.g.*, R. Polk Wagner & Lee Petherbridge, *Is the Federal Circuit Succeeding? An Empirical Assessment of Judicial Performance*, 152 U. PA. L. REV. 1105 (2004); Brook E. Gotberg, *Restructuring the Bankruptcy System: A Strategic Response to* Stern v. Marshall, 87 AM. BANKR. L.J. 191 (2013).

202 *See, e.g.*, USAID, GUIDE TO RULE OF LAW COUNTRY ANALYSIS: THE RULE OF LAW STRATEGIC FRAMEWORK 8–20 (2010).

203 *The Court and Constitutional Interpretation*, SUP. CT. OF THE U.S., https://www.supremecourt.gov/about/constitutional.aspx [perma.cc/9BHJ-VU7S].

204 MODEL JUDICIAL CODE, *supra* note199, at Canons 1–2.

205 LEXMUNDI, *supra* note 192, at 2.

206 *See, e.g.*, Cruz, *supra* note 14, at 350.

207 McGinnis & Pearce, *supra* note 17, at 3041. *See generally*, SUSSKIND & SUSSKIND, *supra* note 57, at 1–3.

208 *See, e.g.*, Cabral et. al., *supra* note 75, at 256; Wolf, *supra* note 53, at 759; Raymond & Shackelford, *supra* note 53, at 486–87; Simshaw, *supra* note 48, at 179 ("The United States is in the midst of an access to justice crisis. Too many people lack access to the legal services they need, usually because they cannot afford them."); Frank, *supra* note 48, at 251. For detailed accounts, see generally JUSTICE GAP REPORT, *supra* note 48; FUTURE OF LEGAL SERVICES REPORT, *supra* note 48; CLOSING THE JUSTICE GAP, *supra* note 48; TECHNOLOGY SUMMIT REPORT, *supra* note 49; Brescia et al., *supra* note 51; Cruz, *supra* note 14, at 357 ("The legal profession is increasingly using technology to assist individuals with their legal needs."); Staudt & Medeiros, *supra* note 51, at 708–710 (discussing the potential of A2J Author and similar tools to advance access to justice).

209 *See* MODEL PENAL CODE: SENTENCING § 6B.09 (AM. L. INST., Tentative Draft No. 2, 2011).

tional components of algorithms as a central goal.[210] Even still, contextualized assessments of algorithms as a means to improve judicial performance spawn both from technologists focused on the computational components of algorithmic systems[211] and legal academics focused on social demands of sentencing specifically.[212] Among all of these, demands for accurate and consistent performance in aiding decision-making are common threads.

Yet, performance demands are far from the only threads. While confidentiality was already a paramount concern of any legal system, algorithmic systems fueled by big data and shared across networked devices raise additional concerns about privacy and security.[213] The literature is also rife with demands for the understandability of algorithmic processes and outcomes. So varied and extensive is the discussion about transparency,[214] interpretability,[215] and explainability,[216] that here we use the summative term "understandability"[217] to point to this important discourse without implying the discussion is settled. By any term, demands for some form of understandability are intently interwoven with values of due process.[218] Taken together, in fact, demands for performance and understandability are preconditions for the ability to hold algorithmic tools accountable to the social contexts in which they are used.[219] Where either performance or understandability falters, the legal system cannot ensure its fundamental need for fairness.[220] These values and demands are even more explicit

---

210 *See generally, e.g.*, Katyal, *supra* note 2; Wexler, *supra* note 2; Citron, *supra* note 8; Deeks, *supra* note 45; Simmons, *supra* note 42; Selbst & Barocas; *supra* note 47.

211 *See, e.g.*, Jiaming Zeng et al., *Interpretable Classification Models for Recidivism Prediction*, 180 J. ROYAL STAT. SOC'Y 689, 689 (2017) (describing a specific Supersparse Linear Integer Model in a search for "predictive models of recidivism that are sufficiently accurate, transparent and interpretable to use for decision making.").

212 *See, e.g.*, Starr, *supra* note 44, at 805–06; Simmons, *supra* note 42, at 1072–73; Bagaric & Wolf, *supra* note 1, at 654 (exploring the capacity of algorithmic tools to enhance sentencing accuracy and predictability and noting at footnote 7 that "the accuracy and quality of computerized decision-making is obviously governed by the quality of the data and the accuracy of the algorithm that is designed to facilitate the decision").

213 *See, e.g.*, Sandra Wachter & Brent Mittelstadt, *A Right to Reasonable Inferences: Re-Thinking Data Protection Law in the Age of Big Data and AI*, 2019 COLUM. BUS. L. REV. 494, 497 (2019).

214 *See* Zeng et al., *supra* note 211; Michael Koliska & Nicholas Diakopoulos, *Disclose, Decode, and Demystify: An Empirical Guide to Algorithmic Transparency*, *in* THE ROUTLEDGE HANDBOOK OF DEVELOPMENTS IN DIGITAL JOURNALISM STUDIES 251 (Scott A. Eldridge II & Bob Franklin eds., 2019).

215 Nicholas Diakopoulos, *Accountability in Algorithmic Decision Making*, 59 COMMC'NS ACM 56, 58 (2016); Lipton, *supra* note 164, at 36.

216 Deeks, *supra* note 45, at 1829, 1833; Edwards & Veale, *supra* note 46, at 67; Selbst & Barocas, *supra* note 47, at 1099; *see* Ananny & Crawford, *supra* note 91, at 982.

217 Certainly "understandability" has its own connotations and limitations (not to mention unwieldiness), but we use it to distance it as an umbrella concept from the more prevalent uses of transparency, interpretability, and explainability without taking sides in the debate, which is not necessary for present discussions.

218 Citron, *supra* note 8, at 1277, 1281.

219 *See, e.g.*, Katyal, *supra* note 2, at 58–60.

220 Citron, *supra* note 8, at 1277.

among frequent commentary citing concerns that algorithms will introduce new avenues for bias[221] or even reintroduce or crystalize existing biases.[222] Where the existence of biases in the data inputs or computations is uncertain or unascertainable, the existence of inequitable results[223] makes plain the obligation for some form of understandability in order to meet due process expectations.[224]

This brief survey allows us to identify a number of core values and demands that, for purposes of the present discussion, can be summarized as follows in Tables 2 and 3.

---

[221] *See, e.g.*, Barocas & Selbst, *supra* note 2, at 1085, 1099.

[222] Tom Simonite, *When It Comes to Gorillas, Google Photos Remains Blind*, WIRED (Jan. 11, 2018, 7:00 AM), https://www.wired.com/story/when-it-comes-to-gorillas-google-photos-remains-blind/ [perma.cc/CT2X-2QP2]; Christopher Slobogin, *Principles of Risk Assessment: Sentencing and Policing*, 15 OHIO ST. J. CRIM. L. 583, 596 (2018) (noting that "the biases that algorithms are meant to prevent will simply be reintroduced" without proper guidance).

[223] Letter from Jonathan J. Wroblewski, Dir., Office of Pol'y & Legis., U.S. Dep't of Just. Crim. Div., to the Hon. Patti B. Saris, Chair, U.S. Sent'g Comm'n 7 (July 29, 2014), https://www.justice.gov/sites/default/files/criminal/legacy/2014/08/01/2014annual-letter-final-072814.pdf [perma.cc/V9FY-66YH] (concluding, "[E]xperience and analysis of current risk assessment tools demonstrate that utilizing such tools for determining prison sentences to be served will have a disparate and adverse impact on offenders from poor communities already struggling with many social ills. The touchstone of our justice system is equal justice, and we think sentences based excessively on risk assessment instruments will likely undermine this principle."); Barocas & Selbst, *supra* note 2, at 677; *see, e.g.*, Eric Holder, Att'y Gen., U.S. Dep't of Just., Address at the Nat'l Ass'n of Crim. Def. Laws. 57th Ann. Meeting & 13th State Crim. Just. Network Conf. (Aug. 1, 2014), https://www.justice.gov/opa/speech/attorney-general-eric-holder-speaks-national-association-criminal-defense-lawyers-57th [perma.cc/87ST-VGGT] (cautioning that recidivism risk assessments "may exacerbate unwarranted and unjust disparities").

[224] *See* Wroblewski, *supra* note 223, at 7; Barocas & Selbst, *supra* note 2, at 729–30; Holder, *supra* note 223; SARAH L. DESMARAIS & JAY P. SINGH, RISK ASSESSMENT INSTRUMENTS VALIDATED AND IMPLEMENTED IN CORRECTIONAL SETTINGS IN THE UNITED STATES 2 (2013), https://csgjusticecenter.org/wp-content/uploads/2020/02/Risk-Assessment-Instruments-Validated-and-Implemented-in-Correctional-Settings-in-the-United-States.pdf [perma.cc/Z9P7-EQSH]; Gardner v. Florida, 430 U.S. 349, 359 (1977) (considering "a capital-sentencing procedure which permits a trial judge to impose the death sentence on the basis of confidential information which is not disclosed to the defendant or his counsel" and holding that "[t]he defendant has a legitimate interest in the character of the procedure which leads to the imposition of sentence even if he may have no right to object to a particular result of the sentencing process.").

TABLE 2: NEEDS INVENTORY—DUE PROCESS/INTEGRITY OF DECISION-MAKING

PERFORMANCE	UNDERSTANDABILITY	FAIRNESS
Accuracy	*Transparency*	*Unbiased*
Predictability	*Interpretability*	*Process/Rule-abiding*
Consistency	*Explainability*	*Independence*

TABLE 3: NEEDS INVENTORY—ACCESS TO LEGAL RESOURCES

EQUITY	ACCOUNTABILITY	INFORMATIONAL INTEGRITY
Availability/Usability	*Competence*	*Confidentiality*
Affordability	*Diligence*	*Privacy/Security*
Independence	*Transparency*	*Candor*

As the first step in applying ASQ to the legal context, we recognize that the values and demands illuminated by this exploration of context ideal represent an aspirational state—target characteristics of a complex and ongoing teleology.[225] As such, these values and demands are not necessarily descriptive of the legal system as it stands at any given moment. Rather, we seek to approximate this ideal end state via innumerable means, and here we ask the reader to consider the extent to which these means should include algorithm-driven tools and, if at all, then how algorithmic tools should be treated. Ideally, a convicted criminal awaiting criminal sentencing or any individual facing, say, civil eviction, then, would have access to well-performing legal counsel and fair adjudication as part of processes that are understandable and accountable. What means best help us to approximate this ideal? Should we invite algorithm-driven tools into the realms of law? To answer such questions, one must consider the extent to which the current state of the system approximates or remains distant from the ideal state.

---

[225] To be sure, this brief needs assessment is incomplete, offered as a starting point. A more fulsome needs assessment would seek additional sources of values and demands and then not only prioritize them but also elucidate interactions among these expectations. Our goal here not to complete the analysis or end the discourse but an invitation to this sort of analysis and further discourse.

2. *Gap Analysis: Despite Diligent Efforts, Performance of the Current System Is Inconsistent, at Best*

Because of technology's power to play a significant role in governing society, any profession should engage in careful diligence and analysis before inviting technology tools—and especially technology tools as powerful as emerging algorithm-driven machines—into positions of decision-making or positions that might otherwise implicate the integrity of the profession. Nonetheless, this diligence must involve a candid assessment of the current ability of current methods to meet system needs, identifying unmet demands, and the gaps where the system does not deliver on ideal values. Only then might we assess the wisdom of technology-driven change and the appropriate approach to algorithm-driven tools.

In applying ASQ to legal decision-making and access to legal resources, then, we conduct a gap analysis, assessing the extent to which the values and demands identified by the context ideal are or are not achieved by the current state. We must ask, therefore: (1) to what extent does the legal decision-making meet demands for performance, understandability, and fairness; and (2) to what extent does the legal service delivery meet demands for equity, accountability, and informational integrity?

In terms of the integrity of legal decision-making, results are mixed, and there is ample evidence to suggest that in some areas the system falls short, including: ideals of performance, understandability, and fairness. Perhaps most notably in the context of criminal sentencing, current methods have not delivered adequate fairness, especially on account of persistent and long-recognized racial disparities in sentencing outcomes[226] that have proven difficult to remedy through reforms to our predominant systems of human decision-making.[227] On a more systemic level, evidence of this ongoing failure exists in mass incarceration rates[228] with disparities drawn sharply along racial lines.[229] In fact, much of

[226] *Written Submission of the Am. C.L. Union on Racial Disparities in Sent'g, Hearing on Reports of Racism in the Just. Sys. of the U.S. Before the Inter-American Comm'n on Human Rts.*, 153d Sess. 1 (2014), https://www.aclu.org/sites/default/files/assets/141027_iachr_racial_disparities_aclu_submission_0.pdf [perma.cc/VD5J-PYCF].

[227] *See, e.g.*, Joshua B. Fischman & Max M. Schanzenbach, *Racial Disparities Under the Federal Sentencing Guidelines: The Role of Judicial Discretion and Mandatory Minimums*, 9 J. EMPIRICAL LEGAL STUD. 729, 729 (2012) (cataloging the limited and uneven success of the U.S. Sentencing Guidelines of the Sentencing Reform Act to achieve a "reduction of unwarranted racial disparities in sentencing").

[228] *See, e.g.*, James Forman, Jr., *Racial Critiques of Mass Incarceration: Beyond the New Jim Crow*, 87 N.Y.U. L. REV. 21, 22 (2012); Robert DeFina & Lance Hannon, *The Impact of Mass Incarceration on Poverty*, 59 CRIME & DELINQ. 562, 563 (2013).

[229] On race in the criminal justice system, see Barbara O'Brien, *A Recipe for Bias: An Empirical Look at the Interplay Between Institutional Incentives and Bounded Rationality in Prosecutorial Decision Making*, 74 MO. L. REV. 999, 1002 (2009); Barbara O'Brien & Catherine M. Grosso, *Confronting Race: How a Confluence of Social Movements Convinced North Carolina to Go Where the* McCleskey *Court Wouldn't*, MICH. ST. L. REV. 463, 464–65 (2011).

the motivation to develop algorithmic tools stems from these shortcomings in performance and resulting fairness.[230] Granted, this example affects a fraction of the overall population, but, in terms of access to legal services more broadly, other shortcomings in the systems are much more widespread.[231]

A look at the success of the current system in providing equity of access to legal services in keeping with the values and demands of the ideal system reveals even wider gaps. For purposes of this Article and this step of ASQ, much of this assessment was described above at Section I.B., which revealed that the current state of legal services delivery fails rather egregiously in terms of equitable access to legal resources and "Equal Justice Under Law."[232] Of course, the Sixth Amendment to the U.S. Constitution guarantees the right to "[a]ssistance of [c]ounsel" for defendants "[i]n all criminal prosecutions,"[233] a right made more meaningful by the decision of *Gideon v. Wainwright* establishing a right to free assistance of counsel for indigent criminal defendants.[234] Nonetheless, even in criminal matters, persistent inequities remain, with abundant doubts about the effective assistance of appointed counsel[235] and clear discrepancies in outcomes across socio-economic categories[236] and racial lines.[237] And with no corresponding right to counsel in civil legal matters, it is difficult to overstate the failure of the US legal system to produce equitable civil legal service delivery.[238] This lack of resources and non-availability of legal services for individu-

---

[230] Bagaric & Wolf, *supra* note 1, at 688 (noting that "[a] major reason for these [criminal sentencing] inconsistencies is that implicit biases and deeply rooted values and beliefs of individual judges often affect their decision-making. Even though American judges make decisions within prescriptive and guideline sentencing systems that have presumptive penalties, there is considerable scope for their personal views of offenders (including those perceptions of which even they are unaware) to affect their decisions.").

[231] See, for example, UTAH WORK GRP. ON REGUL. REFORM, *supra* note 98, at 1 (2019), https://www.utahbar.org/wp-content/uploads/2019/08/FINAL-Task-Force-Report.pdf [perma.cc/6VAB-7EUA], which notes that "86% of civil legal problems reported by low-income Americans in [2016–17] received inadequate or no legal help."

[232] *See* discussion *supra* Section I.B.

[233] U.S. CONST. amend. VI.

[234] Gideon v. Wainright, 372 U.S. 335, 345 (1963).

[235] *See, e.g.*, Jenny Roberts, *Too Little, Too Late: Ineffective Assistance of Counsel, the Duty to Investigate, and Pretrial Discovery in Criminal Cases*, 31 FORDHAM URB. L.J. 1097, 1100 (2004); Daniel S. Medwed, *Anatomy of a Wrongful Conviction: Theoretical Implications and Practical Solutions*, 51 VILL. L. REV. 337, 370 (2006); Eve Brensike Primus, *Structural Reform in Criminal Defense: Relocating Ineffective Assistance of Counsel Claims*, 92 CORNELL L. REV. 679, 686 (2007).

[236] *See, e.g.*, Kaaryn Gustafson, *Degradation Ceremonies and the Criminalization of Low-Income Women*, 3 U.C. IRVINE L. REV. 297, 300 (2013); Cortney E. Lollar, *Criminalizing (Poor) Fatherhood*, 70 ALA. L. REV. 125, 127 (2018).

[237] *See, e.g.*, David S. Abrams et al., *Do Judges Vary in Their Treatment of Race?*, 41 J. LEGAL STUD. 347, 347 (2012); Carlos Berdejó, *Criminalizing Race: Racial Disparities in Plea-Bargaining*, 59 B.C. L. REV. 1189, 1189 (2018).

[238] Chad Flanders & Alexander Muntges, *The Trumpet Player's Lament: Rethinking the Civil* Gideon *Movement*, 17 UDC/DCSL L. REV. 28, 28–29 (2014) ("[I]n *Turner v. Rogers*, the Court rejected the analogous argument that the right to counsel in a civil contempt proceeding was a fundamental right where an indigent, noncustodial parent faces incarceration.");

als in need of civil legal assistance in the United States has persisted despite valiant efforts to bring about change.[239] More than with any other value, the current system has failed to achieve anything near equity in access to legal services; so wide is the gap, in fact, that any analysis of means to approximate the ideal state must consider this current state a failure.

Any full ASQ ought to include an exploration of the root causes of gaps between the current state and ideal system demands. Here, if we take seriously the roles that emerging algorithm-driven tools could play in legal decision-making and access to legal resources, then impediments to effective remedies might include both (1) our blunt/imprecise and imperfect tools used to protect the integrity of legal decision-making in light of technological change and (2) the conception of acontextual algorithms that seemingly undergird them.

As noted, the legal profession often calls upon the blunt instrument of UPL to deny entrance to legal services markets by algorithmic tools that offer expanded access to those underserved by the current system.[240] Yet, at their best, UPL rules are loose proxies for the ideals of accountability and informational integrity. If we ensure that the service providers are licensed legal practitioners, the reasoning goes, then we can hold these providers accountable for the values and demands of the system. Yet, as this brief ASQ demonstrates, UPL has not brought about a high performing system and does nothing to promote equity of access to legal services.[241] Too often, UPL serves as market protection, and the result for many decades has been a wide gap between those who can afford civil legal services and those who cannot.[242]

Relatedly, ongoing adherence to conceptions of acontextual algorithms skews our assessments of their potential. By failing to conceive of algorithmic systems, we may miss access opportunities because we compare algorithmic function to the ideal system rather than to the broken system of which it is a part. That is, we tend to measure tools against perfection rather than reality. To analogize to another context where technological change is occurring, public reaction to harms caused by automated vehicles often suggests that only a perfect system of zero casualties is acceptable and that maintenance of the current system is preferable.[243] Yet, estimates are that well over 90 percent of the ap-

---

Kevin R. Johnson, *An Immigration* Gideon *for Lawful Permanent Residents*, 122 YALE L.J. 2394, 2396 (2013) (The "law sharply demarcates between the many rights available to *criminal* defendants and the significantly more limited bundle of protections for *civil* litigants.").

[239] *See supra* Sections I.B.–C.

[240] DeStefano, *supra* note 14, at 2961.

[241] *Id.* at 2973 (arguing that if lawyers really "are better than nonlawyers at providing legal and law-related services because of their training, expertise, and adherence to professional rules of conduct" they will "be able to retain a monopoly on those services even if statutes against UPL are abolished (or more narrowly defined)").

[242] *Id.* at 2971 (citing James C. Turner, *Lawyer vs. Nonlawyer: ABA Chose Wrong Side in Drafting 'Unauthorized Practice' Rule*, LEGAL TIMES (Feb. 3, 2003), http://www.turnerhome.org/jct/Clips/turner-legal-times-02-03-03.pdf [perma.cc/URC9-5CV8]).

[243] NIDHI KALRA & DAVID G. GROVES, THE ENEMY OF GOOD: ESTIMATING THE COST OF WAITING FOR NEARLY PERFECT AUTOMATED VEHICLES, 2–3 (2017) (ebook); Melissa Bau-

proximately 33,000 annual driving casualties are caused by human error and that—even though some level of harm is certain to persist—AVs will reduce this number significantly.[244] In order to assess the potential of algorithms to improve our legal system, when we weigh the potential virtues and vices of algorithm-driven tools, we must do so conceiving of algorithmic systems, with an understanding of system values and demands and with realistic assessments of the current state.

3. *Algorithmic System Optimization: Designing Workable Approaches for Legal System Improvement*

Following an exploration of context ideal and gap analysis, the last step of ASQ is system optimization—a process of deliberate design aimed at approximating the values and demands of the ideal system via available means. Applied to the legal system, a primary question at hand is the extent to which emerging algorithm-driven tools can serve as part of the means of legal service delivery. The effects of algorithms on the legal system—whether positive or negative—are not automatic, and appropriate outcomes require widespread engagement and thoughtful balancing. Here the conception of algorithmic systems and law—with overlapping spheres of computational components and contextual components—plays a critical role, as it enables a process of joint functional design among technologists, legal thinkers, and relevant stakeholders.[245]

---

man, *Why Waiting for Perfect Autonomous Vehicles May Cost Lives*, RAND CORP. (Nov. 7, 2017) ("Some people think autonomous vehicles must be nearly flawless before humans take their hands off the wheel.").

[244] *See* NAT'L HIGHWAY TRAFFIC SAFETY ADMIN., TRAFFIC SAFETY FACTS: CRITICAL REASONS FOR CRASHES INVESTIGATED IN THE NATIONAL MOTOR VEHICLE CRASH CAUSATION SURVEY 2 (2015), https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812115 [perma.cc/62WS-N9Q2]; NAT'L HIGHWAY TRAFFIC SAFETY ADMIN., QUICK FACTS 2015 (2017), https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812348 [perma.cc/E3K9-CJER].

[245] While too important and substantial a topic to address with any adequacy here, the need to find ways to involve a broader range of stakeholders in processes of AI design, development, and deployment is urgent and challenging. The authors hope that a conception of algorithmic systems and the tools of this Article help to broaden participation, but this will be far from sufficient. On the one hand, we know that some of our most historically marginalized and disempowered communities are likely to suffer some of the negative consequences of ill-advised AI deployment. *See, e.g.*, Sarah Bird et al., *Exploring or Exploiting? Social and Ethical Implications of Autonomous Experimentation in AI*, WORKSHOP ON FAIRNESS, ACCOUNTABILITY, & TRANSPARENCY IN MACHINE LEARNING, 2016 (Oct. 4 2016), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2846909 [perma.cc/3ERX-YMTP]; FILIPPO A. RASO ET AL., *supra* note 148, at 18. On the other hand, examples of effective ethical technology development processes giving meaningful voice to all stakeholders seem rare and subject to intractable challenges. *See, e.g.*, Philip Brey, *Ethics of Emerging Technology*, *in* THE ETHICS OF TECHNOLOGY: METHODS AND APPROACHES 8 (Sven Ove Hansson ed., 2017) (noting that "the ideal of serious moral deliberation under conditions of equality may be difficult to achieve. These approaches require that a substantial number of people are brought to the same table to engage in extensive moral deliberation in a way that follows the elaborate discourse rules of ethicists, moves the discussion beyond prevailing interests, and negates pre-

While the legal system includes its share of innovators, the bar to date has not demonstrated this kind of creative design approach to new technologies or methods of legal-service delivery, an absence that arguably plays a significant role in the persistent gap in access to legal services.[246] In speaking of growing discussions about law specialists and alternative licensing structures at the state level, Deborah Rhode and Lucy Ricca note that "the key focus should not be blocking these innovations from the market, but rather using regulation to ensure that the public's interests are met."[247] To achieve such regulation and progress with algorithm-driven tools is not a simple matter of choosing the perfect means over the imperfect means. Instead, it will require ethical choice and ongoing engagement with the complex interactions between the computational components and contextual components of algorithmic systems. Even this brief ASQ points to some rather certain system optimization design choices and demands—namely, we must take seriously the opportunity for algorithms to enhance access to legal services and we must engage closely with algorithmic systems to prevent *Loomis*-like outcomes.

Almost inarguably, in light of existing system gaps and especially the multi-faceted harms that stem from lack of access to civil legal services, the greater ethical stumble stems not from allowing imperfect algorithm-facilitated legal services but rather from denying access to algorithm-facilitated legal services.[248] The numbers remaining underserved by the law and depths to which these populations suffer as a result simply disallows us to hold on to mythologized visions of perfect, human-only legal-service delivery. Yet, even though it must not be used to justify a blanket prohibition of algorithms, the *Loomis* case provides a reminder of the risks of opening the law to algorithms indiscriminately. As such, even in arenas where we might ultimately continue to deny or slow access for such tools, it seems a moral imperative not to allow blunt instruments like UPL to serve as gatekeepers when a more nuanced balancing of interests and the potential for enhanced access to legal services are within our reach. Toward both the invitation of algorithms to enhance access to legal ser-

---

vailing power relations that may distort the discussion. Even ordinary participatory and deliberative approaches have been difficult to realize in practice."). Despite these challenges, the end goal of meaningful participation among a broad range of stakeholders remains a fundamental need that the authors wished to highlight here.

[246] Drew Simshaw, *supra* note 48, at 181–82, 191, 196, 198. *See generally* Jonathan Rose, *Unauthorized Practice of Law in Arizona: A Legal and Political Problem That Won't Go Away*, 34 ARIZ. ST. L.J. 585 (2002) (detailing this history of UPL in Arizona and concluding that UPL across many jurisdictions reflect the Arizona experience: driven by lawyers who desire to protect their professional markets and, thus, who are very unlikely to embrace change and innovation).

[247] Deborah L. Rhode & Lucy Buford Ricca, *Protecting the Profession or the Public? Rethinking Unauthorized-Practice Enforcement*, 82 FORDHAM L. REV. 2587, 2608 (2014).

[248] *Id.* (noting that "the profession's responsibility to the public requires more than ad hoc reaction to change. Rather, the bar should be explicit about its regulatory objectives. Those objectives should include not only protecting consumers against unethical and unqualified providers, but also facilitating consumer choice and enhancing access to justice").

vices and the engagement with algorithmic systems to protect system integrity, joint functional design offers promise.

What might this kind of system optimization through joint functional design look like in our example context of criminal sentencing? It would start with a shared sense of values and demands, optimizing toward performance, understandability, and fairness. We might imagine a range of available computational tools—some employing handcrafted algorithms and others employing machine learning algorithms—each offering varying capacities to meet system demands, putting the values of accuracy and understandability in tension. Because this is not an algorithm where the accuracy of computational components alone is preeminent but rather an algorithmic system where the contextual components require the maintenance of other values, there will need to be tradeoffs, with a balancing of computational capacities and system values. In one context, accuracy might be most important, whereas due process contexts like criminal sentencing might put additional weight on demands for understandability.[249]

In any case, with a robust ASQ process, those charged with stewardship of the legal system would work with technologists throughout the setting of goals, the design, the interpretation, the application and even the auditing of the algorithm-driven tools, recognizing how computational components and contextual components interact recursively until the algorithmic system is optimized toward the values and demands of the legal system.[250] Such processes do not threaten legal systems; they empower them. And there is reason to be optimistic. Even where tradeoffs must occur, contextualization as algorithmic systems illustrates that the characteristics of computational components might be balanced in ways common and familiar to existing social systems.[251] For example, even in states where data-driven pre-sentencing investigation reports might be encouraged or even required, the judicial systems need not use those tools fully obscured by trade secret.[252] Informed by an understanding of both contextual needs and computational characteristics, then, in terms of design, "we might direct the development of a tool in ways that bolster explainability, even at the cost of some measure of accuracy."[253] Demonstrating such promise, in the

---

[249] Ward, *supra* note 100, at 13 ("A tool with outputs that are high in accuracy but low in transparency and explainability might be appropriate for autonomous vehicles—where accuracy is preeminent—but may be inappropriate for evaluating due process issues—where articulated reasoning is an inextricable part of our conception of fairness.").

[250] Algorithms are rooted in data and "data of any size do not operate in a social vacuum." Kate Crawford et al., *Critiquing Big Data: Politics, Ethics, Epistemology*, 8 INT'L J. COMMC'N. 1663, 1670 (2014).

[251] Slobogin, *supra* note 222, at 583, 587 (offering a balancing approach to "statistically-derived algorithms called 'risk-assessment instruments' (RAIs)" when used "in connection with sentencing, pretrial detention, and police decision-making" that is "governed by three principles—the fit principle, the validity principle, and the fairness principle.").

[252] Kate Crawford & Jason Schultz, *AI Systems as State Actors*, 119 COLUM. L. REV. 1941, 1941–44 (2019) (suggesting the state action doctrine as an avenue towards greater accountability for the government use of AI systems).

[253] Ward, *supra* note 100, at 13.

wake of growing public discourse spawned by the *Loomis* case, researchers have developed deliberately open and transparent tools of equal accuracy, demonstrating that values such as transparency and accuracy that are often perceived to be mutually exclusive by the unengaged can—when understood in light of algorithmic system needs—be balanced and edified.[254]

CONCLUSION

A growing range of algorithm-driven tools knocks upon the door of nearly every industry. To date, the law's reception has been lukewarm and inconsistent at best. As *Loomis* and stories of algorithms gone wrong have made news, we grow appropriately critical about inviting algorithms into our legal systems. Yet, rather than engage with these potentially powerful tools, we prematurely lock the doors. In this article, we advocate not that the door be opened to algorithms indiscriminately but rather that our evaluations of these newcomers require improved conceptual frameworks and better information to evaluate the risks and benefits of algorithmic systems and law.

Maintaining any narrow, acontextual conception of algorithms rather than a conception of algorithmic systems intimately and inextricably embedded in the social systems we care about carries several risks. When we focus only on the computational components alone, we might see algorithms—as one might charge the *Lola* court did—as something to be excluded from the human world of lawyers. That is, when we see algorithms as the stuff of technologists, we exclude ourselves as social thinkers, limit our engagement, and "risk ceding leadership to industry players who may not prioritize societal values among business concerns."[255] More importantly, this abdication forsakes the power that legal thinkers can wield when appropriately engaged with technological choice and design. Algorithm-driven tools will not fit within the law automatically; their computational components need shaping informed by legal expertise (among other voices) in light of contextual demands. As part of the inward and outward exchange among multiple sources of governance, where "law and technology are thoroughly intertwined," we miss an opportunity "to articulate the principles by which technologies are empowered to rule us."[256] Such an abdication also prevents the achievement of an appropriate fit between computational capacities and contextual needs. As noted, blanket attempts to protect the profession from the threats posed by algorithms represent an over-fit in relation to what algorithms can actually achieve, while the visions of employing algo-

---

[254] Cynthia Rudin & Yaron Shaposhnik, *Globally-Consistent Rule-Based Summary-Explanations for Machine Learning Models: Application to Credit-Risk Evaluation* 2–3, 12 (May 28, 2019), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3395422 [https://perma.cc/J53B-GYUT]; Cynthia Rudin & Joanna Radin, *Why Are We Using Block Box Models in AI When We Don't Need To? A Lesson from an Explainable AI Competition*, HARV. DATA SCI. REV., Fall 2019, at 1, 2–7 (Dec. 3, 2019), https://hdsr.mitpress.mit.edu/pub/f9kuryi8/release/5 [perma.cc/V4R5-N95G].

[255] Ward, *supra* note 100, at 14.

[256] JASANOFF, *supra* note 107, at 9–10.

rithms for access to justice initiatives represent an under-fit in relation to what algorithms could provide, missing opportunities to enhance access to the essential tools of the law for those who have long been underserved.

The blunt instruments of UPL and Model Rule 5.4's prohibition against nonlawyer ownership as presently conceived prove largely inadequate for the tasks at hand: to foster careful engagement with algorithm-driven tools and to work creatively to fix broken legal services markets that underserve far too many. Law has long benefitted from self-regulation, of which UPL and Rule 5.4 are a part. Where UPL's market protection serves to maintain the integrity of the legal profession, it is to be commended. Where UPL's market protection serves to exclude those in need of meaningful legal services, however, we must stand ready to criticize. UPL compares algorithm-driven tools to an ideal system rather than to the broken system of which they are a part, evading the balancing of values that would derive from the scrutiny of the larger system. Both UPL and Rule 5.4 as currently oriented and understood focus on *who* delivers services and use the credentials of service providers and owners rather than the effectiveness and equity of service delivery as their primary measurement of success. Such a regulatory framework arguably fails to offer end-to-end consumer protection, and, as algorithm-driven tools grow more capable of helping people to solve their problems, this framework is almost certain to keep too many locks on the door and to shift increasingly toward a function of market exclusion over integrity protection. The gaping access gap and the emerging promise of algorithms demand modernized conceptions of consumer protection, where any threat analysis of algorithms and law be balanced with an opportunity analysis of algorithmic systems and law.

For all of these reasons, we advocate a conception of algorithmic systems—fully contextualized and informed by the values and demands of the legal system—and a resultant ongoing process of ASQ. By emphasizing contextual components, which are already the province of social thinkers like lawyers and the domain of those who experience the effects of the algorithmic systems, a conception of algorithmic systems invites widespread engagement among a range of stakeholders and makes possible fair-minded processes of ASQ. As a result, this mapping into overlapping spheres of computational components and contextual components allows for joint functional design involving technologists and non-technologists alike, emphasizing the inextricable links between technology and its social contexts and allowing algorithms to help bring about a better legal system for the future.

[THIS PAGE INTENTIONALLY LEFT BLANK]