

2-2023

The Death of the Legal Subject

Katrina Geddes
NYU Law

Follow this and additional works at: <https://scholarship.law.vanderbilt.edu/jetlaw>



Part of the [Computer Law Commons](#), and the [Criminal Law Commons](#)

Recommended Citation

Katrina Geddes, *The Death of the Legal Subject*, 25 *Vanderbilt Journal of Entertainment and Technology Law* 1 (2023)

Available at: <https://scholarship.law.vanderbilt.edu/jetlaw/vol25/iss1/1>

This Article is brought to you for free and open access by Scholarship@Vanderbilt Law. It has been accepted for inclusion in *Vanderbilt Journal of Entertainment & Technology Law* by an authorized editor of Scholarship@Vanderbilt Law. For more information, please contact mark.j.williams@vanderbilt.edu.

The Death of the Legal Subject

*Katrina Geddes**

ABSTRACT

The law is often engaged in prediction. In the calculation of tort damages, for example, a judge will consider what the tort victim’s likely future earnings would have been, but for their particular injury. Similarly, when considering injunctive relief, a judge will assess whether the plaintiff is likely to suffer irreparable harm if a preliminary injunction is not granted. And for the purposes of a child custody evaluation, a judge will consider which parent will provide an environment that is in the best interests of the child.

Relative to other areas of law, criminal law is oversaturated with prediction. Almost every decision node in the criminal justice system demands a prediction of individual behavior: does the accused present a flight risk, or a danger to the public (pre-trial detention); is the defendant likely to recidivate (sentencing); and will the defendant successfully reenter society (parole)? Increasingly, these predictions are made by algorithms, many of which display racial bias, and are hidden from public view. Existing scholarship has focused on de-biasing and disclosing algorithmic models, but this Article argues that even a transparent and unbiased algorithm may undermine the epistemic legitimacy of a judicial decision.

Law has historically generated truth claims through discursive and dialogic practices, using shared linguistic tools, in an environment characterized by proximity and reciprocity. In contrast, the truth claims of data science are generated from data processing of such scale and complexity that it is not commensurable with, or reversible to, human reasoning. Data science excludes the individual from the production of knowledge about themselves on the basis that “unmediated” behavioral data (not self-reported or otherwise subject to conscious manipulation by the data subject) offers unrivaled predictive accuracy. Accordingly, data

* JSD Candidate, NYU Law. Thanks to Kathy Strandburg, Mireille Hildebrandt, Terry Fisher, Lewis Kornhauser, Ira Rubinstein, James Wilson, Alma Diamond, Tomer Kenneth, the ILLI fellows, my JSD peers, and attendees at the 2022 Privacy Law Scholars Conference for their thoughtful feedback on earlier drafts of this Article.

science discounts the first-person view of reality that has traditionally underwritten legal processes of truth-making, such as individual testimony.

As judges turn to algorithms to guide their decision making, knowledge about the legal subject is increasingly algorithmically produced. Statistical predictions about the legal subject displace qualitative knowledge about their intentions, motivations, and moral capabilities. The reasons why a particular defendant might refrain from recidivism, for example, become less important than the statistical features they share with historical recidivists. This displacement of individual knowledge with algorithmic predictions diminishes the participation of the legal subject in the epistemic processes that determine their fundamental liberties. This produces the death of the legal subject, or the emergence of new, algorithmic practices of signification that no longer require the input of the underlying individual.

TABLE OF CONTENTS

I.	INTRODUCTION.....	2
II.	THE TRADITIONAL LEGAL SUBJECT	8
	<i>A. Mental Autonomy</i>	10
	<i>B. Physical Autonomy</i>	12
III.	THE ALGORITHMIC SUBJECT	16
	<i>A. Legal Legitimation</i>	19
	<i>B. Biopower</i>	21
	<i>C. The Performance of Personalization</i>	23
IV.	THE DEATH OF THE LEGAL SUBJECT.....	26
	<i>A. Mental Autonomy</i>	27
	<i>B. Physical Autonomy</i>	28
	<i>C. Future Potentiality</i>	33
	<i>D. The Epistemological Inferiority of the Algorithmic Subject</i>	40
	<i>E. The Redistribution of Expressive Power</i>	41
V.	IS THE LEGAL SUBJECT WORTH SAVING?.....	46
VI.	CONCLUSION.....	50

I. INTRODUCTION

Across a range of settings, legal decision making relies increasingly on predictive algorithms to determine individual rights

and interests.¹ Scholarship on algorithmic decision making has focused on the pernicious effects of algorithmic bias and opacity.² This literature assumes that if algorithmic models can be disclosed and de-biased, their use in legal contexts is otherwise permissible.³ This perspective overlooks the epistemic effect of algorithmic knowledge on the construction of legal subjectivity—the capacity to be recognized by law as possessing legal rights and responsibilities. As judges turn to algorithms for “objective” predictions of recidivism, the personal narratives of defendants become less important than the statistical features they share with historical recidivists.⁴ This displacement of embodied and experiential knowledge with algorithmic prediction diminishes the participation of the legal subject in the epistemic processes that determine their fundamental liberties. Given the impenetrability and perceived objectivity of algorithmic models, it is difficult for legal subjects to counter the prejudicial effect of algorithmic predictions. The resulting exclusion of legal subjects from the production of knowledge about themselves has participatory, dignitary, and expressive effects, as power over self-articulation is transferred from the legal subject to the data capitalist.

Constructing the legal subject from statistical correlations also destabilizes a core epistemological foundation of law—namely, the one-to-one correspondence between a flesh-and-blood individual and their persona in law. Traditionally, legal subjectivity derives credibility from its close approximation of the underlying individual, through careful evaluation of their mental and physical autonomy, prior to any assignment of legal liability.⁵ This effort to paint a more complete and accurate portrait of the underlying individual (using coherent causal

1. See, e.g., Julia Angwin, Jeff Larson, Surya Mattu & Lauren Kirchner, *Machine Bias*, PROPUBLICA, May 23, 2016, <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing> [<https://perma.cc/8N6N-PAZW>] (describing the use of racially biased algorithms in criminal sentencing); Sandra Mayson, *Bias In, Bias Out*, 128 YALE L.J. 2218, 2218 (2019); Danielle Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249, 1257 (2008); Joshua A. Kroll, Joanna Huey, Solon Barocas, Edward W. Felten, Joel R. Reidenberg, David G. Robinson & Harlan Yu, *Accountable Algorithms*, 165 PENN. L. REV. 633, 636 (2017); Danielle Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 2 (2014); Aziz Z. Huq, *A Right to a Human Decision*, 106 VA. L. REV. 611, 613 (2020); Andrew Tutt, *An FDA For Algorithms*, 69 ADMIN. L. REV. 83, 91 (2017); Andrew Selbst, *An Institutional View Of Algorithmic Impact Assessments*, 35 HARV. J.L. & TECH. 117, 128 (2021).

2. See *supra* note 1.

3. For example, through technical adjustments, algorithmic impact assessments, and mandatory disclosure requirements, see *supra* note 1.

4. See Mayson, *supra* note 1, at 2251.

5. See Nicola Lacey, *The Resurgence of Character: Responsibility in the Context of Criminalization*, in PHILOSOPHICAL FOUNDATIONS OF CRIMINAL LAW 171 (R.A. Duff & Stuart Green eds., 2011).

explanations) often legitimates the coercive power of the state in circumstances where such power may be fiercely resisted—for example, in the context of criminal law, where defendants resist the imposition of severe legal sanctions.⁶

In contrast, the algorithmic subject is a “probabilistically determined behavioral profile”⁷ constructed from correlations identified in population-level data. The descriptive term *algorithmic* refers to the high-speed computational processes that collect and compare physical, transactional, and behavioral data from the digital surveillance technologies of information networks.⁸ The purpose of algorithmic subjectivity is not to faithfully portray the underlying flesh-and-blood individual using a one-to-one correspondence, but to facilitate their classification for “stochastic governance” through the identification of high-level behavioral patterns.⁹ The algorithmic subject is a fragmented digital avatar, drawn from heterogeneous data flows, and subject to constant disassembly and reassembly, depending on the needs of data profilers. It is designed to manifest global behaviors that will facilitate classification of almost any sub-population based on shared statistical features.¹⁰ For this purpose, the algorithmic subject deliberately *avoids* the underlying individual; information that is untethered to specific bodies can enjoy universal passage across multiple databases while maintaining a stable quantitative value.¹¹ Such information is “objective” precisely because it has not been chosen or mediated by the underlying individual.¹² Accordingly, an algorithmic model does not interrogate an individual’s subjective intentions because they are statistically preempted, just as the individual’s future behavior is

6. *See id.*

7. JULIE COHEN, BETWEEN TRUTH AND POWER 69 (2019).

8. Networked information architectures are the public and private digital platforms that collect, share, replicate, modify, and cross-reference personal data across vast and overlapping databases. *See id.* at 76; *see also* SHOSHANA ZUBOFF, THE AGE OF SURVEILLANCE CAPITALISM: THE FIGHT FOR A HUMAN FUTURE AT THE NEW FRONTIER OF POWER 240 (2019).

9. Carrie Sanders & James Sheptycki, *Policing, Crime and ‘Big Data’: Towards a Critique of the Moral Economy of Stochastic Governance*, 68 CRIME L. SOC. CHANGE 1, 4 (2017).

10. *See, e.g.*, Lauren Wilcox, *Embodying Algorithmic War*, 48 SEC. DIALOGUE 11, 21 (2017); Donna Haraway, *A Cyborg Manifesto: Science, Technology, and Socialist Feminism in the Late Twentieth Century*, in SIMIANS, CYBORGS AND WOMEN: THE REINVENTION OF NATURE 164 (1991); N. KATHERINE HAYLES, HOW WE BECAME POSTHUMAN: VIRTUAL BODIES IN CYBERNETICS, LITERATURE, AND INFORMATICS 11 (1999) [hereinafter HOW WE BECAME POSTHUMAN]; N. KATHERINE HAYLES, MY MOTHER WAS A COMPUTER: DIGITAL SUBJECTS AND LITERARY TEXTS 19 (2005) [hereinafter MY MOTHER WAS A COMPUTER].

11. HOW WE BECAME POSTHUMAN, *supra* note 10.

12. *Id.*

inferred from the historical behavior of their statistical peers.¹³ These statistical correlations dispense with judges' need to develop coherent causal explanations of individual behavior, to understand why a legal subject may have acted in a particular way, and thus the likelihood of repeat behavior.¹⁴ This produces the death of the legal subject, or the emergence of new, algorithmic forms of knowledge that no longer require the input of the underlying individual.¹⁵

Data science also challenges the formal equality of individual legal subjects, who previously represented a privileged source of information about their intentions, motivations, and moral capabilities.¹⁶ This allowed legal subjects to explain and defend their behavior by accessing and communicating their embodied subjective knowledge.¹⁷ Predictive algorithms, in contrast, locate "superior" knowledge about the legal subject in data flows that lie beyond human perception and require machinic mediation.¹⁸ Forming intentions towards future action is no longer a profoundly embodied experience (taking place within the human mind), but a disembodied process of automatically detecting correlations within large datasets.¹⁹ Accordingly, the rights and interests of legal subjects turn on their statistical relations with third parties, rather than their individual experience.²⁰ This de-centering and discounting of experiential knowledge contradicts empirical evidence that self-perceptions of risk can perform within range of leading risk assessment tools.²¹ In other words, individuals are relatively good at predicting their own behavior.²²

The observation that algorithmic and legal subjectivities derive from and participate in different epistemologies is not a

13. Antoinette Rouvroy & Thomas Berns, *Algorithmic Governmentality and Prospects of Emancipation*, 177 RÉSEAUX 163, 170–71 (2013).

14. *Id.* at 173.

15. *Id.* at 174–75.

16. *See id.* at 182.

17. *See id.*

18. Laurence Barry, *The Rationality of the Digital Governmentality*, 23 J. FOR CULTURAL RSCH. 365, 369 (2019); Evelyn Ruppert, *The Governmental Topologies of Database Devices*, 29 THEORY, CULTURE & SOC. 116, 117 (2012).

19. Deborah Lupton, *How Do Data Come to Matter? Living and Becoming with Personal Data*, BIG DATA & SOC., July–Dec. 2018, at 4.

20. Katharina Pistor, *Rule by Data: The End of Markets?*, 83 LAW & CONTEMP. PROBS. 101, 102 (2020).

21. Jennifer Skeem, Sarah M. Manchak, Charles W. Lidz & Edward P. Mulvey, *The Utility of Patients' Self-Perceptions of Violence Risk: Consider Asking the Person Who May Know Best*, 64 PSYCHIATRIC SERVS. 410, 411 (2013).

22. *Id.*

recommendation to prohibit the use of algorithms in judicial decision making. The utility of predictive algorithms in modern jurisprudence is a complex question that lies beyond the scope of this Article. Even in the narrow context of criminal law, it is difficult to reach a firm conclusion about the net effects of predictive algorithms. The benefits of risk assessment tools at one decision node (for example, diverting low-risk offenders from pretrial detention)²³ are difficult to weigh against the harms generated by their use at other decision nodes (for example, the exacerbation of racial and socioeconomic disparities in sentencing).²⁴ Instead, this Article advances an epistemological account of the harms of risk assessment tools in criminal sentencing. How is the basic unit of liberal society—the legal subject—transformed by the elevation of algorithmic knowledge? How are they differently represented? Is the actuarial project of algorithmic governance compatible with law’s normative commitment to individualized justice?

In answering these questions, one should conceive the law not only as a system of coercive interference, but as a mechanism for regulating human behavior and communicating moral condemnation. Accordingly, the rituals of law, including legal subjecthood, matter not only as devices for achieving certain legal outcomes, but as affirmations of respect for the individual.²⁵ To recognize someone as a subject in law is not merely to afford them certain rights and duties, but to communicate a message about their moral value and acknowledge their subjective interests as imposing legitimate constraints on their treatment by others.²⁶ Much of society’s commitment to democratic values turns on this view of the citizen as a “responsible agent entitled to be praised or blamed depending upon [their] free choice of conduct.”²⁷ In contrast, a conception of citizens as alterable, predictable, or manipulable things “is the foundation of a very different social order.”²⁸ When the basic unit of a liberal society is no longer an autonomous, unknowable individual, but an algorithmic subject anticipating its own

23. Jon Kleinberg, Himabindu Lakkaraju, Jure Leskovec, Jens Ludwig & Sendhil Mullainathan, *Human Decisions and Machine Predictions*, 133 Q.J. ECON. 237, 244 (2017).

24. See Megan T. Stevenson & Jennifer L. Doleac, *Algorithmic Risk Assessment in the Hands of Humans 2* (Human Cap. & Econ. Opportunity Glob. Working Grp., Working Paper 2020-055, 2021), <https://ssrn.com/abstract=3489440> [<https://perma.cc/8DMR-3EZB>].

25. Laurence H. Tribe, *Trial by Mathematics: Precision and Ritual in the Legal Process*, 84 HARV. L. REV. 1329, 1361 (1971); see also YALE KAMISAR, FRED E. INBAU & THURMAN W. ARNOLD, *CRIMINAL JUSTICE IN OUR TIME* 141–44 (A. E. Dick Howard ed., 1965).

26. See TOMASZ PIETRZYKOWSKI, *PERSONHOOD BEYOND HUMANISM* ch. 2 (2018).

27. Sanford H. Kadish, *The Decline of Innocence*, 26 CAMBRIDGE L.J. 273, 287 (1968).

28. *Id.*

datafication, the law ceases to address free and equal subjects and instead manages the “threat posed by particular categories” of people.²⁹

The shifting epistemology of legal subjectivity, then, presents a unique opportunity to re-evaluate how the legal subject *should* be constructed. Western liberalism has long reified the rational, self-determining legal subject, who occupies a sphere of autonomy constructed by individual rights.³⁰ Yet this liberal conception of bounded individualism is increasingly incompatible with contemporary understandings of systemic injustice and evolving norms of collective responsibility based on mutual interdependence.³¹ Mass incarceration, for example, cannot be explained by individual pathology and cannot be solved through individual-level intervention.³² Crime is a deeply social phenomenon, sustained by social, cultural, political, and economic relations that exist beyond the control of any individual.³³ Yet predictive algorithms reflect persistent optimism that individual-level interventions can overcome the structural forces that sustain patterns of criminality.³⁴ Risk assessment tools target the “criminogenic” features of individuals, rather than the circumstances that shape and constrain their behavior. As a result, society neglects investments in social infrastructure in favor of predicting individual behavior using models that require the persistence of existing disparities in order to be effective.³⁵ A more nuanced and realistic understanding of legal responsibility (including our collective responsibility for crime) requires a more nuanced and realistic conception of the legal subject, one which pays greater attention to the relations that constitute and constrain individual behavior.³⁶ These are not the data relations of algorithmic subjectivity, but the social, cultural, and political relations that are meaningful to the individual. A more relational understanding of legal

29. Lacey, *supra* note 5, at 156.

30. *Id.* at 177.

31. See JENNIFER NEDELSKY, *LAW'S RELATIONS: A RELATIONAL THEORY OF SELF, AUTONOMY, AND LAW*, ch. 6 (2012).

32. *Cf. id.* at 248–50.

33. *Cf. id.*

34. Kelly Hannah-Moffat, *The Uncertainties of Risk Assessment: Partiality, Transparency, and Just Decisions*, 27 *FED. SENT'G REP.* 244, 244 (2015).

35. See KASPER LIPPERT-RASMUSSEN, *BORN FREE AND EQUAL? A PHILOSOPHICAL INQUIRY INTO THE NATURE OF DISCRIMINATION* ch. 3 (2014); Ben Green & Salomé Viljoen, *Algorithmic Realism: Expanding the Boundaries of Algorithmic Thought*, *FAT* '20: PROCEEDINGS OF THE 2020 CONFERENCE ON FAIRNESS, ACCOUNTABILITY, AND TRANSPARENCY*, Jan. 27–30, 2020, at 22.

36. NEDELSKY, *supra* note 31.

subjectivity will help us to recognize not just the limits of our power as individuals, but the kinds of power we can wield as a collective.³⁷

II. THE TRADITIONAL LEGAL SUBJECT

Law has always recognized legal subjecthood on the basis of highly specific metaphysical, empirical, and axiological beliefs about the state of the world and the kind of subject the law should serve.³⁸ Slaves, for example, were once considered “property” rather than persons, and married women were denied separate legal personhood from their husbands.³⁹ Both the construction and experience of legal subjectivity are historically contingent, reflecting prevailing social norms and evidentiary technologies.⁴⁰ In pre-modern societies, for example, local communities collected “character evidence” about the accused and adjudicated criminal responsibility on the basis of the accused’s standing and reputation without inquiring into their individual state of mind.⁴¹ Contemporary conceptions of criminal responsibility evolved over time in response to Enlightenment-era theories of agency and utilitarian beliefs in the capacity of legal sanctions to deter rational actors from wrongdoing.⁴² Premodern beliefs in fate and theological determinism (divine providence) were slowly replaced by modern conceptions of autonomy as free will.⁴³ Developments in the fields of psychology and psychiatry also led to increased optimism about the susceptibility of the mind to both evaluation and treatment, resulting in a more psychological view of personal responsibility.⁴⁴ Meanwhile, as industrialization and urbanization made communities more diverse and anonymous, juries could no longer rely so heavily on evidence of “character” to determine criminal culpability.⁴⁵ Statutory provisions affirming the right of the accused to testify on their own behalf reflected this emerging conception

37. *Id.*

38. Ngaire Naffine, *Who are Law’s Persons—From Cheshire Cats to Responsible Subjects*, 66 MOD. L. REV. 346, 349 (2003); *see, e.g.*, Dominique Bauer, *The Twelfth Century and the Emergence of the Juridical Subject—Some Reflections*, 90 ZEITSCHRIFT DER SAVIGNY-STIFTUNG FÜR RECHTSGESCHICHTE: KANONISTISCHE ABTEILUNG 207–27 (2004).

39. Naffine, *supra* note 38, at 347; *see, e.g.*, VISA A. J. KURKI, A THEORY OF LEGAL PERSONHOOD ch. 2 (2019).

40. *See* Naffine, *supra* note 38, at 347.

41. Lacey, *supra* note 5, at 159.

42. *Id.* at 171.

43. Phillip Cary, *A Brief History of the Concept of Free Will: Issues That Are and Are Not Germane to Legal Reasoning*, 25 BEHAV. SCI. & L. 165, 166 (2007).

44. Lacey, *supra* note 5.

45. *Id.* at 160.

of “criminal responsibility as residing in psychological states of mind.”⁴⁶ Today, the conception of criminal responsibility as requiring mental autonomy is so deeply engrained in the moral legitimacy of the criminal law that strict liability offenses are “mentioned in hushed tones as an embarrassing and uncivilized exception.”⁴⁷

It is important to note that legal subjectivity occupies a spectrum of abstraction.⁴⁸ At one end, the faceless rights holder of constitutional texts bears no more identifying features than natural personhood and the possession of fundamental rights.⁴⁹ This legal subject expresses liberal society’s commitment to formal equality and the moral worth of all individuals.⁵⁰ Further along the spectrum is the reasonable person in tort law, whose characteristics are sketched in greater detail in order to capture variation in norms of reasonable behavior across different fields.⁵¹ This legal subject provides the standard against which judges evaluate the behavior of tort defendants.⁵² At the other end of the spectrum is the criminal legal subject, whose mental and physical autonomy receive the most detailed evaluation due to the severity of criminal sanctions.⁵³ The careful construction of the criminal legal subject expresses the law’s commitment to the presumption of innocence and the value of individual liberty.⁵⁴ This Part will examine the traditional features of the contemporary criminal subject given the growing use of predictive algorithms at almost every decision node in the criminal justice

46. Nicola Lacey, *In Search of the Responsible Criminal Subject: History, Philosophy and Social Sciences in Criminal Law Theory*, 64 MOD. L. REV. 350, 353 (2001).

47. *Id.* at 354. Although, ironically, the distinction between strict liability crimes and those with a mens rea requirement is increasingly blurred by the pressure placed on defendants to plead guilty, and the limited scope of criminal defenses.

48. See *infra* notes 49–53 and accompanying text.

49. See NEDELSKY, *supra* note 31, at 237.

50. *Id.*

51. *Id.* at 237.

52. See *id.* at 299.

53. MICHAEL MOORE, *PLACING BLAME: A GENERAL THEORY OF THE CRIMINAL LAW* 79 (1997).

54. See, e.g., Naffine, *supra* note 38, at 351; ELIZABETH WOLGAST, *ETHICS OF AN ARTIFICIAL PERSON: LOST RESPONSIBILITY IN PROFESSIONS AND ORGANIZATIONS* 69 (1992); Richard Tur, *The ‘Person’ in Law*, in *PERSONS AND PERSONALITY: A CONTEMPORARY INQUIRY* 121–24 (Arthur Peacocke & Grant Gillett eds., 1987); Ngaire Naffine, *Legal Persons as Abstractions*, in *LEGAL PERSONALITY: ANIMALS, ARTIFICIAL INTELLIGENCE AND THE UNBORN* 21–25 (Visa A. J. Kurki & Tomasz Pietrzykowski eds., 2017); MICHAEL MOORE, *LAW AND PSYCHIATRY RETHINKING THE RELATIONSHIP* ch. 2 (1984); MOORE, *supra* note 53.

system.⁵⁵ Furthermore, this Part will argue that, to justify the imposition of severe legal sanctions, the common law has generally attributed to the criminal legal subject mental autonomy (the ability to form individual thoughts, intentions, and interpretations of the law) and physical autonomy (the ability to act on one's intentions with causal efficacy).⁵⁶ This careful construction of the criminal legal subject will subsequently be compared with the non-individualized approach of algorithmic prediction.⁵⁷

A. Mental Autonomy

At a very basic level, the law, as a series of textual instructions for moral behavior, assumes that individuals possess the mental autonomy required to interpret and apply such instructions to their particular circumstances.⁵⁸ This process of interpretation is always subjective; when an individual approaches a text, the meaning of the text is not fully formed and predetermined.⁵⁹ Its meaning must be constructed to suit the individual's specific needs and preferences.⁶⁰ For example, the human need for coherence, or principled consistency, will often compel legal subjects to understand legal doctrines as part of a reasonable, consistent, and nonarbitrary scheme of human regulation.⁶¹ Jack Balkin calls this "rational reconstruction," or the attempt to find normative coherence within the law.⁶² This process is inherently subjective because different individuals will form different views about the substantive rationality of the law depending on their moral and political beliefs, their knowledge of the legal system, and the extent of

55. At least five states (Arizona, Oklahoma, Kentucky, Ohio, and Pennsylvania) require the use of risk assessments in criminal sentencing. Many other states merely permit the use of risk assessments in criminal sentencing to guide judicial discretion. *See, e.g.*, Danielle Kehl, Priscilla Guo & Samuel Kessler, *Algorithms in the Criminal Justice System: Assessing the Use of Risk Assessments in Sentencing*, RESPONSIVE COMMUNITIES, July 2017, at 2.

56. *See, e.g.*, H.L.A. HART, PUNISHMENT AND RESPONSIBILITY 187 (1968); GEORG WILHELM FRIEDRICH HEGEL, THE PHILOSOPHY OF RIGHT, (T. Knox trans., Oxford Univ. Press 1942) (1821); C.S. Lewis, *The Humanitarian Theory of Punishment*, 30 RES JUDICATAE 224, 224 (1953); Herbert Morris, *Persons and Punishment*, 52 THE MONIST 475, 476 (1968); R.A. DUFF, TRIALS AND PUNISHMENTS ch. 8 (1986); ANDREW VON HIRSCH, CENSURE AND SANCTIONS 5 (1993); ANDREW ASHWORTH, LUCIA ZEDNER & PATRICK TOMLIN, PREVENTION AND THE LIMITS OF THE CRIMINAL LAW ch. 2 (2013).

57. *See infra* Parts III & IV.

58. Jack M. Balkin, *Understanding Legal Understanding: The Legal Subject and the Problem of Legal Coherence*, 103 YALE L.J. 105, 108 (1993).

59. *Id.*

60. *Id.*

61. *Id.* at 112.

62. *Id.*

their cognitive exertion on its normative consistency.⁶³ In this sense, the coherence or non-coherence of the law is constituted by individual processes of subjectification: how an individual personally interprets a legal text and applies it to their circumstances.⁶⁴ Mental autonomy is thus essential for legal subjecthood because legal interpretation is a deeply subjective, socially situated process in which the legal subject both constructs, and is constructed by, the legal text.⁶⁵

The importance of mental autonomy for the construction of the criminal legal subject rests on fundamental conceptions of the minimum conditions required for the attribution of moral blame.⁶⁶ In other words, individuals should not be blamed for immoral (or illegal) behavior unless they knowingly and intentionally violated a moral norm (or the law).⁶⁷ This requirement of intent (*mens rea*) as a necessary condition for moral blameworthiness helps to distinguish, for example, the act of perjury from an innocent misstatement.⁶⁸ It reflects society's normative commitment to individual autonomy.⁶⁹ Mental conditions that excuse criminal responsibility are tolerated for the same reason that civil transactions are invalidated upon proof of coercion or undue influence: actions performed under those circumstances do not represent genuine choice.⁷⁰ The law enables individuals to exert control over their futures by giving effect to their informed and considered choices.⁷¹ A legal system that considers an individual's mental state maximizes the efficacy of those choices within the coercive framework of the law.⁷² Individuals are better able to predict whether and when the sanctions of the law will apply to them because their individual

63. *Id.*

64. *Id.*

65. *Id.*; see also JOSEPH RAZ, *THE MORALITY OF FREEDOM* 372 (1988) (arguing that what is required for an autonomous life includes an adequate range of options, independence, and the mental abilities to form intentions of a sufficiently complex kind and to plan their execution).

66. Claire Finkelstein, *The Inefficiency of Mens Rea*, 88 CAL. L. REV. 895, 895 (2000).

67. *Id.* at 906–07.

68. *Id.* Most criminal offenses continue to have a mental state requirement, despite the watering down of *mens rea* through strict liability offences, and “objective” liability standards, where the court imputes to the defendant knowledge or intent that they may not really have had, but which an average person would have had.

69. *Id.* at 895; see also Gerald H. Gordon, *Subjective and Objective Mens Rea*, 17 CRIM. L.Q. 355, 355 (1975); Jeremy M. Miller, *Mens Rea Quagmire: The Conscience or Consciousness of the Criminal Law*, 29 WASH. ST. U.L. REV. 21, 27 (2001).

70. HART, *supra* note 56, at 14.

71. *Id.* at 47.

72. *See id.*

choices are determinative.⁷³ As a result, they can identify in advance the space left open to them, “free from the law’s interference.”⁷⁴

In contrast, under a system of strict liability, an individual could neither predict nor control the interference of the law based on their subjective intentions; every blow, even if accidental or careless, could give rise to liability.⁷⁵ H.L.A. Hart explains that our moral preference for a legal system that requires mental conditions of responsibility reflects a normative commitment to personal autonomy.⁷⁶ Although this approach bears more risk to public safety (not interfering until harm has occurred), that risk is “the price we pay for general recognition that a man’s fate should depend upon his choice.”⁷⁷ What protects an individual from the interference of the law, then, is precisely those choices. To abandon the consideration of mens rea and to substitute a system in which the mere occurrence of harm would give rise to liability would expose every individual to unlimited legal sanction, for the test would not be our intentions but “sheer accident; and accident, by definition, may befall us all.”⁷⁸

B. Physical Autonomy

After the collapse of medieval society and its rigid class hierarchy, the economic opportunities of the marketplace enhanced the power and importance of individual choice.⁷⁹ Social status became less determinative of future opportunities and less important than the “personal projects of free individuals undertaken within the protected space created for them by the law.”⁸⁰ The introduction of universal schooling also enhanced the efficacy of individual choice; the state regarded educated individuals as more competent actors within society, prompting greater emphasis on individual agency, rather than fate.⁸¹ These developments imbued the individual with moral sovereignty and new rights and responsibilities consistent with their newfound

73. *Id.*

74. *Id.* at 181–82.

75. *Id.* at 182.

76. *Id.* at 183.

77. *Id.* at 182.

78. Kadish, *supra* note 27, at 288; *see also* HERBERT PACKER, *THE LIMITS OF THE CRIMINAL SANCTION* ch. 6 (1968).

79. RECONSTRUCTING INDIVIDUALISM: AUTONOMY, INDIVIDUALITY, AND THE SELF IN WESTERN THOUGHT 5 (Thomas C. Heller, Morton Sosna & David E. Wellbery eds., 1986) [hereinafter RECONSTRUCTING INDIVIDUALISM].

80. *Id.*

81. John W. Meyer, *Myths of Socialization and of Personality*, in RECONSTRUCTING INDIVIDUALISM, *supra* note 79.

competencies.⁸² States viewed individualism as an important complement to the expansion of modern Western society.⁸³

As part of this liberal project, Western legal systems emphasized the autonomy of the legal subject.⁸⁴ Without autonomy to choose between different courses of action, an individual could not reasonably be held responsible for the consequences of those choices.⁸⁵ In the words of Lon Fuller, “[t]o embark on the enterprise of subjecting human conduct to the governance of rules involves of necessity a commitment to the view that man is, or can become, a responsible agent, capable of understanding and following rules, and answerable for his defaults.”⁸⁶ Only an autonomous individual could “respond through acts of volition to the requirements of normative order.”⁸⁷ Naturally, the relationship between an autonomous individual and a normative order is complex and interdependent; the range of autonomy available to an individual will necessarily be constrained by the normative order.⁸⁸ In this sense, “full” autonomy has always been a fallacy; individual choices are always constrained by the environment in which they are made. But this does not alter the fact that some minimum amount of autonomy underwrites assumptions about the reasonableness of imposing legal sanctions on the choices made by individuals.⁸⁹

Law’s normative commitment to individual autonomy partially explains judicial reluctance to adjudicate liability exclusively on the

82. *Id.* at 214, 220.

83. *Id.* at 220; *see also* ALEX INKELES & DAVID HORTON SMITH, *BECOMING MODERN* ch. 2 (1974).

84. *See Meyer, supra* note 81, at 220.

85. Susanna Lindroos-Hovinheimo, *Excavating Foundations of Legal Personhood: Fichte on Autonomy and Self-Consciousness*, 28 *INT’L J. SEMIOTICS L.* 687, 688 (2015).

86. Lon L. Fuller, *THE MORALITY OF LAW* 162 (Yaakov Elman & Israel Gershoni eds., Yale Univ. Press 2000) (1969).

87. Neil MacCormick, *My Philosophy of Law*, in *THE LAW IN PHILOSOPHICAL PERSPECTIVES* 121, 128 (L.J. Wintgens ed., 1999).

88. *See Lindroos-Hovinheimo, supra* note 85.

89. Note that the autonomy necessary for legal subjectivity is thinner than the (thicker) conception of autonomy required for general human flourishing. *See, e.g.*, THOMAS MAY, *AUTONOMY, AUTHORITY, AND MORAL RESPONSIBILITY* 24 (1998); Jeremy Waldron, *How Law Protects Dignity*, 71 *CAMBRIDGE L.J.* 200, 208 (2012); H.L.A. HART, LESLIE GREEN, JOSEPH RAZ & PENELOPE A. BULLOCH, *THE CONCEPT OF LAW* 128 (3d. ed. 2012) (“the exercise of choice is necessary because ‘we are men, not gods’: we cannot anticipate all the circumstances the future may bring”); Michael Veale & Irina Brass, *Administration by Algorithm? Public Management Meets Public Sector Machine Learning*, in *ALGORITHMIC REGULATION* 1, 20 (Karen Yeung & Martin Lodge eds., 2019); Antoinette Rouvroy, *The End(s) of Critique: Data Behaviourism Versus Due Process*, in *PRIVACY, DUE PROCESS, AND THE COMPUTATIONAL TURN* 143, 145 (Mireille Hildebrandt ed., 2013).

basis of statistical evidence.⁹⁰ In 1945, the victim of a bus accident sought judgment against the defendant bus company on the basis that the defendant was the only company authorized to operate on the street where the accident occurred.⁹¹ In other words, the statistical odds suggested that the defendant's bus had caused the relevant injury.⁹² No other evidence was adduced because the victim did not recall specific details about the bus that had injured them.⁹³ Although the mathematical odds favored the plaintiff's version of events, the court held that this statistical evidence was insufficient to establish liability on the part of the defendant bus company.⁹⁴ If such evidence were sufficient, bus companies would have less incentive to improve the safety of their services because liability would bear no relationship to their individual conduct.⁹⁵ In the absence of any other identifying evidence, the largest operator in any given area would always be held liable for any unexplained accidents.⁹⁶ In this particular case, although it was statistically likely that the defendant bus company had caused the accident (given its authorization to operate on the street in question), this did not preclude the possibility that a private or chartered bus had caused the accident instead.⁹⁷

Statistical evidence, because it is probative in aggregate, sacrifices interests in individual accuracy and thereby undermines the efficacy of individual choice.⁹⁸ For example, if Amy purchases a ticket to a concert, but 99 percent of concert attendees do *not* purchase a ticket, and Amy is subsequently prosecuted on the basis that, statistically speaking, she is unlikely to have purchased a ticket, the absence of any connection between her liability and her individual conduct strips the latter of causal efficacy.⁹⁹ The prioritization of

90. See, e.g., *People v. Collins*, 438 P.2d 33, 40 (Cal. 1968); *State v. Sneed*, 414 P.2d 858, 862 (N.M. 1966); *People v. Risley*, 214 N.Y. 75, 84–85 (1915); *Smith v. Rapid Transit, Inc.*, 58 N.E.2d 754, 755 (1945); *Miller v. State*, 399 S.W.2d 268, 270 (Ark. 1966). Of course, there are also circumstances in which statistical evidence *is* sufficient to establish liability—for example, in Title VII disparate-impact claims or in the use of DNA evidence to prove criminal liability. See also Jonathan J. Koehler, *When Do Courts Think Base Rate Statistics Are Relevant?*, 42 JURIMETRICS J. 373, 380–85 (2002).

91. See Tribe, *supra* note 25, at 1341.

92. See *id.*

93. See *Smith*, 58 N.E.2d at 755.

94. See *id.*

95. See Craig Callen, *Adjudication & the Appearance of Statistical Evidence*, 65 TUL. L. REV. 457, 474 (1991).

96. See Tribe, *supra* note 25, at 1349.

97. See *Smith*, 58 N.E.2d at 755.

98. See Callen, *supra* note 95, at 458–59.

99. See *id.* at 473–74.

statistical evidence undermines Amy's individual decision to purchase a ticket (to engage in lawful behavior) because Amy is being punished for the actions of third parties over whom she exerts no control.¹⁰⁰ This loss of causal efficacy undermines Amy's individual autonomy.¹⁰¹

The promotion of law-abiding behavior, then, is an instrumental reason to adjudicate liability on the basis of individualized rather than statistical evidence.¹⁰² Individuals have little incentive to obey the law if they will be punished for the lawlessness of their statistical peers.¹⁰³ Moreover, as a mechanism for regulating human behavior, the law should be concerned with creating incentives for law-abiding conduct.¹⁰⁴ The incentive-corrupting effect of reliance on statistical evidence does not occur with individual evidence, including individual evidence that is probabilistically equivalent.¹⁰⁵ For example, consider the case where a pedestrian is injured by a ride-sharing vehicle, and there is eyewitness testimony (that has been shown to be 80 percent reliable) that the vehicle was an Uber. If, instead, there is no eyewitness testimony, but we have statistical evidence that 80 percent of the ride-sharing vehicles operating in the area are Ubers, is that a sufficient basis on which to ground liability? Although both forms of evidence are probabilistically equivalent, courts are likely to view the individual (eyewitness) evidence as a more legitimate basis for liability than the statistical (market share) evidence.¹⁰⁶ If this were not the case,

100. See Tribe, *supra* note 25, at 1349–50.

101. See, e.g., Thomas Hurka, *Why Value Autonomy?*, 13 SOC. THEORY & PRAC. 139, 143 (1987); Jiwei Ci, *Evaluating Agency: A Fundamental Question for Social and Political Philosophy*, 42 METAPHILOSOPHY 261, 271 (2011).

102. See Callen, *supra* note 95.

103. See, e.g., David Enoch, Levi Spectre & Talia Fisher, *Statistical Evidence, Sensitivity and the Legal Value of Knowledge*, in 40 PHIL. & PUB. AFFS. 197, 217–18 (2012); Ronald J. Allen, *On the Significance of Batting Averages and Strikeout Totals: A Clarification of the 'Naked Statistical Evidence' Debate, the Meaning of "Evidence," and the Requirement of Proof Beyond a Reasonable Doubt*, 65 TUL. L. REV. 1093, 1105 (1991); Callen, *supra* note 95; Charles Nesson, *The Evidence or the Event?: On Judicial Proof and the Acceptability of Verdicts*, 98 HARV. L. REV. 1357, 1381 (1985); Michael J. Saks & Robert F. Kidd, *Human Information Processing and Adjudication: Trial by Heuristics*, 15 L. & SOC. REV. 123, 140 (1980); Daniel Shavero, *Statistical-Probability Evidence and the Appearance of Justice*, 103 HARV. L. REV. 530, 544 (1989); Judith Jarvis Thomson, *Liability and Individualized Evidence*, in RIGHTS, RESTITUTION, AND RISK: ESSAYS IN MORAL THEORY 199, 205–06 (1986); Tribe, *supra* note 25, at 1349–50; V. C. Ball, *The Moment of Truth: Probability Theory and Standards of Proof*, 14 VAND. L. REV. 807, 822–23 (1961); Ronald M. Dworkin, *The Model of Rules*, 35 CHI. L. REV. 14, 43–44 (1967); Harold A. Ashford & D. Michael Risinger, *Presumptions, Assumptions, and Due Process in Criminal Cases: A Theoretical Overview*, 79 YALE L.J. 165, 177–78 (1969).

104. See David Enoch & Talia Fisher, *Sense and "Sensitivity": Epistemic and Instrumental Approaches to Statistical Evidence*, 67 STAN. L. REV. 557, 581 (2015).

105. See *id.* at 609.

106. See *id.* at 559.

other ride-sharing operators (like Lyft) would have little incentive to improve their individual safety records, because Uber would act as their insurer.¹⁰⁷ Thus, judicial reluctance to establish liability exclusively on the basis of statistical evidence is partially explained by the desire to incentivize law-abiding behavior.¹⁰⁸

III. THE ALGORITHMIC SUBJECT

The algorithmic subject is a “probabilistically determined behavioral profile”¹⁰⁹ constructed from correlations identified in population-level data. It is descended from the statistical subject that emerged during the eighteenth and nineteenth centuries, when developments in statistical and actuarial modeling produced new tools for measuring and managing populations.¹¹⁰ Through the universalization of birth certificates, Social Security numbers, and other types of persistent formatting, individuals became fastened to, and made legible by, predefined categories of data.¹¹¹ American philosopher Colin Koopman describes the emergence of identifying documentation as “our delivery into databases.”¹¹² From one information system to the next, individuals became statistical subjects whose lives and identities became “more fixed and provable” by virtue of their identifying documentation and, thus, their membership within statistical populations.¹¹³

As markets and states adopted information processes that made individuals measurable, traceable, and manipulable,¹¹⁴ the statistical subject became the target of actuarial interventions.¹¹⁵ After the Civil War, many American families purchased life insurance policies as a means of preserving social status, keeping widows out of the workforce,

107. *See id.*

108. There are, of course, some exceptions to this general statement. *See, e.g.*, George L. Priest, *Market Share Liability in Personal Injury and Public Nuisance Litigation: An Economic Analysis*, 18 SUP. CT. ECON. REV. 109, 111 (2010).

109. *See* COHEN, *supra* note 7.

110. *See id.* at 150; *see also* IAN HACKING, *THE TAMING OF CHANCE 2* (1990).

111. *See* COLIN KOOPMAN, *HOW WE BECAME OUR DATA* 64–65 (2019).

112. *See id.*

113. *See* BERNARD HARCOURT, *EXPOSED: DESIRE AND DISOBEDIENCE IN THE DIGITAL AGE 1* (2015).

114. *See* Marion Fourcade & Kieran Healy, *Seeing Like a Market*, 15 SOCIO-ECON. REV. 1, 3 (2017).

115. *See* Rodrigo Ochigame, *The Long History of Algorithmic Fairness*, PHENOMENAL WORLD (Jan. 30, 2020), <https://www.phenomenalworld.org/analysis/long-history-algorithmic-fairness/> [https://perma.cc/EJ7U-A4XW].

or avoiding the embarrassment of a pauper's burial.¹¹⁶ At the turn of the twentieth century, life insurers began to standardize their methods of risk classification. They retained medical examiners to identify the healthy and reject the sick in order to maintain low premiums, attract more customers, and expand capital reserves for investment.¹¹⁷ This created tension between medical examiners, who tended to reject applicants, and insurance agents, whose commissions incentivized them to accept applicants.¹¹⁸ To overcome this tension, New York Life's Oscar Rogers introduced "sub-standard" life insurance policies to approve at higher premiums applicants who would ordinarily be rejected from insurance coverage.¹¹⁹ Rogers encouraged actuaries to classify rather than to aggregate, to "personalize" risk ratings, and to construct risk classes.¹²⁰

The adoption of numerical methods by life insurers helped to standardize risk classification.¹²¹ From 1904 onwards, every applicant for life insurance received a single score, indicating their relative risk of death.¹²² A score lower than 100 (considered the average score) suggested longevity, whereas a score higher than 125 was considered substandard.¹²³ To generate these scores, insurance clerks would begin with an individual's "build" (height-to-weight ratio), and then adjust this value upwards or downwards, depending on the "impact" of isolated factors (for example, add five points for height, or subtract five points for family history).¹²⁴ Numerical methods offered a cheap and efficient means of "predicting" relative mortality; clerks could use mortality tables to "calculate" risk ratings from paper applications, rather than consulting medical professionals.¹²⁵ Life insurers eventually used these mortality tables to promote preventative medical treatment on the basis that longer life spans would generate more premiums and reduce costs from death claims.¹²⁶ Meanwhile, similar developments were taking place in the consumer reporting industry, as credit bureaus

116. See DAN BOUK, HOW OUR DAYS BECAME NUMBERED: RISK AND THE RISE OF THE STATISTICAL INDIVIDUAL 5–6 (2015).

117. See *id.* at 64.

118. See *id.* at 63.

119. See *id.* at 82–83.

120. See *id.* at 84 (noting that the Actuarial Society of America published a *Specialized Mortality Investigation* in 1903, which catalogued ninety-eight classes of risk for individuals ranging from sawmill workers to asthmatics).

121. See *id.* at 87–88.

122. See *id.* at 152.

123. See *id.*

124. See *id.* at 153.

125. See *id.* at 181.

126. See *id.* at 128.

began to develop more sophisticated tools for evaluating creditworthiness.¹²⁷ Actuarial risk models replaced character interviews as credit scoring became the primary means of distributing financial credit.¹²⁸ Fair, Isaac & Company promoted the concept of “statistical objectivity” in order to shield their credit scorecards (which incorporated protected characteristics such as race) against anti-discrimination regulation.¹²⁹

Historian Caley Horan describes the second half of the twentieth century as America’s “actuarial age,” in which the ideology of actuarial science normalized the risk classification of credit applicants and insurance holders.¹³⁰ Insurers framed economic security as an individual responsibility rather than a right of citizenship, justifying a reduced role for the state and securing the indispensability of their own services.¹³¹ Promotional materials for private insurance enlisted citizens to “defend” distinctly American values of individualism and free enterprise against the normative threat of communism.¹³² Older, more inclusive forms of social security founded on solidarity, interdependence, and mutual aid were replaced by the separationist logic of actuarialism, which emphasized differences, rather than mutuality, as the means of refining risk pools and “shielding” individuals from the costs of others.¹³³ In this way, the anti-redistributive normative foundation of private insurance—“actuarial fairness,” or the principle that each person should only pay for their own risk—was preserved.¹³⁴

Today, the data economy’s unrelenting scrutiny of individual behavior as the sole determinant of economic status reinforces the ideology of neoliberal self-governance.¹³⁵ By conditioning access to

127. *See id.* at 66.

128. *See* Ochigame, *supra* note 115; *see also* JOSH LAUER, CREDITWORTHY: A HISTORY OF CONSUMER SURVEILLANCE AND FINANCIAL IDENTITY IN AMERICA 201 (2017).

129. *See* Ochigame, *supra* note 115; *see also* Martha A. Poon, What Lenders See: A History of the Fair Isaac Scorecard 169 (2012) (Ph.D. dissertation, University of California San Diego), available at <https://escholarship.org/uc/item/7n1369x2> [<https://perma.cc/W548-KZD3>].

130. *See* Caley Dawn Horan, *Actuarial Age: Insurance and the Emergence of Neoliberalism in the Postwar United States* 7 (Aug. 2011) (Ph.D. dissertation, University of Minnesota), available at <https://conservancy.umn.edu/handle/11299/115896> [<https://perma.cc/R36B-4NMP>].

131. *See id.* at 28.

132. *See id.* at 67.

133. *See id.* at 27.

134. *See id.* at 158.

135. For a helpful analysis of the importance of countering the neoliberal paradigm of “individual” responsibility with institutional responsibility and resilient design, including acknowledgment of the vulnerability of individuals as “particularly situated, substantively

economic resources on the strength of algorithmic profiles, neoliberal markets encourage consumers to embrace algorithmic subjectivity as a legitimate mode of individuation.¹³⁶ Individuals assemble themselves as responsible algorithmic subjects, wearing fitness trackers and refreshing credit scores, constantly engaged in “self-surveillant algorithmic adjustment” before a vast, unblinking audience of data brokers.¹³⁷ Data capitalists aggregate, store, and analyze digital traces of individual habits, preferences, and behaviors across multiple datasets in order to classify individuals with increasing granularity.¹³⁸ Any individual behavior that can be observed and measured can be commodified. This means matching a high net worth individual with a specific credit card or a cash-poor debtor with a high interest loan.¹³⁹ As long as individual behaviors are “visible” to the market, they can form the subject of a profitable exchange.¹⁴⁰ The actuarial subject of the twentieth century has been reborn as the algorithmic subject of the twenty-first.¹⁴¹

A. Legal Legitimation

Data capitalists defend their practices of surveillance and extraction on the basis that personal data is a “raw” resource, freely available for “productive appropriation.”¹⁴² This romantic narrative of data prospecting legitimates intrusive forms of surveillance as the “discovery” of natural resources and normalizes efforts to manipulate user engagement in order to maximize opportunities for data extraction.¹⁴³ The framing of personal data as “raw” also obscures the normative choices that influence what kind of information is collected as data and how it is measured, labeled, classified, and stored.¹⁴⁴ The “rawness” of data also confers epistemic authority on the processes used

embodied” human subjects, see generally Martha McCluskey, *Countering Neoliberal Logic With The Vulnerable Human Subject*, CTR. FOR PROGRESSIVE REFORM (Sept. 14, 2021), <https://progressivereform.org/cpr-blog/countering-neoliberal-logic-vulnerable-human-subject/> [<https://perma.cc/2W37-T8TR>].

136. See Celia Lury & Sophie Day, *Algorithmic Personalization as a Mode of Individuation*, 36 THEORY, CULTURE & SOC’Y 17, 30 (2019).

137. Dan L. Burk, *Algorithmic Legal Metrics*, 96 NOTRE DAME L. REV. 1148, 1194 (2021).

138. See Fourcade & Healy, *supra* note 114.

139. See *id.* at 11.

140. See *id.* at 17.

141. See *id.* at 3–4.

142. See COHEN, *supra* note 7, at 71.

143. See, e.g., Mark Ledwich & Anna Zaitsev, *Algorithmic Extremism: Examining YouTube’s Rabbit Hole of Radicalization*, ARXIV, Dec. 2019, at 1–2.

144. See COHEN, *supra* note 7, at 64.

by data capitalists to refine data into valuable knowledge products, designating them as “sites of legal privilege.”¹⁴⁵

Intuitively, the construct of personal data as a “raw” resource seems inconsistent with the non-rivalrous nature of informational goods, given that facts are neither patentable nor copyrightable.¹⁴⁶ But this intuition underestimates the economic imperative to exclude others from use and the legal entitlements that have evolved to meet the demands of information capital.¹⁴⁷ Julie Cohen describes the enclosure of information flows as part of the longstanding (and highly productive) relationship between law and economic power.¹⁴⁸ Intellectual property doctrines, Cohen explains, have created powerful path dependencies for the reconstitution of non-rivalrous information as an excludable form of capital.¹⁴⁹ The legal construct of the public domain, for example, performs the promise of a public good (access to knowledge) until a public domain work is transformed into a sufficiently original (and economically valuable) copyrighted work.¹⁵⁰ Similarly, the “biopolitical public domain” of personal data is freely available for appropriation until the data is “parsed, enhanced, and systematized through [the] productive labor” of data capitalists into economically valuable data products.¹⁵¹

Although patent and copyright law have laid much of the conceptual groundwork for the enclosure of data as capital, data itself is neither patentable nor copyrightable.¹⁵² Accordingly, data capitalists have engineered the de facto proprietization of data “where the map of formal legal entitlements ends,”¹⁵³ using a combination of contractual provisions, technical protocols, and trade secrecy protection.¹⁵⁴ This “intellectual property entrepreneurship” has allowed data capitalists to

145. See *id.* at 49.

146. Copyright law explicitly does not cover facts, and databases only receive protection in very specific circumstances. See, e.g., Amy Kapczynski, *The Law of Informational Capitalism*, 129 YALE L.J. 1460, 1501 (2020); Lothar Determann, *No One Owns Data*, 70 HASTINGS L.J. 1, 11 (2018); Mark A. Lemley, *Private Property*, 52 STAN. L. REV. 1545, 1549 (2000); Pamela Samuelson, *Privacy as Intellectual Property?*, 52 STAN. L. REV. 1125, 1128 (2000); Jessica Litman, *Information Privacy/Information Property*, 52 STAN. L. REV. 1283, 1294 (2000).

147. See COHEN, *supra* note 7, at 269.

148. See *id.* at 36.

149. See *id.* at 50.

150. See *id.*

151. See *id.* at 64.

152. See, e.g., 17 U.S.C. § 102(b); *Feist Publ'ns, Inc. v. Rural Tel. Serv. Co.*, 499 U.S. 340, 344 (1991); cf. Council Directive 96/9, art. 3, 1996 O.J. (L 77) 25 (EC) (describing copyright protection for databases in the EU).

153. See COHEN, *supra* note 7, at 45.

154. See *id.* at 175.

reconfigure intangible property rights around new kinds of extractive practices.¹⁵⁵ These de facto property rights gain “powerful normative force from both their continual assertion and reassertion and their propagation within algorithmically intermediated environments.”¹⁵⁶

B. Biopower

Like its actuarial ancestors, the algorithmic subject is designed to facilitate the “statistical construction, management of, and trade in populations,” and is thus a form of biopower.¹⁵⁷ In contrast to the physical discipline of a sovereign, biopower refers to invisible forms of population management through the development of population-level statistics and the dissemination of disciplinary norms and expectations to promote state security, individual optimization, and capital accumulation.¹⁵⁸ As a form of biopower, algorithmic subjectivity is not designed to faithfully represent the underlying flesh-and-blood individual in a one-to-one correspondence, but to classify and match consumer populations to differentiated surplus extraction strategies.¹⁵⁹ Although the algorithmic subject is merely a probabilistic behavioral profile, its epistemic authority is propagated by three legitimating narratives.¹⁶⁰ The first, as previously discussed, is the construct of personal data as a “raw” resource, freely available for extraction, refinement, and appropriation by data capitalists.¹⁶¹ The second narrative frames the behavioral patterns, predictions, and forecasts derived from personal data as “new forms of datafied and depoliticized truth” previously invisible to the human eye.¹⁶² This narrative justifies the exclusion of the individual from the production of knowledge about themselves on the basis that “unmediated” behavioral data (not self-reported or otherwise subject to conscious manipulation by data subjects) offers unrivaled predictive accuracy.¹⁶³ This narrative of data

155. See *id.* at 25; see also Kapczynski, *supra* note 146 (citing *Bilski v. Kappos*, 561 U.S. 593, 611–12 (2010) (algorithms are difficult to patent); *Mayo Collaborative Servs. v. Prometheus Labs., Inc.*, 566 U.S. 66, 72 (2012) (machine-learning techniques are arguably discovering natural patterns)).

156. See COHEN, *supra* note 7, at 45.

157. See *id.* at 67; see also MICHEL FOUCAULT, *THE WILL TO KNOWLEDGE: THE HISTORY OF SEXUALITY* VOLUME 143 (Robert Hurley trans., 1998) (1976).

158. See M.H. Nadesan, *Biopower*, in *ENCYCLOPEDIA OF CRITICAL PSYCHOLOGY* 167–70 (Thomas Teo ed., 2014).

159. See COHEN, *supra* note 7, at 71.

160. See *id.* at 70.

161. See *id.*

162. See *id.* at 94.

163. See *id.* at 84.

objectivity fortifies the epistemic claims of data capitalists and shields their practices from regulatory scrutiny on the basis that they are delivering statistical “truth.”¹⁶⁴

The third narrative claims “personalized” knowledge about individual subjects, despite the fact that the exclusion of the individual from the knowledge production process forms the very basis of “Big Data’s” claim to objectivity.¹⁶⁵ The algorithm generates statistical “knowledge” automatically, without any underlying causal theory and with minimal human intervention.¹⁶⁶ This is the manner in which Google translates sentences into Chinese with no underlying linguistic knowledge: through the use of large datasets.¹⁶⁷ The identification of correlations in consumer preference data (what individuals like, search, purchase, and share, relative to others) allows the algorithm to address not “*the* you” but “*a* you,” refracted through multiple layers of relational data.¹⁶⁸ Big Data thereby “avoid[s] all forms of subjectivity,” even as it claims to possess “personalized” knowledge about the very individual it ignores, and to whom it is entirely indifferent.¹⁶⁹ French philosopher Bernard Stiegler criticizes this statistical “knowledge” as “mimetic” “correlationist mythology,”¹⁷⁰ which replaces real, living knowledge (“dreaming, wanting, reflecting, and deciding”) with a closed loop of self-referential digital traces that construct a “personalized” simulation of consumerist drives.¹⁷¹

The algorithmic subject is only tenuously connected to an underlying flesh-and-blood individual because it is constructed from population-level behavioral data—data that can afford to lose an individual data point because its accuracy lies in the *aggregate*.¹⁷² Data scientist Kristian Lum explains this as a sacrifice in individual accuracy: individuals assigned to a specific risk group (for example, for a pre-trial risk assessment tool) may vary widely in their individual propensity toward the outcome being predicted (for example, the probability of failing to appear), but every individual in the risk group

164. See *id.* at 90.

165. See Rouvroy & Berns, *supra* note 13, at 163–96.

166. See *id.*

167. See BERNARD STIEGLER, AUTOMATIC SOCIETY: THE FUTURE OF WORK 52 (2017).

168. See Lury & Day, *supra* note 136, at 20.

169. See *id.* at 23.

170. BERNARD STIEGLER, THE NEGANTHROPOCENE 139–40 (Daniel Ross trans., 2018).

171. STIEGLER, *supra* note 167, at 138.

172. COHEN, *supra* note 7, at 67.

will receive the same score.¹⁷³ In other words, the probability of a specific individual (assigned to risk group g) failing to appear (P_i) might be quite different from the group probability (P_g) that is attributed to them.¹⁷⁴ Within a specific risk group (g), the distribution of P_i might be tight, so that individuals within that group effectively have the same probability of failing to appear.¹⁷⁵ Alternatively, the distribution of P_i around the group-wise mean could be diffuse, so that individuals within the same risk group have very different individual probabilities of failing to appear.¹⁷⁶ Yet the same group probability, P_g , will represent both underlying distributions despite their difference in variance. In other words, the model will not reflect differences between individuals “along dimensions that are not captured by covariates.”¹⁷⁷ In fact, the authors of this study expressed low confidence that an individual’s personal probability of failing to appear was similar to the probability ascribed to them by their risk group.¹⁷⁸ This result is not always harmful but illustrates that risk assessment tools may sacrifice individual accuracy for simplicity in the aggregate.¹⁷⁹

C. The Performance of Personalization

The promise of personalized goods and services encourages consumers to participate in the data economy in ways that maximize opportunities for data extraction.¹⁸⁰ Fitness trackers, for example, encourage users to embrace “self-surveillant algorithmic adjustment”¹⁸¹ by incrementally improving their fitness persona, embodied in glowing biometric statistics.¹⁸² Users embrace the “disciplinary effect of algorithmic commensuration” as a site of self-improvement, rather than panoptic self-surveillance.¹⁸³ Data science recalibrates the physical body as a site of information processing so that users are motivated by

173. Kristian Lum, David B. Dunson & James Johndrow, *Closer Than They Appear: A Bayesian Perspective on Individual-Level Heterogeneity in Risk Assessment*, ROYAL STAT. SOC’Y, Feb. 1, 2021, at 588; see also Stephen Hart & David Cooke, *Another Look at the (Im-)Precision of Individual Risk Estimates Made Using Actuarial Risk Assessment Instruments*, 31 BEHAV. SCIS. & L. 81, 85 (2013).

174. Lum et al., *supra* note 173, at 594; Hart & Cooke, *supra* note 173.

175. Lum et al., *supra* note 173, at 594; Hart & Cooke, *supra* note 173.

176. Lum et al., *supra* note 173, at 594; see also Hart & Cooke, *supra* note 173.

177. Lum et al., *supra* note 173, at 595; see also Hart & Cooke, *supra* note 173.

178. Lum et al., *supra* note 173; Hart & Cooke, *supra* note 173.

179. See Hart & Cooke, *supra* note 173.

180. Lury & Day, *supra* note 136, at 17.

181. Burk, *supra* note 137, at 1179.

182. *Id.*

183. *Id.*

biometric data obtained through self-surveillance, rather than bodily signs of hunger, pain, and stress.¹⁸⁴ This statistical knowledge is sold as self-awareness, even as it decontextualizes data from lived experience in order to generate numeric homogeneity for quantitative data processing.¹⁸⁵ The gamified surveillance environments of many fitness applications makes self-measurement pleasurable and social, keeping “the surveillance economy’s data harvesting pipelines full and flowing.”¹⁸⁶

In most instances, individuals recognize algorithmic personalization as a performance and perceive the distance between their algorithmic and their authentic selves.¹⁸⁷ However, where algorithmic intermediation is a condition of access to essential services, individuals have no choice but to submit to algorithmic measurement.¹⁸⁸ Given the wide-ranging uses of credit scores, for example, debtors are compelled to participate in the credit score game in order to counter its marginalizing effects.¹⁸⁹ This means performing data-generating behaviors in order to be “creditworthy” to data capitalists.¹⁹⁰ Individuals feel compelled to perform a set of alien practices (for example, making purchases exclusively with credit cards) in order to realign a “quantitative abstraction with a felt qualitative reality.”¹⁹¹ These behaviors do not alter the “riskiness” of the underlying financial subject, but are designed to make debtors appear more “trustworthy” to financial institutions.¹⁹² A poor credit score can trap individuals in cycles of financial precarity that affirm the score’s prediction, as where, for example, more punitive credit terms for a “high-risk” debtor increases the debtor’s risk of default.¹⁹³ As a result,

184. Tobias Matzner, *The Human Is Dead—Long Live the Algorithm! Human-Algorithmic Ensembles and Liberal Subjectivity*, 36 THEORY, CULTURE & SOC’Y 123, 134 (2019); see also Irma Van der Ploeg, *Biometrics and the Body as Information: Normative Issues of the Socio-technical Coding of the Body*, in SURVEILLANCE AS SOCIAL SORTING 57–73 (David Lyon ed., 2005).

185. Burk, *supra* note 137.

186. COHEN, *supra* note 7, at 82.

187. Mark Kear, *Playing the Credit Score Game: Algorithms, “Positive” Data and the Personification of Financial Objects*, 46 ECON. & SOC’Y 346, 348 (2017).

188. *Id.* at 352.

189. *Id.* at 353; see also Akos Rona-Tas, *The Off-Label Use of Consumer Credit Ratings*, 42 HIST. SOC. RSCH. 52, 57 (2017).

190. Kear, *supra* note 187, at 359; Rona-Tas, *supra* note 189.

191. Kear, *supra* note 187, at 349.

192. *Id.* at 350.

193. *Id.* at 362; see Marion Fourcade & Kieran Healy, *Classification Situations: Life-Chances in the Neoliberal Era*, 38 ACCT., ORGS. & SOC’Y 559, 566 (2013) (“Personalized” credit assessments represent economic opportunities to exploit social differences through service differentiation in terms of the type of credit offered (home equity, credit card,

consumers align their behavior with the disciplinary effects of credit scoring in an attempt to regain control over their algorithmic identities.¹⁹⁴ This “paradoxical combination of heightened reputational sensibility and diminished control over reputational development”¹⁹⁵ fuels a cycle of algorithmic self-surveillance in which individuals perform recorded behaviors to influence a probabilistic profile derived from populations over whom they exert no control.

For this reason, remedies focused on increasing the transparency of predictive profiling in order to give individuals greater “control” over their algorithmic scores have ultimately failed to address the underlying harms.¹⁹⁶ Giving individuals the means of “gaming” their algorithmic score further legitimates the market for data intermediaries and the practice of self-surveillant algorithmic adjustment.¹⁹⁷ Whatever gains are made in algorithmic legibility may be offset by losses in privacy and autonomy.¹⁹⁸ As credit scholar Mark Kear observes, giving individuals the “means of conforming to the gaze of the ‘surveillant assemblage’ . . . should not be confused with emancipation from the subjectivizing apparatuses” of surveillance capitalism.¹⁹⁹ When individuals perform the classifications required for algorithmic governance rather than the behaviors that serve their own interests and values, they internalize the disciplining effects of algorithmic surveillance.²⁰⁰ Algorithmic surveillance thus reconstructs autonomy as a series of economic choices within a bounded consumer matrix, carefully circumscribed by “rational” behaviors such as the

payday loan), the amount extended, and the price charged (interest rate, origination payment, additional fees).).

194. Fourcade & Healy, *supra* note 193, at 565.

195. COHEN, *supra* note 7, at 80.

196. Kear, *supra* note 187, at 364.

197. *Id.* at 349.

198. *Id.* at 365 (“A person who wants to buy a car but has bad credit can now get the loan they need by allowing lenders to track and control their movements with so-called starter interrupt devices, which allow lenders to remotely disable a car’s ignition. Want to lower your car insurance premiums? Let us track your driving patterns by GPS. Can’t afford health insurance? Maybe you can with a new health insurance start-up called Oscar that will give you your own fitness tracker. Oscar will monitor your calories burned, steps taken and hours slept and pay you for your healthful behaviour.”).

199. *Id.*; cf. ZUBOFF, *supra* note 8, at 484–85.

200. Kear, *supra* note 187, at 349; see also Joseph E. Stiglitz & Andrew Weiss, *Credit Rationing in Markets with Imperfect Information*, 71 AM. ECON. REV. 393, 393–410 (1981); Mireille Hildebrandt, *Privacy as Protection of the Incomputable Self: From Agnostic to Agonistic Machine Learning*, 20 THEORETICAL INQUIRIES L. 83, 105 (2019) (“Overdependence on computational decision-systems may result in a shrinking of the inner self, as we learn to internalize the logic of computational feedback to better adapt to our new environment.”).

avoidance of risk.²⁰¹ The responsible consumer, for example, refuels at a “low-risk” gas station within a safe radius of their billing address.²⁰² Outside this radius, their credit card may automatically be declined, as fraud monitoring systems establish an invisible boundary between permissible and impermissible consumption.²⁰³ This data-driven pseudo-autonomy inculcates a “vigorous materialist individualism”²⁰⁴ characterized by the constant anticipation of datafication.²⁰⁵

IV. THE DEATH OF THE LEGAL SUBJECT

The “death” of the legal subject refers to the emergence of new algorithmic practices of signification that no longer require input from the underlying individual. Knowledge about the legal subject is increasingly algorithmically produced in a way that discounts and displaces qualitative knowledge about an individual’s subjective intentions and motivations.

Whereas legal subjectivity historically derived legitimacy from its close approximation of the underlying individual (through careful evaluation of their mental and physical autonomy), algorithmic subjectivity derives its epistemic authority from population-level insights.²⁰⁶ The relationality of data, rather than its uniqueness, is what drives its predictive value.²⁰⁷ A predictive model cannot be sustained by information about just one data subject; it needs information about populations of data subjects so that the relations *between data subjects* can be used to generate statistically significant insights.²⁰⁸ For this reason, the provenance of data is less important than its capacity to classify and categorize subjects based on shared preferences and behavioral patterns.²⁰⁹ Predictive profiling therefore apprehends data subjects not as unique individuals, but as patterns of behavior, so that the marginal cost of losing one person’s data is relatively low.²¹⁰ In contrast, individualized knowledge about a single

201. Lois McNay, *Self As Enterprise: Dilemmas of Control and Resistance in Foucault’s The Birth of Biopolitics*, 26(6) THEORY, CULTURE & SOC’Y 55, 58 (2009); see Jacques Donzelot, *Michel Foucault and Liberal Intelligence*, 37 ECON. & SOC’Y 115, 132 (2008).

202. See McNay, *supra* note 201, at 61.

203. See *id.*; cf. Meyer, *supra* note 81.

204. McNay, *supra* note 201, at 60.

205. COHEN, *supra* note 7, at 77.

206. Salome Viljoen, *A Relational Theory of Data Governance*, 131 YALE L.J. 573, 580 (2021).

207. See *id.* at 610.

208. *Id.* at 580.

209. *Id.* at 583.

210. Viljoen, *supra* note 206, at 610.

person is essential to realizing law's normative commitment to individualized justice. If a judge is evaluating a child custody order, for example, evidence about a particular parent is necessary to inform an evaluation of their parenting quality. The judge does not need to collect data about every other parent, but just this particular parent, and, in particular, what the history of their relationship with their child reveals about their particular parent-child dynamic.

A. Mental Autonomy

The algorithmic subject is a statistical avatar for how individuals are likely to behave in certain circumstances—for example, their likelihood of default, or employment, or recidivism.²¹¹ Because the algorithmic subject is constructed from population-level statistics, it necessarily excludes the internal mental processes that guide individual behavior as well as the unique emotional experiences and traumas that influence individual choices but resist datafication.²¹² A model developer could, of course, ask a specific individual what they intend to do in the future, but soliciting this kind of subjective input would undermine the statistical “objectivity” of the predictive model.²¹³

Alternatively, a data scientist could collect very intimate and revealing information about an individual in order to model their mental processes.²¹⁴ For example, virtual reality headsets use a system of cameras and sensors to record an individual's involuntary responses to digital stimuli, including eye movements, pupil dilation, facial muscles, and brain activity via electroencephalography.²¹⁵ This deeply revealing information (sometimes referred to as “biometric psychography”) could be integrated into existing datasets to develop detailed psychological profiles.²¹⁶ Setting aside the privacy concerns associated with such invasive forms of surveillance, many critics question the ability of computational models to capture the complexity of internal mental processes.²¹⁷ Accordingly, in the absence of any mechanism to record or represent mental autonomy, the “intentions” of

211. Rouvroy & Berns, *supra* note 13.

212. *Id.* at 186.

213. *Id.* at 170.

214. Brittan Heller, *Watching Androids Dream of Electric Sheep: Immersive Technology, Biometric Psychography, and the Law*, 23 VAND. J. ENT. & TECH. L. 1, 9 (2021).

215. *Id.* at 10.

216. See, e.g., Sophie Von Stumm & Robert Plomin, *Using DNA to Predict Intelligence*, 86 INTELLIGENCE 1, 2 (2021).

217. See, e.g., Lisa Feldman Barrett, Ralph Adolphs, Stacy Marsella, Aleix M. Martinez & Seth D. Pollak, *Emotional Expressions Reconsidered: Challenges to Inferring Emotion From Human Facial Movements*, 20 PSYCH. SCI. PUB. INT. 1, 1 (2019).

algorithmic subjects are simply inferred from the historical behavior of their statistical peers.²¹⁸ The algorithmic subject is not required to formulate or express individual desires or preferences because they are statistically preempted.²¹⁹ This is the governance of statistical relations, not individuals.²²⁰

B. Physical Autonomy

As replicants of historical individuals, algorithmic subjects have no physical autonomy.²²¹ Their actions are predetermined by the average historical behavior of their statistical predecessors.²²² Accordingly, if individuals with blue hair and a history of orange juice consumption go on to become fighter pilots, then that is what the algorithmic subject bearing these statistical markers will also be predicted to do. This absence of mental and physical autonomy distinguishes algorithmic subjects from traditional legal subjects.²²³ This creates more than just a difference in characterization; when the algorithmic subject displaces the analog legal subject as the target of decision making, the opportunities available for the legal subject to exercise their full autonomy are reduced.²²⁴

Consider, for example, a judge who chooses to sentence a defendant for x additional years above the retributively defined minimum because they believe that the defendant is likely to recidivate, and they want to physically prevent them from doing so. This preventive incarceration denies the defendant the opportunity to disprove the prediction through their autonomous actions.²²⁵ The criminogenic effects of sentence enhancements exacerbate this outcome: individuals who are incarcerated for longer periods of time will have greater difficulty re-integrating into the community upon

218. Rouvroy & Berns, *supra* note 13.

219. *See id.*

220. *See, e.g.*, James Beniger, THE CONTROL REVOLUTION 2 (1989); Wendy Nelson Espeland & Mitchell L. Stevens, *Commensuration as a Social Process*, 24 ANN. REV. SOCIO. 313, 325 (1998); David Ellerman, *The Kantian Persons/Things Distinction in Political Economy*, 22 J. OF ECON. ISSUES 1109, 1110 (1988).

221. Barbara D. Underwood, *Law and the Crystal Ball: Predicting Behavior with Statistical Inference and Individualized Judgment*, 88 YALE L.J. 1408, 1414 (1979).

222. *Id.* at 1408.

223. *Id.*

224. *Id.* at 1414.

225. *Id.* at 1439.

release, and are more likely to recidivate as a result.²²⁶ The prediction itself affects the outcome it claims to predict.²²⁷

Incapacitation, as an approach to sentencing, also reveals the conceptual incoherence of the criminal law.²²⁸ Throughout its history, criminal law has been torn between its twin desires for deterrence and retribution.²²⁹ Its primary justification for the imposition of severe legal sanctions (moral blameworthiness) has always sat uneasily with its desire to prevent the commission of future crime.²³⁰ The same philosophical foundation that justifies severe deprivations of liberty and informs almost every aspect of judicial due process (the presumption of innocence, the burden of proof, the right to trial) struggles to coexist with a system of preventive incarceration based on predictions of future behavior.²³¹ This system conditions punishment on proof of autonomous conduct, yet justifies incarceration, in part, by anticipating the future criminality of the incarcerated.²³² If incapacitation of dangerous individuals was the sole objective of criminal law, there would be little reason to wait until a crime had been committed before imposing criminal sanctions; screening a population for factors predictive of crime would represent a more efficient use of public resources.²³³ The orthogonal tasks of assigning blame for past crime and assessing risk for future crime are difficult to integrate in a

226. Robert D. Crutchfield & Gregory A. Weeks, *The Effects of Mass Incarceration on Communities of Color*, 32(1) ISSUES IN SCI. AND TECH. 46, 48 (2015); see also Dina R. Rose & Todd R. Clear, *Incarceration, Social Capital, and Crime: Implications for Social Disorganization Theory*, 36 CRIMINOLOGY 441, 445 (1998).

227. Adrian Mackenzie, *The Production of Prediction: What Does Machine Learning Want?*, 18 EUR. J. CULTURAL STUD. 429, 442 (2015).

228. Paul Robinson, *Punishing Dangerousness: Cloaking Preventive Detention as Criminal Justice*, 114 HARV. L. REV. 1429, 1438 (2001).

229. See *id.* at 1429.

230. *Id.* at 1432.

231. *Id.* at 1447.

232. See *id.* This is a system of punishment that has publicly committed to the distribution of punishment commensurate with the crime. If incapacitation could theoretically be justified by the prevention of future crime (in the same way that quarantine is justified by public health outcomes), then the evidence of its necessity should be subject to periodic review; the conditions of preventive detention should be nonpunitive; the defendant should be held at the minimum level of restraint necessary for public safety (e.g., house arrest, ankle bracelet); and defendants should receive treatment or rehabilitation services that reduce the duration and intrusiveness of detention. See *id.*

233. *Id.* at 1440. If criminal law starts to be viewed exclusively as a form of social hygiene (focused on the prevention of future crime rather than the punishment of past behavior), it might lose its moral authority. This is the authority that allows criminal law to shape community norms through its moral condemnation of specific behavior. Without this authority, criminal law has no crime-control power; it cannot stigmatize offenders, and thereby deter prohibited conduct. The growing sense of the institution's illegitimacy undermines its social efficacy. *Id.*

coherent system of punishment.²³⁴ Circumstances, such as poverty, that might mitigate blameworthiness and reduce incarceration under a theory of retribution might also increase the risk of future crime and justify a longer sentence under a theory of deterrence.²³⁵

If incapacitation itself is autonomy-eroding, how do predictive algorithms alter that effect, if at all? Judicial reliance on predictive algorithms exacerbates the autonomy-eroding effects of incapacitation in at least three ways.²³⁶ First, the reliance on statistical evidence treats the defendant as if their future conduct could reliably be inferred from the frequency of misconduct around them or the dead hand of their own past, as if they were “determined rather than free.”²³⁷ This ignores a defendant’s capacity to diverge both from their own past and from their statistical peers—that is, their capacity to be an outlier.²³⁸ This form of data determinism is inconsistent with the law’s “commitment to treat the defendant as an autonomous individual”—as the author of their own destiny, rather than the object of statistical relations.²³⁹ Because behavioral patterns at the population level may have no bearing on an individual’s propensity towards recidivism, statistical inferences effectively punish the individual for the historical behavior of third parties.²⁴⁰

Secondly, an algorithmic score cannot be “controlled” by the individual it claims to represent because its design depends on the behavioral data of populations over whom the individual has no control.²⁴¹ Nor will an individual have control over the statistical

234. John Monahan & Jennifer L. Skeem, *Risk Assessment in Criminal Sentencing*, 12 ANN. REV. CLINIC PSYCH. 489, 502 (2016); Robinson, *supra* note 228, at 1444.

235. Monahan & Skeem, *supra* note 234, at 497 (quoting Attorney General Eric Holder).

236. See David T. Wasserman, *The Morality of Statistical Proof and the Risk of Mistaken Liability*, 13 CARDOZO L. REV. 935, 945 (1991).

237. *Id.* at 952.

238. *Id.* at 943.

239. Kadish, *supra* note 27 (citing Wasserman, *supra* note 236, at 943); cf. JOAN FEINBERG, *THE MORAL LIMITS OF THE CRIMINAL LAW* vol. 3, ch. 18 (1984).

240. See, e.g., Richard W. Wright, *Causation, Responsibility, Risk, Probability, Naked Statistics, and Proof: Pruning the Bramble Bush by Clarifying the Concepts*, 73 IOWA L. REV. 1001, 1041 (1988); Nesson, *supra* note 103, at 1378; Thomson, *supra* note 103, at 225, 230; Mark Colyvan, Helen M. Regan & Scott Ferson, *Is it a Crime to Belong to a Reference Class?*, 9 J. POL. PHIL. 168, 171–72 (2001); Richard Lempert, *The Economic Analysis of Evidence Law: Common Sense on Stilts*, 87 VA. L. REV. 1619, 1669 (2001); Denise Meyerson, *Risks, Rights, Statistics and Compulsory Measures*, 31 SYDNEY L. REV. 507, 521 (2009); Rebecca Haw Allensworth, Note, *Prediction Markets and Law: A Skeptical Account*, 122 HARV. L. REV. 1217, 1229 (2009).

241. See Lindroos-Hovinheimo, *supra* note 85, at 690. People are partly defined by what they are *not* (what exists outside the self) and they have (some) control over what they are not. But if your algorithmic identity is largely constructed from the behavioral data of populations that you cannot control your resemblance to, and whose behavior you also cannot control, you lose control

populations used to represent them, as the algorithm may choose variables that are fundamentally (e.g., race) or ethically (e.g., religion) unchangeable.²⁴² As a result, reliance on an algorithmic prediction effectively punishes the underlying individual for membership of a statistical group, where membership is neither voluntary nor causally related to the outcome being predicted.²⁴³ Equivant’s risk assessment tool, for example, over-predicts recidivism for Black defendants and under-predicts recidivism for White defendants.²⁴⁴ To the untrained eye, this racial correlation erroneously suggests that being Black is “causative” of crime and that Black defendants are inherently predisposed towards criminal activity at a higher rate than White defendants.²⁴⁵ This disparity in racial outcomes effectively punishes Black defendants for society’s history of racial discrimination in resource distribution, law enforcement, and mass incarceration.²⁴⁶ This is not to say that restricting the choice of predictive variables to those with a “plausible” causal connection to the predicted outcome would preserve the autonomy of the decision subject.²⁴⁷ Rather, the

over defining what you are *not*, and thus also partially over what you *are*. In other words, the self-conscious individual (“I”) is partially constituted by what it is not: the “not-I” that resists, and thus defines the limits of, the “I” as a determinate entity. The statistical subject, in contrast, cannot be so defined because it represents the swollen, messy accumulation of all the “not-I”s that are statistically correlated with the outcome being predicted. There is no subjectivity (“I”) because the intersubjectivity that defines it (the “not-I”) cannot be controlled. *Id.*

242. Wasserman, *supra* note 236, at 948 (“We may be grouped in an indefinite number of ways for statistical analysis; there is no map which can tell us which neighborhoods to avoid.”); see LIPPERT-RASMUSSEN, *supra* note 35, at 300.

243. Wasserman, *supra* note 236, at 944.

244. See Angwin et al., *supra* note 1.

245. Northpointe’s recidivism prediction algorithm, COMPAS, over-predicted recidivism for Black defendants, and under-predicted recidivism for White defendants. Black defendants who did *not* reoffend were predicted to reoffend at a rate of 44.9%, nearly twice as likely as Whites (23.5%), while White defendants who *did* reoffend were predicted to *not* recidivate at a much higher rate (47.7%) than their Black peers (28%). See *id.*; Julia Dressel & Hany Farid, *The Accuracy, Fairness, and Limits of Predicting Recidivism*, SCI. ADVANCES, Mar. 30, 2018, at 1.

246. Angwin et al., *supra* note 1.

247. Causation is a normative judgement, and many causes of an outcome are beyond individual control. For this reason, it provides a shaky foundation on which to stake claims about the morality of using certain predictive variables. Causes, in turn, have causes, and the “directness” of the relationship between a particular cause and a particular event depends entirely on the number of concurrent or intervening events a fact-finder chooses to acknowledge. Causal attribution is thus a value judgment about the relative contribution made by different causes to a particular outcome. As a subjective choice between probable and possible causes, causation cannot provide an “objective” basis for classificatory decision making. Fact-finders will diverge widely in their choice of causal theory, and different theories will have different normative implications. See Lily Hu, *Disparate Causes*, PHENOMENAL WORLD (Oct. 17, 2019), <https://www.phenomenalworld.org/analysis/disparate-causes-pt-ii/> [https://perma.cc/9NT6-8NGA]; Regina Austin, *The Insurance Classification Controversy*, 131 U. PA. L. REV. 517, 559

autonomy-eroding effect of prediction is exacerbated by the use of variables that unfairly stigmatize particular groups by attributing causal power to irrelevant characteristics.²⁴⁸

Thirdly, a defendant may be unable to meaningfully counter an algorithmic prediction with qualitative information about their personal circumstances and intentions due to the prejudicial effect of automation bias.²⁴⁹ Unlike standalone statistical evidence, algorithmic predictions carry the imprimatur of “datafied and depoliticized truth.”²⁵⁰ Despite their undetermined accuracy at the individual level, algorithmic predictions are marketed as “personalized” and “objective” assessments of an individual’s propensity toward a specific behavioral outcome.²⁵¹ The aggregation of vast flows of heterogeneous data relating to an individual lends the algorithmic prediction greater epistemic authority than a standalone statistic.²⁵² The disembodied omniscience of data surveillance amplifies the prejudicial effect of the algorithmic prediction or the probability that it will be assigned greater weight than any qualitative evidence produced by the individual subject.

There is substantial empirical evidence that human decision makers tend to accept, rather than challenge, quantitative assessments and to assign greater weight, amongst a set of variables, to the variable that has been quantified.²⁵³ This bias is especially likely when the algorithm provides its recommendation in simple terms and its

(1983); Barbara Kiviat, *The Moral Limits of Predictive Practices: The Case of Credit-Based Insurance Scores*, 84 AM. SOC. REV. 1134, 1137 (2019).

248. Douglas Laycock & Teresa A. Sullivan, *Sex Discrimination as Actuarial Equality: A Rejoinder to Kimball*, 6 AM. BAR FOUND. RSCH. J. 221, 225 (1981).

249. See Lum et al., *supra* note 173.

250. *Id.*

251. See Burk, *supra* note 137, at 1165–66. Individuals assigned to a specific risk group (for example, by a pre-trial risk assessment tool) may vary widely in their individual propensity toward the outcome being predicted (for example, the probability of failing to appear) but every individual in the risk group will receive the same score. See Lum et al., *supra* note 173, at 589; see also Hart & Cooke, *supra* note 173.

252. See COHEN, *supra* note 7, at 64–65.

253. See, e.g., Raja Parasuraman & Victor Riley, *Humans and Automation: Use, Misuse, Disuse, Abuse*, 39 HUM. FACTORS 230, 238–244 (1997) (discussing excessive trust in, or overreliance on, automated systems, and insensitivity to contradictory sources of evidence); Kathleen Mosier & Linda Skitka, *Human Decision Makers and Automated Decision Aids: Made for Each Other?*, in AUTOMATION AND HUMAN PERFORMANCE: THEORY AND APPLICATIONS 201, 203–06 (Raja Parasuraman & Mustapha Mouloua eds., 1996) (discussing the path of least cognitive resistance); Andrew D. Selbst, Danah Boyd, Sorelle A. Friedler, Suresh Vankatasubramanian & Janet Vertesi, *Fairness and Abstraction in Sociotechnical Systems*, in FAT* ’19: PROCEEDINGS OF THE CONFERENCE ON FAIRNESS, ACCOUNTABILITY, AND TRANSPARENCY 62–63 (2019) (discussing how we privilege, among a set of variables, the factor that is quantified).

calculations are opaque.²⁵⁴ This means that the risk of future crime, because it has been quantified, may receive greater weight in a sentencing decision, resulting in the prioritization of deterrence over retribution.²⁵⁵ As a result, actuarial sentencing may redistribute criminal sanctions on the basis of prevention, rather than desert.²⁵⁶ An empirical study of the impact of risk assessment tools on judicial decision making found that they reversed the effect of poverty from a mitigating factor that reduced the probability of retributivist incarceration to a risk factor that increased the probability of preventive incarceration.²⁵⁷

C. Future Potentiality

A predictive algorithm does not perceive the future as undetermined; it views the future as entirely knowable and predictable through the lens of historical data.²⁵⁸ In this way, the algorithm constructs a specific temporal relation—between past, present, and future—in which historical patterns recur throughout, thereby lending the algorithm its preemptive power.²⁵⁹ The algorithm’s focus on individual behavior as the sole determinant of the outcome being predicted also obscures the constraining conditions of circumstance, i.e., the structural inequalities that produce perceived differences in individual propensity.²⁶⁰ Investments in education, housing, and

254. See generally Karen Yeung, *‘Hypernudge’: Big Data as a Mode of Regulation by Design*, 20 INFO., COMM’N & SOC’Y 118 (2017). For a recent example of automation bias, see Kashmir Hill, *Wrongfully Accused by an Algorithm*, N.Y. TIMES (Aug. 3, 2020), <https://www.nytimes.com/2020/06/24/technology/facial-recognition-arrest.html> [https://perma.cc/3WQG-Y77M] (discussing the false arrest of an innocent Black man for shoplifting due to misidentification by a facial recognition algorithm, where the police officers largely accepted the algorithm’s suspect identification without obtaining corroborating evidence such as eyewitness testimony or location data).

255. See Sonja B. Starr, *The New Profiling: Why Punishing Based on Poverty and Identity Is Unconstitutional and Wrong*, 27 FED. SENT’G REP. 229, 234 (2015).

256. See *id.*

257. See Jennifer Skeem, John Monahan & Nicholas Scurich, *Impact of Risk Assessment on Judges’ Fairness in Sentencing Relatively Poor Defendants*, 44 LAW & HUM. BEHAVIOR 51, 56–58 (2020). The same risk assessment information reduced the likelihood of incarceration for relatively affluent defendants but increased the likelihood of incarceration for relatively poor defendants (61.2% vs. 44.4%) after controlling for a judge’s sex, race, politics, and jurisdiction. *Id.* at 56.

258. See Bonnie Sheehey, *Algorithmic Paranoia: The Temporal Governmentality of Predictive Policing*, 21 ETHICS & INFO. TECH. 49, 53–57 (2019).

259. See *id.*

260. See Green & Viljoen, *supra* note 35 (“Because significant aspects of the social and political world are illegible within algorithmic reasoning, these features are held as fixed constants “outside” of the algorithmic system.”).

healthcare, for example, would alter baseline conditions of inequality and thus the “propensity” of individuals within certain groups toward specific behavioral outcomes. However, predictive models can only conceive of social possibilities in line with their technical capabilities,²⁶¹ so they ignore such investments as targets of intervention in favor of discriminatory profiling practices that require the persistence of existing disparities in order to be effective.²⁶² Applying a fairness constraint to account for the effects of structural inequalities would reduce the accuracy of the predictive model and its ability to use historical data to predict future outcomes.²⁶³

Public faith in the ability of predictive algorithms to preempt and thus control individual behavior is likely to increase their use in a variety of decision-making contexts, beyond criminal sentencing. This persistent focus on individual behavior as the “cause” of social problems may also reduce the likelihood of investments in social infrastructure.²⁶⁴ As policymakers neglect such investments in the belief that predictive models are successfully predicting and controlling individual behavior, the persistence of socioeconomic disparities may reproduce the very behaviors that predictive models were designed to prevent.²⁶⁵ Over time, the reproduction of inequality in algorithmically intermediated environments will constrain the range of substantive autonomy that is available to members of underserved communities.

In times of relative peace and stability, states may feel comfortable committing to a system of justice based on proof of individualized responsibility. But during periods of insecurity, when “the costs of determining individual capacity-based responsibility” seem intolerably high, and technology appears able to control risk, it is not hard to see how perceptions of criminality located in “stable” personal features might increase in popularity.²⁶⁶ Today, the algorithmic construction of the criminal legal subject again reflects prevailing social anxieties and scientific theories. The mythology of Big Data reassures an anxious public that the behavior of individual criminals can be “predicted” and “controlled,” thereby reducing the need for system-level interventions, such as investments in social infrastructure.²⁶⁷

261. See Jenna Burrell & Marion Fourcade, *The Society of Algorithms*, 2021 ANN. REV. SOCIO. 213, 226 (2021); Green & Viljoen, *supra* note 35.

262. See generally, e.g., LIPPERT-RASMUSSEN, *supra* note 35.

263. See, e.g., Ignacio Cofone & Warut Khern-am-nuai, *The Cost of AI Fairness in Criminal Justice: Not a Big Deal* (Sept. 1, 2020) (unpublished manuscript) (on file with author).

264. See Underwood, *supra* note 221, at 1417.

265. See *id.*

266. See Lacey, *supra* note 5.

267. See Yeung, *supra* note 254.

Consider, for example, the use of historical wage data to calculate the likely future earnings of a tort victim. Historically, Hispanic workers have earned lower wages, on average, than their White counterparts.²⁶⁸ To award a lower sum of damages to a young Hispanic tort victim on the basis of historical wage differentials would cabin the child's future potentiality within the prism of historical inequality.²⁶⁹ Not only would the prediction fail to consider the ways in which the child might deviate from their statistical average, it would reproduce baseline conditions of inequality as "fixed" and "inevitable" rather than inherently changeable.²⁷⁰ Similarly, the algorithm used to predict the grades of British high school students during the coronavirus pandemic constrained the potentiality of each student within historical limits.²⁷¹ Regardless of their individual performance, no student could achieve a grade higher than the historical maximum, which especially affected high-performing students at historically low-performing schools.²⁷² Through its reproduction of historical limits, the algorithm restricted each student's future potentiality. When decision makers uncritically accept the "likely future outcomes" predicted by algorithmic models, they narrow their decisional aperture to the permutations of the past and thereby foreclose the future potentiality of the targets of prediction.²⁷³

Proponents of prediction usually issue three rejoinders to the claim that predictive models foreclose future potentiality. The first is that the decisions themselves, rather than the algorithmic predictions, foreclose future potentiality. It is certainly true that the decision to do "x" inherently forecloses the potentiality of "not-x" (to the extent that these options are mutually exclusive), but this foreclosure is different from the narrowing of the decisional aperture that occurs with algorithmic predictions. For example, if an employer has three job applicants, A, B, and C, and can only choose one, the decision to hire

268. See *G.M.M. v. Kimpson*, 116 F. Supp. 3d 126, 143–46 (E.D.N.Y. 2015) (presenting charts detailing how projected life earnings differ based on an individual's race).

269. See *id.* at 141–42; Kimberly A. Yuracko & Ronen Avraham, *Valuing Black Lives: A Constitutional Challenge to the Use of Race-Based Tables in Calculating Tort Damages*, 106 CAL. L. REV. 325, 333 (2018).

270. See *G.M.M.*, 116 F. Supp. 3d at 141–42; Yuracko & Avraham, *supra* note 269.

271. See Melissa Fai, Jen Bradley & Erin Kirker, *Lessons in 'Ethics by Design' from Britain's A Level Algorithm*, GRANT + TOBIN (Sept. 11, 2020), <https://www.gtlaw.com.au/insights/lessons-ethics-design-britains-level-algorithm> [<https://perma.cc/DG6S-ZF2E>].

272. See, e.g., *id.*; Alex Hern, *Do the Maths: Why England's A-level Grading System is Unfair*, GUARDIAN (Aug. 14, 2020, 12:24 PM), <https://www.theguardian.com/education/2020/aug/14/do-the-maths-why-englands-a-level-grading-system-is-unfair> [<https://perma.cc/SF9N-BNDU>].

273. See Hildebrandt, *supra* note 200, at 99–100.

only one employee necessarily forecloses the possibility of hiring either of the other two applicants. In the process of deciding *which* applicant to hire, however, the employer might rely on an algorithm to predict which employee is likely to achieve the highest performance. If the algorithm has been trained on historical data about the performance of employees like *A* and *B*, but it has no data on employees like *C*, then the algorithm will never recommend *C*.²⁷⁴ As a result, the algorithm's prediction (that *A* or *B* will achieve the highest performance, but not *C*) will narrow the decisional aperture from applicants *A*, *B*, and *C* to just *A* and *B*.²⁷⁵ That narrowing will foreclose the unseen potential of applicant *C* in ways that the decision itself (to hire only one applicant) does not.²⁷⁶ In this sense, algorithmic predictions, trained on historical data, foreclose future potentiality in ways that future-oriented decision making itself does not.²⁷⁷ This is because the algorithm cannot “predict”—project into the future—what it has not already seen and does not already know.²⁷⁸

Consider, for another example, what might occur if an aerospace engineering firm used an algorithm to automatically screen job applicants. If the algorithm relies on historical data about former employees to determine the characteristics of a “desirable” job candidate, and the firm has exclusively hired White men in the past, the algorithm will never recommend a Black woman as a desirable job candidate.²⁷⁹ It will only recommend White men, because they exclusively constitute the historical dataset on which the algorithm was trained.²⁸⁰ This narrowing of the decisional aperture will foreclose the future potentiality of Black female job candidates in a way that the decision to hire a single candidate will not.²⁸¹

A second common rejoinder is that even if predictive algorithms lack imagination, humans do not, and they are the ultimate decision makers. But this response ignores the influence of automation bias—the tendency of human decision makers to accept, rather than challenge, quantitative assessments.²⁸² An overburdened decision maker, searching for ways to make efficient decisions under significant

274. *See id.*

275. *See id.*

276. *See id.*

277. *See id.*

278. *See id.* This Article deliberately avoids here any discussion of deep-learning algorithms, the ethical consequences of which would demand analysis in a separate article.

279. *See id.*

280. *See id.*

281. *See id.*

282. *See, e.g., supra* note 254.

time pressure, may rely uncritically on an algorithmic prediction, treating it as a “fixed” attribute of the decision subject without considering the subject’s capacity to disprove the prediction.²⁸³ Repeated use of a predictive system encourages users to act as if the prediction were true, so that users treat outliers (for example, a “high-risk” recidivist never reoffends) as sources of model error, rather than outcomes that should be encouraged.²⁸⁴ Reliance on predictive tools creates a perverse incentive to support the “correctness” of the algorithm’s prediction—and thus the “rightness” of the decision made upon it—when, in reality, social welfare would improve if the prediction was wrong (for example, a “high-risk” recidivist never reoffends).²⁸⁵ Due to automation bias, human decision makers cannot reliably recognize and protect an individual’s future potentiality. Instead, the presence of a human-in-the-loop may inadvertently insulate the algorithm from further scrutiny.²⁸⁶

A third common rejoinder is that, in some circumstances, the imaginative range of a human decision maker may be just as narrow as that of a predictive algorithm.²⁸⁷ It is certainly true that all humans are limited by their own experiences. A community organizer, for example, living in a historically Black neighborhood disproportionately affected by mass incarceration might be able to imagine a future in which the neighborhood receives investments in education, housing, and employment. A White judge, living in an affluent zip code hundreds of miles away, might not. Their degrees of imaginative separation would, in turn, likely influence their perception of the probability of recidivism

283. Underwood, *supra* note 221, at 1417.

284. *Id.*

285. The “mystery” of mathematical arguments—“the relative obscurity that makes them at once impenetrable by the layman and impressive to him”—creates a risk that such arguments will be given a credence they do not deserve. Tribe, *supra* note 25, at 1334. This is not to say that quantitative evidence can never be admitted, but that it can be difficult to intelligently combine with more impressionistic forms of evidence, without overpowering them. Laurence Tribe describes this as the “tendency of more readily quantifiable variables to dwarf those that are harder to measure, in part from the uneasy partnership of mathematical precision and certain important values, in part from the possible incompatibility of mathematics with open-ended and deliberately ill-defined formulations, and in part from the intrinsic difficulty of applying techniques of maximization to the rich fabric of ritual and to the selection of ends as opposed to the specification of means.” *Id.* at 1393; *see also* People v. Collins, 438 P.2d 33, 33 (1968) (“Mathematics, a veritable sorcerer in our computerized society, while assisting the trier of fact in the search for truth, must not cast a spell over him.”).

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

287. *See, e.g.*, Amos Tversky & Daniel Kahneman, *Judgment Under Uncertainty: Heuristics and Biases*, 185 SCI. 1124, 1127–28 (1974) (describing biases of imaginability).

within this community.²⁸⁸ But it is “never a reason for adding to injustice that we are already guilty of some.”²⁸⁹ Whereas an algorithm is structurally bound by its historical data inputs, human decision makers can choose not to cabin an individual’s future potentiality within the limits of their own experience. Therefore, human decision making, as flawed and inadequate as it may be, is at least capable of accommodating experiential anomalies. Algorithms are not.²⁹⁰

As predictive algorithms foreclose future potentiality to the same social groups, categorical inequality endures across generations.²⁹¹ Pattern-based discrimination produces a “seemingly permanent economic underclass,” bound on all sides by historical data and the self-reinforcing loop of predictive profiling.²⁹² As mentioned above, Equivant’s risk assessment tool over-predicts recidivism for Black defendants and under-predicts recidivism for White defendants.²⁹³ Bernard Harcourt explains that, over time, the extended incarceration of a particular social group generates disproportionality between their share of the offending population and their share of the carceral population.²⁹⁴ Because institutions will erroneously assume that Black defendants’ share of the carceral population reflects their share of the offending population, they will direct more law enforcement resources to Black communities, thus reinforcing this disproportionality.²⁹⁵ This is consistent with empirical evidence that

288. *See id.*

289. Kadish, *supra* note 27, at 284.

290. *See, e.g.,* Laurence Tribe, *An Ounce of Detention: Preventive Justice in the World of John Mitchell*, 56 U. VA. L. REV. 371, 404 (1970).

291. *See* COHEN, *supra* note 7, at 180 (citing VIRGINIA EUBANKS, *AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR* (2018); SAFIYA UMOJA NOBLE, *ALGORITHMS OF OPPRESSION: HOW SEARCH ENGINES REINFORCE RACISM* (2018)).

292. *See id.*

293. *See supra* notes 241–48 and accompanying text. Black defendants who did not reoffend were expected to reoffend at a rate of 44.9%, nearly twice as likely as Whites, while White defendants who did reoffend were predicted to not recidivate at a much higher rate (47.7%) than their Black peers (28%). *See* Dressel & Farid, *supra* note 245, at 4; Angwin et al., *supra* note 1.

294. *See* BERNARD HARCOURT, *AGAINST PREDICTION: PROFILING, POLICING, AND PUNISHING IN AN ACTUARIAL AGE* 243 (2007).

295. Families separated by incarceration experience greater economic insecurity (which in turn increases the likelihood of criminal activity), and formerly incarcerated individuals struggle to find sustainable employment after release. Communities that lose large segments of their population to prison experience significant disruption and disintegration, and children of incarcerated individuals struggle with educational attainment. The overrepresentation of the profiled group within the carceral population also generates a distorted sense of that group’s criminality within the public imagination, contributing to the development of harmful stereotypes. *See, e.g.,* Crutchfield & Weeks, *supra* note 226, at 47; Rose & Clear, *supra* note 226, at 441; HARCOURT, *supra* note 294; Dorothy E. Roberts, *Digitizing the Carceral State*, 132 HARV.

risk assessment use can increase racial disparities in sentencing.²⁹⁶ Economists Megan Stevenson and Jennifer Doleac observed the sentencing practices of judges who were most responsive to risk assessment and found that the probability of incarceration for Black defendants increased by four percentage points relative to Whites and the length of the sentence increased by approximately seventeen percent.²⁹⁷ Judges were more likely to deviate downward for White defendants with high risk scores than for Black defendants.²⁹⁸

Accordingly, judicial reliance on predictive algorithms has the potential to reproduce socioeconomic disparities through “data determinism.”²⁹⁹ Through its unequal distribution of future potentiality, the algorithm splits the future into two racially distinct times: a White time that is “futurally open” (indeterminate), and a non-White time that is “futurally closed” (predetermined).³⁰⁰ Philosopher Charles Mills describes this as the “racialization of time”—the transfer of time from one set of lives to another.³⁰¹ The algorithmic administration of populations, or “stochastic governance,”³⁰² secures the data freedom of a minority of elites while categorizing and disciplining the “risky” majority, whose performance of everyday activities (as consumer, passenger, debtor, patient, guest) is subject to constant, quantitative evaluation.³⁰³ This is how the apparatuses of algorithmic governmentality—the predictive computational models that exert outsized influence across a range of decision-making contexts—exert power, not in the present, but in the future, by controlling what we are “likely” to become, and thus who we are allowed to be.³⁰⁴

L. REV. 1695, 1708 (2019) (reviewing VIRGINIA EUBANKS, *AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE* (2018)).

296. See Stevenson & Doleac, *supra* note 24.

297. *Id.* at 3.

298. *Id.* at 29.

299. See Bernard E. Harcourt, *Risk as a Proxy for Race: The Dangers of Risk Assessment*, 27 FED. SENT’G REP. 237, 237 (2015); Edith Ramirez, Chairwoman, Fed. Trade Comm’n, Keynote Address at Technology Policy Institute Aspen Forum: The Privacy Challenges of Big Data: A View From the Lifeguard’s Chair at 7–8 (Aug. 19, 2013).

300. Sheehey, *supra* note 258, at 57.

301. See Charles Mills, *White Time: The Chronic Injustice of Ideal Theory*, 11 DU BOIS REV. 27–42 (2014); see also JOHANNES FABIAN, *TIME AND THE OTHER: HOW ANTHROPOLOGY MAKES ITS OBJECT* 11–12 (1983); see generally ALFRED SCHUTZ & THOMAS LUCKMAN, *THE STRUCTURES OF THE LIFE-WORLD* (Richard M. Zaner & H. Tristram Engelhardt, Jr. trans., 1973); MARTIN HEIDEGGER, *BEING AND TIME*, (John Macquarrie & Edward Robinson trans., 1962).

302. See Sanders & Sheptycki, *supra* note 9, at 1–15.

303. See José van Dijck, *Datafication, Dataism and Dataveillance: Big Data Between Scientific Paradigm and Ideology*, 12 SURVEILLANCE & SOC. 197, 198–99 (2014).

304. See Rouvroy & Berns, *supra* note 13, at 181.

D. The Epistemological Inferiority of the Algorithmic Subject

The commensuration of individuals along a statistical distribution erases qualitative differences between them.³⁰⁵ These qualitative differences often correspond to aspects of an individual's character, history, and circumstances that are illegible to quantified systems, which then overlook the ways in which these qualitative features affect the outcome being predicted.³⁰⁶ Although almost any human experience or characteristic can be “quantified” in some form, many are physically or ethically difficult to observe or record, so that there is limited data from which to construct a sufficiently complex model.³⁰⁷ For example, twins growing up in the same household may experience the same resource constraints and many of the same emotional experiences, but a computational model will struggle to capture how differently each of those factors is *experienced* by each twin. Instead, computational models recognize “differences” between individuals using data labels, categories, and statistical classifications that are meaningful to the model but less so to individuals.³⁰⁸ Consider, for example, an algorithmic prediction of parenting quality. The algorithm's assessment will incorporate various institutional data points—an eviction notice, a poor credit score, a brush with law enforcement—but it will miss all the other ways in which a parent cares for their child, for which no quantitative data exists.³⁰⁹ This creates a lopsided situation in which the algorithm assigns greater epistemic weight to public institutional data than the unrecorded experience of parenting.³¹⁰ The algorithm creates its own metrics of parenting, based

305. See Espeland & Stevens, *supra* note 220, at 320; RAZ, *supra* note 65, at ch. 13; Cass Sunstein, *Incommensurability and Valuation in Law*, 92 MICH. L. REV. 779, 783–85 (1993).

306. See, e.g., Hildebrandt, *supra* note 200, at 91–92; ALAIN DESROSIÈRES, *POUR UNE SOCIOLOGIE HISTORIQUE DE LA QUANTIFICATION: L'ARGUMENT STATISTIQUE I* at ch. 1 (2008); THEODORE M. PORTER, *TRUST IN NUMBERS*, ch. 2 (1996); ALAIN DESROSIÈRES, *PROUVER ET GOUVERNER* ch. 3 (2014).

307. See, e.g., Jose Luis Bermudez & Michael S. Pardo, *Risk, Uncertainty, and “Super-risk,”* 29 NOTRE DAME J.L., ETHICS, & PUB. POLICY 471, 473, 484 (2015); Michael Power, *The Risk Management of Nothing*, 34 ACCT., ORGS. & SOC. 849, 853 (2009); Hildebrandt, *supra* note 200, at 91–93.

308. See COHEN, *supra* note 7, at 66. For example, platform-intermediated digital communication relies on shorthand chosen by the platform (like, share, follow) and predefined data labels (male, female, business, social) that facilitate standardized data capture, using “artificial and instrumental forms of personalization based on externally determined logics.” *Id.*

309. See Public Books 101, *Data & Humanity (with Mimi Onuoha, Lam Thuy Vo, and Annie Galvin)* (May 17, 2021) (accessed on Apple Podcasts).

310. *Id.*; see, e.g., SIMONE BROWN, *DARK MATTERS: ON THE SURVEILLANCE OF BLACKNESS* 15 (2015).

on what is accessible to measurement, and thereby erases the lived experience it claims to be able to predict.³¹¹

This oversight of incomputable factors is partly technical but also intentional. As aforementioned, the epistemic authority of the algorithmic subject stems from the “unmediated” nature of data collection.³¹² The algorithmic subject is a “disembodied data stream,” reconstructed from digital traces inadvertently left by the flesh-and-blood individual as they move through the data economy.³¹³ Big Data uses these traces, stripped of their meaning-giving context, to build supra-individual models of behavior without ever asking the individual to describe themselves.³¹⁴ To solicit such subjective input from the underlying individual would be to undermine the “statistical objectivity” of Big Data predictions.³¹⁵ In contrast, legal processes of truth making (including individual testimony and affidavits) frequently invite legal subjects to provide evidence of their subjective intentions because establishing their mental and physical autonomy is a precondition for legal liability.³¹⁶ As a result, preventing legal subjects from offering knowledge about themselves undermines the epistemic legitimacy of the final legal decision.³¹⁷

E. The Redistribution of Expressive Power

Philosophers and jurists have long recognized the importance of speech for both identity-formation and individual expression.³¹⁸ As the clothing of individual thoughts, language enables the self to “find its uniqueness by articulating distinctions of experience, engaging in dialogue with the self and others, and permitting a personal indexing

311. See Tarleton Gillespie, *The Relevance of Algorithms*, in MEDIA TECHNOLOGIES: ESSAYS ON COMMUNICATION, MATERIALITY, AND SOCIETY 167 (Tarleton Gillespie, Pablo J. Boczkowski & Kirsten A. Foot eds., 2014) (citing Ganaele Langlois, *Participatory Culture and the New Governance of Communication: The Paradox of Participatory Media*, 14 TELEVISION & NEW MEDIA 91–105 (2013)); Burk, *supra* note 137; Friedrich August von Hayek, *The Pretence of Knowledge*, 39 AM. ECON. REV. 3, 3–7 (1989).

312. See *supra* notes 162–64 and accompanying text.

313. Burrell & Fourcade, *supra* note 261, at 231; Rouvroy, *supra* note 89, at 157; Tyler Reigeluth, *Why Data is Not Enough: Digital Traces as Control of Self and Self-Control*, 12 SURVEILLANCE & SOC. 234, 249 (2014); see also JOHN CHENEY-LIPPOLD, WE ARE DATA: ALGORITHMS AND THE MAKING OF OUR DIGITAL SELVES 5–9 (2017).

314. See Rouvroy & Berns, *supra* note 13, at 168.

315. See Gillespie, *supra* note 311, at 179.

316. See, e.g., *id.* at 167.

317. See *id.*

318. See, e.g., Jessica Vizuette, *Language and Identity: the Construction of the Self*, ARCADIA (June 7, 2022), <https://www.byarcadia.org/post/interaction-between-language-and-society-101-language-and-identity> [<https://perma.cc/AJ3D-WLPX>].

of an external good.”³¹⁹ Philosophers such as Jacques Lacan have identified the production of speech as the production of subjectivity.³²⁰ The individual “who speaks promises to be what he affirms himself to be, precisely because he is just that.”³²¹ The opportunity to give account of oneself in one’s own words is a fundamental aspect of self-constitution, including as a legal subject.³²² First Amendment jurisprudence frames the value of speech in primarily civic terms: through self-articulation, in dialogue with others, the individual citizen becomes “part of a process in which one declares, converses, becomes challenged and resituated, and perhaps takes a step in a new direction.”³²³ Free speech facilitates civic awakening³²⁴ and the generation of consensus around norm evolution.³²⁵ But courts have also recognized the dignitary value of speech and its importance for identity formation and self-realization.³²⁶

319. Brian C. Murchison, *Speech and the Self-Realization Value*, 33 HARV. C.R.-C.L. L. REV. 443, 477 (1998); CHARLES TAYLOR, HUMAN AGENCY AND LANGUAGE, PHILOSOPHICAL PAPERS ch. 10 (1985); CHARLES TAYLOR, SOURCES OF THE SELF: THE MAKING OF THE MODERN IDENTITY ch. 4 (1992); Judith Butler, *Wrong-doing, Truth-telling: The Case of Sexual Avowal*, in FOUCAULT AND THE MAKING OF SUBJECTS 77–92 (Laura Cremonesi, Orazio Irrera, Daniele Lorenzini & Martina Tazzioli eds., 2016).

320. See, e.g., Gilles Arnaud & Stijn Vanheule, *The Division of the Subject and the Organization: A Lacanian Approach to Subjectivity at Work*, 20 J. ORG. CHANGE MGMT. 359, 360 (2007); Terezie Smejkalová, *Legal Performance: Translating into Law and Subjectivity in Law*, 22 TILBURG L. REV. 62, 66 (2017); Deborah Schiffrin, *Narrative as Self-Portrait: Sociolinguistic Constructions of Identity*, 25 LANGUAGE SOC’Y 167, 168 (1996); NIKOLAS ROSE, INVENTING OUR SELVES: PSYCHOLOGY, POWER, AND PERSONHOOD ch. 8 (1996). See generally ANTHONY GIDDENS, MODERNITY AND SELF-IDENTITY: SELF AND SOCIETY IN THE LATE MODERN AGE (1991).

321. See, e.g., SOURCES OF THE SELF, *supra* note 323; MICHEL FOUCAULT, WRONG-DOING, TRUTH-TELLING: THE FUNCTION OF AVOWAL IN JUSTICE 16 (Fabienne Brion & Bernard E. Harcourt eds., Stephen B. Sawyer trans., 2014).

322. See, e.g., Smejkalová, *supra* note 319, at 65; Daniele Lorenzini, *Foucault, Regimes of Truth and the Making of the Subject*, in FOUCAULT AND THE MAKING OF SUBJECTS, *supra* note 319, at 63–76; FOUCAULT, *supra* note 321, at 144–45; Butler, *supra* note 319; Celine Chan, *The Right to Allocution: A Defendant’s Word on Its Face or under Oath*, 75 BROOK. L. REV. 579, 582 (2009); Kimberly A. Thomas, *Beyond Mitigation: Towards a Theory of Allocution*, 75 FORDHAM L. REV. 2641, 2673–74 (2007).

323. Murchison, *supra* note 319, at 461.

324. See *id.* at 498.

325. See, e.g., Thomas Emerson, *Toward A General Theory of the First Amendment*, 72 YALE L.J. 877, 886 (1963); see also Martin Redish, *The Value of Free Speech*, 130 U. PA. L. REV. 591, 594 (1982).

326. *Procunier v. Martinez*, 416 U.S. 396, 427–48 (1974) (Marshall, J., concurring) (“The First Amendment serves not only the needs of the polity but also those of the human spirit—a spirit that demands self-expression. Such expression is an integral part of the development of ideas and a sense of identity. To suppress expression is to reject the basic human desire for recognition and affront the individual’s worth and dignity. . . . It is the role of the First Amendment and this Court to protect those precious personal rights by which we satisfy such basic

In the criminal justice context, defendant speech is one of the only forms of protection against the coercive power of the state.³²⁷ Accordingly, the defendant has multiple opportunities to speak (e.g., the right to testify, the right to allocute, and the right to represent themselves, as well as the right to remain silent).³²⁸ In practice, however, these opportunities for speech are rarely used.³²⁹ Ninety-five percent of defendants never go to trial, and, of those who do, very few testify.³³⁰ The prevalence of plea bargains erodes the defendant's constitutional rights, and ritualized plea colloquies ("Do you understand the rights you are giving up?" "Yes") legitimate the suppression of defendant speech.³³¹ The result is that defendant speech is ordinarily routed through legal counsel, who will convey the defendant's story in terms that are legible to the law.³³² And, like any discourse of power, the limited discursive space constituted by legal scripts will constrain the range of subjectivity it can accommodate.³³³

Given the infrequency of criminal trials, the right of allocution at sentencing represents a rare opportunity for defendants to share

yearnings of the human spirit."); *Gardner v. Florida*, 430 U.S. 349, 358 (1977) ("The 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.").

327. See Alexandra Natapoff, *Speechless: The Silencing of Criminal Defendants*, 80 N.Y.U. L. REV. 1449, 1449–50 (2005).

328. *Id.* at 1479 ("These expressive privileges flow from a combination of principles: the Fifth Amendment right to remain silent and various aspects of the Sixth Amendment including the right to put on witnesses in defense . . .").

329. *Id.* at 1499; see also William J. Stuntz, *The Substantive Origins of Criminal Procedure*, 105 YALE L.J. 393, 417 (1995).

330. Natapoff, *supra* note 327, at 1450.

331. *Id.* at 1464, 1482.

332. Dragan Milovanovic, *Rebellious Lawyering: Lacan, Chaos, and the Development of Alternative Juridico-Semiotic Forms*, 20 LEGAL STUD. F. 295, 305 (1996).

333. Smejkalová, *supra* note 320; see also Dimitris Papadopoulos, *In the Ruins of Representation: Identity, Individuality, Subjectification*, 47 BRITISH J. SOC. PSYCH. 139, 149–50 (2008) ("Discourse analysis cannot deal with something which is not already represented in discourse. . . identity is always in the making because it entails a non-expressed otherness, a nondiscursified and imagined possibility of social relations . . . when we speak about identity we have then to presuppose that the individual is not exhausted in the signifying practices which he/she employs. Identity cannot be conceived without a constitutive outside which surpasses existing meanings and practices in the discourse. To put it another way, identity corresponds continuously with a prescriptive lack: a lack consisting of unanswered or unperceived possibilities for relating to the self and the other possibilities which have never been realized. Identity is a closure, an exclusion, an attachment to a specific spatialized position only because it can be so and not because it has to be so. Thus, the employment of an identity does not necessarily regulate or overdetermine the individual's existence, but positions the subject in the tension between coercion by institutional mechanisms (meanings and practices) and articulation through them.").

their story in their own words.³³⁴ Despite the changes that have occurred in criminal law since allocution was introduced over three hundred years ago (including the right to counsel and the right to testify), courts have recognized that “[t]he most persuasive counsel may not be able to speak for a defendant as the defendant might . . . speak for himself.”³³⁵ Accordingly, many state and federal statutes explicitly provide for a right of allocution at sentencing.³³⁶ Practitioners often view allocution as an opportunity for the defendant to share information that will reduce the severity of the sentence imposed, but it also bears non-instrumental value beyond sentence mitigation.³³⁷ The opportunity to speak can have cognitive, dignitary, and participatory benefits for defendants who feel that they have had an opportunity to shape their legal destiny with their own words.³³⁸ Individuals who participate expressively in their own cases may be more likely to accept the final outcome as a result.³³⁹

Allocution may offer systemic benefits as well.³⁴⁰ When criminal defendants have few meaningful opportunities to share their personal stories, the institution suffers the loss of their perspective.³⁴¹ Defendant silence maintains the ignorance of institutional actors “who never hear the full story about the individuals” they punish, nor the deficiencies of the system they serve.³⁴² As a result, judges and prosecutors rarely understand the “social circumstances that breed crime and violence from the perspectives of those who must survive under them.”³⁴³ Where complex and contextualized narratives could illuminate the structural forces that shape individual behavior, public conceptions of crime are instead sated with easy stereotypes.³⁴⁴ This information deficit helps to

334. Thomas, *supra* note 322.

335. *Id.* at 2648; Green v. United States, 365 U.S. 301, 304 (1961); *see also* Harris v. State, 306 Md. 344, 359 (1986) (noting that the allocutory process serves a unique and “significant function [that] no other procedural device can completely replace”).

336. Thomas, *supra* note 322, at 2649; *see, e.g.*, FED. R. CRIM. P. 32.

337. Thomas, *supra* note 322, at 2655; *see also* Martha C. Nussbaum, *Equity and Mercy*, 22 PHIL. & PUB. AFFS. 83, 98 (1995) (“Any fully adequate moral or legal judgment must be built upon a full grasp of all the particular circumstances of the situation, including the motives and intentions of the agent.”).

338. Natapoff, *supra* note 327, at 1450.

339. *See, e.g.*, William M. O’Barr & John M. Conley, *Litigant Satisfaction Versus Legal Adequacy in Small Claims Court*, 19 LAW & SOC’Y REV. 661, 667 (1985).

340. Natapoff, *supra* note 327, at 1452.

341. *Id.*

342. *Id.* at 1499.

343. *Id.* at 1489–99.

344. *See, e.g.*, Austin Sarat, *Narrative Strategy Death Penalty Advocacy*, 31 HARV. C.R.-C.L. L. REV. 353, 355–56 (1996); Richard Delgado, *Storytelling for Oppositionists and*

sustain a coercive and punitive institution that is shielded from, and unresponsive to, the voices of its subjects.³⁴⁵ Through the practice of allocution, defendant speech could contribute to the discourse that shapes criminal justice.³⁴⁶

There are many ways in which the criminal justice system effectively silences criminal defendants, and increased judicial reliance on predictive algorithms exacerbates this suppression of defendant speech.³⁴⁷ As judges turn to algorithms for “objective” predictions of individual behavior, the personal narratives of defendants become less important than the statistical features they share with historical recidivists.³⁴⁸ Data science de-centers the embodied and experiential knowledge of the legal subject.³⁴⁹ The “objectivity” and “omniscience” of Big Data is difficult to counter with a personal narrative shared in halting tones by an individual who may not understand or trust the judicial process.³⁵⁰ Predictive algorithms are generally inaccessible to the layperson, even if data scientists disclose their internal construction.³⁵¹ When Eric Loomis contested his algorithmic classification as a “high-risk” recidivist, the Supreme Court of Wisconsin acknowledged its ignorance about how the classification had been calculated.³⁵² Nevertheless, the court held that Loomis’ ability to verify his responses to the algorithm’s questionnaire and to challenge the resulting risk score provided sufficient protection of his due process right to be sentenced on the basis of accurate information.³⁵³ The court did not interrogate the variables selected by the algorithm, the weights

Others: A Plea for Narrative, 87 MICH. L. REV. 2411, 2412–15 (1989); see also Binny Miller, *Telling Stories About Cases and Clients: The Ethics of Narrative*, 14 GEO. J. LEGAL ETHICS 1, 4 (2000).

345. Natapoff, *supra* note 327, at 1599.

346. See *id.* at 1450–56; see also Thomas, *supra* note 322.

347. Natapoff, *supra* note 327, at 1450.

348. See Huq, *supra* note 1.

349. Cf. Barry, *supra* note 18, at 367.

350. Resolving the expressive disempowerment of criminal defendants will require concerted efforts to secure meaningful opportunities for legal subjects to speak, and thereby participate in the production of legally relevant knowledge about themselves. Although defendants may face many barriers to self-articulation, including a lack of confidence, education, or trust in authority, the faculty of speech is fundamentally more accessible than the technical ability to challenge an algorithmic prediction. The primary ontology of speech gives every individual the opportunity to establish and assert subjectivity; speech is an assertion of sovereignty that implies a relationship of equality and reciprocity with other speaking subjects—this is the primary contract of language.

351. See COHEN, *supra* note 7, at 43.

352. *State v. Loomis*, 371 Wis. 2d 235, 259 (2016) (noting that the score does not explain “how the COMPAS program uses information to calculate the risk scores”).

353. *Id.* at 257–65.

assigned to them, the training data used to construct the model, or the population data against which Loomis was compared.³⁵⁴

Similarly, when Willie Allen Lynch appealed his conviction for the sale of crack cocaine, alleging that he had been misidentified by a facial recognition algorithm, the District Court of Appeal of Florida affirmed his conviction on the basis that the trial result would not have been different if Lynch had had access to the other photographs in the facial recognition database.³⁵⁵ Despite the impenetrability of many evidentiary technologies, courts continue to indulge them with uncritical deference, exacerbating the power imbalance between the defendant and the prison industrial complex.³⁵⁶ Prosecutors have a longstanding duty, affirmed in *Brady v. Maryland*, to disclose potentially exculpatory evidence.³⁵⁷ Courts, however, have been unwilling to recognize algorithmic tools as meeting the *Brady* standard,³⁵⁸ thereby instantiating the power of private capital over the conditions of human freedom.³⁵⁹ Inscrutable evidentiary tools “threaten to make the legal system seem even more alien and inhuman” than it already does to so many.³⁶⁰ As legal scholar Laurence Tribe explains, judicial reliance on inscrutable tools erodes the public’s sense that the law’s fact-finding apparatus is operating in a “comprehensible way, on the basis of evidence that speaks, at least in general terms, to the larger community that the processes of adjudication must ultimately serve.”³⁶¹

V. IS THE LEGAL SUBJECT WORTH SAVING?

As algorithmic epistemology reshapes the legal arena, key questions about the relevance of legal subjectivity remain: Is there a fundamental incompatibility between the algorithmic subjectivity normalized by data capitalism and the subjectivity underpinning a system of coercive interference? Is the actuarial project of algorithmic governance fundamentally at odds with the law’s normative commitment to individualized justice?

354. *Id.* at 259–63.

355. *Lynch v. State*, 260 So. 3d 1166, 1170–71 (Fla. Dist. Ct. App. 2018).

356. *See id.*

357. *Brady v. Maryland*, 373 U.S. 83, 87 (1963).

358. *Id.*; RASHIDA RICHARDSON, JASON M. SCHULTZ, & VINCENT M. SOUTHERLAND, LITIGATING ALGORITHMS 2019 US REPORT: NEW CHALLENGES TO GOVERNMENT USE OF ALGORITHMIC DECISION SYSTEMS 30–32 (Sept. 2019), available at <https://ainowinstitute.org/litigatingalgorithms-2019-us.pdf> [<https://perma.cc/E79N-ZJUT>]; Andrew Ferguson, *Big Data Prosecution and Brady*, 67 UCLA L. REV. 180, 237 (2020).

359. COHEN, *supra* note 7, at 156, 159.

360. Tribe, *supra* note 25, at 1376.

361. *Id.*

In answering these questions, it is helpful to conceive of law not only as a system of coercive interference, but as a mechanism for regulating human behavior and communicating moral condemnation. Accordingly, the rituals of law, including legal subjecthood, matter not only as devices for achieving certain legal outcomes, but as affirmations of respect for the individual as an end in themselves and as a reminder of the normative ideals of liberal democracy.³⁶² Democratic self-governance relies upon a conception of the individual as a “responsible agent entitled to be praised or blamed depending upon [their] free choice of conduct.”³⁶³ A conception of citizens as alterable, predictable, or manipulable things “is the foundation of a very different social order indeed.”³⁶⁴ When the basic unit of a liberal society is no longer an autonomous, unknowable individual, but an algorithmic subject anticipating its own datafication, society is significantly altered.³⁶⁵ Individual behaviors become traceable and predictable components of surveillant disciplinary outcomes, and actuarial predictions foreclose opportunities for meaningful autonomy.³⁶⁶ The law no longer addresses free and equal subjects but manages the threats posed by categories of people.³⁶⁷

The shifting epistemology of legal subjectivity presents a unique opportunity to reexamine the traditional paradigm of legal subjecthood. The dominant liberal conception of the bounded, rational, and “self-determining” legal subject is increasingly inconsistent with contemporary understandings of systemic injustice and mutual interdependence.³⁶⁸ The traditional subject of Western liberalism occupies a sphere of autonomy constructed by individual rights.³⁶⁹ Within this bounded sphere, the liberal legal subject is protected from threats to its autonomy from outsiders, including the state.³⁷⁰ As long as this boundary can be maintained (with the help of private property rights), the liberal subject can remain isolated and “in control.”³⁷¹ The liberal fantasy of autonomy-as-control fosters illusions of independence that can only be sustained through harmful practices of domination.³⁷²

362. *Id.* at 1370; *see also* KAMISAR ET AL., *supra* note 25.

363. Kadish, *supra* note 27.

364. *Id.*

365. KOOPMAN, *supra* note 111.

366. Lindroos-Hovinheimo, *supra* note 85.

367. Lacey, *supra* note 5, at 173.

368. JENNIFER COBBE, *BIG DATA, SURVEILLANCE, AND THE DIGITAL CITIZEN* 17 (2019).

369. *Id.*

370. Lacey, *supra* note 5, at 156.

371. COBBE, *supra* note 368.

372. NEDELSKY, *supra* note 31, at ch. 7.

Social interactions necessarily involve affecting and being affected by other autonomous individuals. Autonomy cannot be unilaterally possessed or manifested because it represents a particular quality of human relations.³⁷³ For people to enjoy autonomy, they need to exist in autonomous relations with others.³⁷⁴ Every individual is embedded within a web of nested relations (intimate, social, cultural, and political) that profoundly shape their capacity for autonomy.³⁷⁵ In this sense, the traditional liberal conception of the bounded, rational, self-determining legal subject fails to reflect the realities of human interdependence.³⁷⁶

The rhetoric of individual rights—Western liberalism’s primary means of expressing and protecting selfhood—focuses on the rights-holder asserting individual entitlement, rather than the circumstances that shape the exercise of these rights.³⁷⁷ Rights discourse perpetuates an “alienating and unrealistic individualism” in which the liberal subject engages in ostensibly individuated actions, disengaged from the social context in which those actions are occurring.³⁷⁸ Anthropologist Sally Merry has shown that the adoption of a rights consciousness can be a strange and alienating experience for new legal subjects.³⁷⁹ For battered women in Hilo, Hawai’i, for example, reporting domestic abuse to the police requires a substantial shift in self-perception.³⁸⁰ Instead of defining themselves in terms of their family and kin (who might describe them as “bad wives” for reporting abuse), battered women come to see themselves in the terms offered by the law—as legal subjects with individual rights.³⁸¹ But because this legal subjectivity requires abandoning former subject positions (including as wife, mother, and kin), its adoption is fraught with hesitation and vacillation.³⁸² Battered women will often request the assistance of law enforcement, retreat, and then ask again, as they track “back and forth across a significant line of identity

373. Lindroos-Hovinheimo, *supra* note 85.

374. NEDELSKY, *supra* note 31; *see also* FEMINIST CONTENTIONS: A PHILOSOPHICAL EXCHANGE 13, 46 (Seyla Benhabib, Judith Butler, Drucella Cornell & Nancy Fraser eds., 1995).

375. Lindroos-Hovinheimo, *supra* note 85.

376. *Id.*

377. McNay, *supra* note 201, at 70.

378. *See* Susan Sibley & Austin Sarat, *Dispute Processing in Law and Legal Scholarship: From Institutional Critique to the Reconstruction of the Juridical Subject*, 66 DENV. L. REV. 437, 478–89 (1989).

379. Sally Engle Merry, *Rights Talk and the Experience of Law: Implementing Women’s Human Rights to Protection from Violence*, 25 HUM. RIGHTS Q. 343, 381 (2003).

380. *Id.* at 350.

381. *Id.* at 346.

382. *Id.* at 354–55.

transformation.”³⁸³ They are experimenting with a new kind of subjectivity, “no longer mediated by their embeddedness in family relationships, but now standing alone in relation to the state.”³⁸⁴ This process of “disembedding” from social relations can be lonely and deeply alienating.³⁸⁵

The jurisprudence of rights directs us to view social problems as solvable through individual-level interventions—specifically, the exercise of individual entitlements.³⁸⁶ Crime, for example, can be “solved,” defendant by defendant, particularly with the help of predictive technologies. The reality, however, is that the pervasiveness of crime cannot be explained by individual pathology or occasional personal inclination; crime is a deeply social phenomenon, sustained by social, cultural, institutional, and economic relations that exist beyond the control of any individual.³⁸⁷ Without altering the structure of relations that produce criminal behavior, enforcing prohibitions on individual conduct will not effectively reduce crime.³⁸⁸

Predictive algorithms, however, reflect persistent optimism that individual-level interventions can overcome the deep-seated social and structural forces that sustain patterns of criminality.³⁸⁹ The use of risk assessment tools reflects a choice to focus the deterrent gaze of the law on the criminogenic features of individuals, rather than the circumstances that shape their behavior. It is a choice to intervene at the level of the defendant, based on assumptions about the ability of algorithms to predict and thus control their behavior.³⁹⁰ Algorithms insulate these political choices from scrutiny by reinforcing the narrative that individual criminal behavior can be both predicted and prevented. This is the same approach used by data capitalists to justify data-driven profiling—namely, that the target of intervention must always be individual behavior, rather than state-level investments in social infrastructure.³⁹¹ Even as it withholds the means of control over algorithmic profiles, the neoliberal market encourages consumers to assemble themselves as responsible algorithmic subjects by framing

383. *Id.* at 345; see also Renée Römken, *Law as Trojan Horse: Unintended Consequences of Right-Based Interventions to Support Battered Women*, 12 YALE J.L. & FEMINISM 265, 283 (2001).

384. Merry, *supra* note 379, at 353.

385. *Id.* at 352, 367–69.

386. COBBE, *supra* note 368.

387. Lacey, *supra* note 46, at 351–52.

388. *Id.*

389. See Lindroos-Hovinheimo, *supra* note 85.

390. See Hannah-Moffat, *supra* note 34, at 245.

391. See Barry, *supra* note 18, at 368.

access to credit and other resources as an individual responsibility.³⁹² This unrelenting examination of individual behavior obscures the effect of historical and structural forces³⁹³ and minimizes the state's responsibility to its citizens on the basis that "enterprising" individuals can produce their own security through consumption.³⁹⁴

The false security of rights, of limited personal responsibility, helps society to ignore the overwhelming nature of human interconnectedness. However, an unrealistic understanding of autonomy—generated by the dominant liberal conception of the bounded, rational legal subject—will generate an unrealistic assignment of responsibility. Contemporary legal systems need a new conception of self, a new legal subject, that retains and expresses our fundamental commitment to equality and autonomy but pays greater attention to the social relations that constitute the self and, therefore, the legal subject.³⁹⁵ It is time for society's conception of the legal subject to evolve in line with its evolving understanding of human interconnectedness.³⁹⁶

VI. CONCLUSION

This Article does not seek to answer the question of whether predictive algorithms should or should not be used in judicial decision making. Even in the context of criminal law, it is difficult to reach a firm conclusion about the net utility of algorithmic guidance. Instead, this Article contributes an observation about the epistemic effect of algorithmic knowledge on the construction of the legal subject. Specifically, the elevation of algorithmic knowledge represents a transfer of narrative power from the individual (whose behavior is being predicted) to the data capitalist (whose prediction now forms the basis for decision making).

In marketing their computational products, data capitalists make monopolistic claims to "objective truth" by undermining the epistemic authority of the embodied individual. They frame knowledge as "objective" only after it has been extracted from its original

392. See Katelyn Esmonde & Shannon Jette, *Assembling the 'Fitbit Subject': A Foucauldian-sociomaterialist Examination of Social Class, Gender, and Self-surveillance on Fitbit Community Message Boards*, 24 HEALTH 299, 300–01 (2020).

393. McCluskey, *supra* note 135 (offering a helpful analysis of the importance of countering the neoliberal paradigm of "individual" responsibility with institutional responsibility and resilient design, including acknowledgment of the vulnerability of individuals as "particularly situated, substantively embodied" human subjects).

394. See McNay, *supra* note 201; see also Donzelot, *supra* note 201, at 129.

395. Barry, *supra* note 18, at 373.

396. *Id.* at 341.

source: the human subject. Making the credibility of personal information contingent on its disembodiment paints the individual as “untrustworthy.” It suggests that the embodied individual must be bypassed because discursive representation is too vulnerable to deception and indeterminacy to represent a credible source of truth.³⁹⁷ Instead, data capitalists use population-level data to build supra-individual models of behavior without ever asking the individual to describe themselves or their intentions.³⁹⁸ This avoidance of reflexive discourse suggests that the truth cannot be found in conversation with the object of study. That would give the embodied individual too much power over the production of knowledge about themselves. Moreover, it would threaten data capitalists’ monopoly on “truth.”

Prioritizing algorithmic knowledge also shifts the plane of communication from one of proximity and reciprocity (using shared linguistic tools) to an algorithmic and actuarial plane in which data capitalists hold the tools of meaning. And this shift in epistemological terrain cedes ultimate epistemic authority to data capitalists. They become essential intermediaries, unearthing “objective” knowledge about human propensity from data streams that lie beyond human perception. In generating these predictions, the data capitalist decides what information is “relevant” to the prediction of a specific behavioral outcome and how such information will be collected, measured, and weighted. These decisions will inevitably exclude from measurement information that is experiential, embodied, and highly subjective, such as emotions, experiences, and traumas. This is not normatively problematic in all decisional contexts; there are contexts in which algorithmic knowledge is rightfully prioritized. But law, as an instrument of coercive power, depends for its legitimacy on procedural justice, which requires a hard look at the forms of knowledge used to reach a legal decision and who was able to participate in that epistemic process.³⁹⁹ Data science, with its focus on “objective” and “unmediated” data, discounts the first-person view of reality that has traditionally underwritten legal processes of truth-making, including individual testimony. Its exclusion of legal subjects from the production of legally relevant knowledge about themselves is fundamentally incompatible with law’s normative commitment to individualized justice.⁴⁰⁰ The elevation of algorithmic knowledge above personal narrative ultimately

397. See, e.g., Wilcox, *supra* note 10, at 25; HOW WE BECAME POSTHUMAN, *supra* note 10, at 133–34; MY MOTHER WAS A COMPUTER, *supra* note 10, at 241–43.

398. Rouvroy & Berns, *supra* note 13.

399. See Lacey, *supra* note 46, at 351.

400. McNay, *supra* note 201, at 68.

produces the death of the legal subject or the emergence of new, algorithmic practices of signification that no longer require the input of the underlying individual.