

**BEYOND THE THREE LAWS:
AN ARGUMENT FOR REGULATING DATA
SCIENTISTS AS FIDUCIARIES**

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Cite as: William Goodrum & Jacqueline Goodrum, *Beyond the Three Laws: An Argument for Regulating Data Scientists as Fiduciaries*, 27 RICH. J.L. & TECH., no. 3, 2021.

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I. INTRODUCTION

[1] In the short story *Runaround*, science fiction author Isaac Asimov first introduced the world to an ethical framework for artificial intelligence known as the Three Laws of Robotics.¹ These laws state: (1) “a robot may not injure a human being or, through inaction, allow a human being to come to harm”; (2) “a robot must obey the orders given it by human beings except where such orders would conflict with the First Law”; and (3) “a robot must protect its own existence as long as such protection does not conflict with the First and Second Laws.”² On the surface, the Three Laws appear to provide a tidy regulatory framework for alleviating society’s concerns regarding how and when machines may adversely interact with humans, preventing harm or even death. These Three Laws are particularly appealing in our current time where robots and artificial intelligence are no longer the stuff of science fiction, but rather increasingly part of our everyday lives.³ Yet, society cannot rely on Asimov’s Three Laws of Robotics to provide a much-needed regulatory framework for artificial intelligence. These Laws are not only fictional, but also practically flawed because they place the legal, as well as the ethical,⁴ duties on the artificial intelligence and not on the actual intelligence—the human—behind the machine.⁵

[2] The current legal framework in the United States for artificial intelligence and machine learning (AI/ML) is little better, however. There

¹ ISAAC ASIMOV, *Runaround*, in *ASTOUNDING SCIENCE FICTION* (1942), reprinted in I, ROBOT 27 (1970).

² *Id.*

³ Jeremy Nolan, *A Look at Robots in Everyday Life*, BAIRESDEV (Nov. 27, 2019), <https://www.bairesdev.com/blog/everyday-life-robots/> [<https://perma.cc/J6Q5-B8XH>].

⁴ See ASIMOV, *supra* note 1.

⁵ Peter W Singer, *Isaac Asimov’s Laws of Robotics Are Wrong*, BROOKINGS (May 18, 2019), <https://www.brookings.edu/opinions/isaac-asimovs-laws-of-robotics-are-wrong/> [<https://perma.cc/GJV7-NTRS>].

is no federal regulatory regime specific to AI/ML.⁶ The federal government, as well as most state and local governments, have largely taken a hands-off approach to regulating AI/ML and the data on which these technologies rely.⁷ Only recently have federal, state, and local lawmakers begun to change course following a series of high-profile public failures of AI/ML.⁸ Such failures include Uber’s autonomous vehicle fatality⁹ bias in facial recognition technology,¹⁰ and wrongful arrests due to discrimination in predictive policing algorithms.¹¹ Even so,

⁶ See R. David Edelman, *Here’s How to Regulate Artificial Intelligence Properly* (Jan. 13, 2020, 6:00 AM), <https://www.washingtonpost.com/outlook/2020/01/13/heres-how-regulate-artificial-intelligence-properly/> [<https://perma.cc/63U8-GCC3>] (arguing that, while the White House recently provided some federal regulatory guidance, the federal government needs to craft “substantive, tailored AI policies that look at the ways these technologies are used in public contexts as well as private ones.”).

⁷ See Exec. Order No. 13859, 3 C.F.R. 3967 (2019); Lee Tiedrich & Nooree Lee, *AI Update: New York City, Vermont, and Other State and Local Governments Evaluating AI Trustworthiness*, COVINGTON (July 16, 2019), <https://www.insidetechnia.com/2019/07/16/ai-update-new-york-city-vermont-and-other-state-and-local-governments-evaluating-ai-trustworthiness/> [<https://perma.cc/32T3-BM6Z>].

⁸ See Karen Hao, *Congress Wants to Protect You From Biased Algorithms, Deepfakes, and Other Bad AI*, MIT TECH. REV. (Apr. 15, 2019), <https://www.technologyreview.com/2019/04/15/1136/congress-wants-to-protect-you-from-biased-algorithms-deepfakes-and-other-bad-ai/> [<https://perma.cc/D724-MGEK>].

⁹ ‘Inadequate Safety Culture’ Contributed to Uber Automated Test Vehicle Crash – NTSB Calls for Federal Review Process for Automated Vehicle Testing on Public Roads, N.T.S.B. (Nov. 19, 2019), <https://www.nts.gov/news/press-releases/Pages/NR20191119c.aspx> [<https://perma.cc/FD3R-GUSP>]; *Uber’s Self-Driving Operator Charged Over Fatal Crash*, BBC (Sept. 16, 2020), <https://www.bbc.com/news/technology-54175359> [<https://perma.cc/E36V-EECL>].

¹⁰ See Sigal Samuel, *Activists Want Congress to Ban Facial Recognition. So They Scanned Lawmakers’ Faces.*, VOX (Nov. 15, 2019, 10:10 AM), <https://www.vox.com/future-perfect/2019/11/15/20965325/facial-recognition-ban-congress-activism> [<https://perma.cc/HKE6-74TS>].

¹¹ 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/5SUX-2SGE>].

these laws and regulations are limited in scope, focusing on the technologies and ignoring their creators.¹²

[3] As such, current efforts to regulate AI/ML ultimately suffer from the same flaw as Asimov's Three Laws of Robotics because they fail to address the legal and ethical duties of the humans behind the machines: the data scientists.¹³ These quantitative experts, skilled in the use of statistical algorithms and computer programming for data analysis, are typically the humans programming the decision-support systems that use AI/ML algorithms to turn raw data into predictive insights, descriptive charts, or automated processes.¹⁴ Critically, data scientists are also responsible (though not as of yet liable) for harms that result as a consequence of AI/ML.¹⁵

¹² See, e.g., Angela Chen, *This is How You Kick Facial Recognition out of Your Town*, MIT TECH. REV. (Oct. 4, 2019), <https://www.technologyreview.com/2019/10/04/132745/facial-recognition-law-enforcement-surveillance-private-industry-regulation-ban-backlash/> [<https://perma.cc/GRV9-2SMW>] (discussing how laws and ordinances are primarily aimed at regulating *who* can use facial recognition technologies); Guidance for Regulation of Artificial Intelligence Applications, 85 Fed. Reg. 1825 (Jan. 13, 2020) (requesting comments on draft guidance documents, which focus on promoting advancements in technology and innovation).

¹³ See, e.g., Eric B. Krauss, *Autonomous Vehicles and Asimov's Three Laws of Robotics*, LEXOLOGY (Nov. 8, 2016), <https://www.lexology.com/library/detail.aspx?g=98545a46-ed6a-49da-9cc8-09c27899de71> [<https://perma.cc/T6UQ-SRRA>] (focusing on technology, as opposed to its creators, by asserting how Tesla technology "should function effectively to protect humans from harm to the fullest extent possible" to comply with Asimov's First Law of Robotics).

¹⁴ See Sayantan Dasgupta, *CMOs, Predict Your Wins With AI and Predictive Analysis*, ENTREPRENEUR INDIA (Nov. 02, 2020), <https://www.entrepreneur.com/article/358890> [<https://perma.cc/87YJ-9XHX>].

¹⁵ See generally *What is Data Science?*, CODECADEMY (Oct. 22, 2020), https://news.codecademy.com/what-is-data-science/?utm_source=ccblog&utm_medium=ccblog&utm_content=what_does_a_ds_do [<https://perma.cc/8EL2-3EM5>] (discussing how data scientists "may build and tune machine learning models to make predictions or find patterns in data" and use "data to gain insight into areas of marketing, research, and development"); Mari-Sanna Paukeri, *AI and Ethics: Time to Talk About Responsibility*, THE DRUM (Mar. 11, 2020, 12:03 PM), <https://www.thedrum.com/industryinsights/>

[4] Yet, the lack of regulatory oversight of data scientists and their work means these experts often are not held accountable for the negative impacts of bad, biased, or discriminatory algorithms that they have developed or trained. Although the law offers possible remedies in certain scenarios, such as equal protection for racist predictive policing algorithms,¹⁶ AI/ML demands the development of new regulations because AI/ML are advanced technologies that promise to transform every facet of society and existing law is ill equipped to address the full ramifications of this.¹⁷ If the law is to truly regulate AI/ML to protect the public, then such laws must also expressly regulate data scientists.

[5] The idea of regulating expert professions is not novel; doctors, lawyers, and accountants are examples of professionals regulated externally by the government or internally by members of the profession itself.¹⁸ Presently, data scientists have neither external governmental regulation nor internal professional self-regulation.¹⁹ The profession lacks

2020/03/11/ai-and-ethics-time-talk-about-responsibility [https://perma.cc/VCC2-4LWY] (outlining three responsible parties for AI tools and products, including AI model and product developers).

¹⁶ Renata M. O'Donnell, Note, *Challenging Racist Predictive Policing Algorithms Under the Equal Protection Clause*, 94 N.Y.U. L. REV. 544, 564, 566–67 (2019).

¹⁷ See, e.g., Aarian Marshall, *Why Wasn't Uber Charged in a Fatal Self-Driving Car Crash?*, WIRED (Sept. 17, 2020, 2:55 PM), <https://www.wired.com/story/why-not-uber-charged-fatal-self-driving-car-crash/> [https://perma.cc/9K8N-36VU] (discussing how criminal negligence charge against Uber's safety driver for "distracted driving" is easier for a jury to understand than "more complicated story about how driverless cars work and what Uber did wrong").

¹⁸ See generally VA. CODE ANN. § 54.1-3900 (2020) (regulating practice of law in Virginia); VA. CODE ANN. § 54.1-2400 (2020) (regulating practice of medicine in Virginia); MODEL RULES OF PRO. CONDUCT (AM. BAR ASS'N 2020) (outlining self-governing ethical code of conduct for lawyers); CODE OF MEDICAL ETHICS PmbI. (AM. MEDICAL ASS'N 2016) (outlining self-governing ethical code for physicians).

¹⁹ Cf. RoseTechnologies, *Should Data Science Become a Profession?*, YOUTUBE (Apr. 10, 2013), https://www.youtube.com/watch?feature=player_embedded&v=67TEgYBQBbo [https://perma.cc/GN6W-LBEM] (discussing why self-regulation would be beneficial to data scientists and why the government should not be left in charge of

a common code of conduct, adheres to no agreed standards of best practice, and has no requirements for competency as the law expects of other professions that carry equivalent power to affect individuals and society.²⁰

[6] This article argues for regulating data scientists as fiduciaries and illustrates how this model would address legal and ethical issues that data scientists face in current practice. This article begins by briefly explaining the practice of data science and situating it in the context of the ongoing data revolution. Next, this article discusses common legal and ethical issues that arise in data science practice, including issues of privacy, bias, informed consent, and lack of data literacy. Finally, this article outlines a regulatory model for fiduciary data science, explaining why the law should recognize data scientists as information fiduciaries and why such regulation is necessary for a robust data regulatory regime. For these reasons, regulating data science practitioners is a necessary next step to ensure a robust data regulatory regime.²¹

making these regulations).

²⁰ See Jesse Freeman, *Is It Time for a Data Scientist Code of Ethics?*, MEDIUM (June 28, 2019), <https://towardsdatascience.com/is-it-time-for-a-data-scientist-code-of-ethics-210b4f987a8> [<https://perma.cc/KRK4-UFDK>] (“And while a google search for ‘data scientist code of ethics’ returns results, the fact that there is no single truth is something we need to address before it’s too late.”); Usama Fayyad & Hamit Hamutcu, *Toward Foundations for Data Science and Analytics: A Knowledge Framework for Professional Standards*, HARV. DATA SCI. REV., June 2020, at 3–4, <https://hdr.mitpress.mit.edu/pub/6wx0qmkl/release/3> [<https://perma.cc/9XSU-6XNF>] (discussing a need for standards and defined competency for data scientists); see, e.g., MODEL RULES OF PRO. CONDUCT r. 1.1 (AM. BAR ASS’N 2020) (providing the competency requirements for attorneys).

²¹ *Universal Principles of Data Ethics: 12 Guidelines for Developing Ethics Codes*, ACCENTURE, 2016, at 2, https://www.accenture.com/_acnmedia/pdf-24/accenture-universal-principles-data-ethics.pdf [<https://perma.cc/7RE9-MLRJ>] (“This is why establishing a shared set of norms is critically important for data scientists and practitioners (and those making requests of them).”).

II. BACKGROUND

A. What is Data Science?

[7] “Data science,” which includes “data mining,” refers to the practice of learning quantitative patterns from empirical data to inform decision-making.²² Data science lies at the intersection of computer science, statistics, and information theory.²³ In typical practice, data scientists may use “past information to construct patterns based not solely on the input data, but also the *logical consequences* of those data.”²⁴ Data science developed in part out of a book on “exploratory data analysis” published by John W. Tukey in the late 1970s.²⁵ Tukey’s framework analyzing empirical data brought acceptability within the field of statistics to a graphical approach to data analysis that emphasized elucidating patterns from data.²⁶ Statisticians generally had considered such analysis

²² See Leonard Heller, *Difference of Data Science, Machine Learning and Data Mining*, TECHTARGET (Mar. 20, 2017, 10:30 AM), <https://www.datasciencecentral.com/profiles/blogs/difference-of-data-science-machine-learning-and-data-mining> [<https://perma.cc/2DDP-J9EB>] (“Data science is an umbrella for several techniques... used for extracting the information and the insights of data.”); see also *Data Mining: What Is It & Why It Matters*, SAS, https://www.sas.com/en_us/insights/analytics/data-mining.html [<https://perma.cc/38BJ-9X3D>] (“Data mining is the process of finding anomalies, patterns and correlations within large data sets to predict outcomes.”).

²³ Alex Castrounis, *What is Data Science, and What Does a Data Scientist Do?*, INNOARCHITECH (Sep 02, 2020), <https://www.innoarchitech.com/blog/what-is-data-science-does-data-scientist-do> [<https://perma.cc/4ZL3-53QF>].

²⁴ ROBERT NISBET ET AL., *HANDBOOK OF STATISTICAL ANALYSIS & DATA MINING APPLICATIONS* 19 (2009).

²⁵ See generally JOHN W. TUKEY, *EXPLORATORY DATA ANALYSIS* (Frederick Mosteller ed., 1977) (providing techniques for data analysis).

²⁶ See NAT’L INST. OF STANDARDS & TECH., *NIST/SEMATECH E-HANDBOOK OF STATISTICAL METHODS* § 1.1.1 (2013), <https://www.itl.nist.gov/div898/handbook/index.htm> [<https://perma.cc/5WEH-5PKF>] (explaining that “EDA is an approach to data analysis that postpones the usual assumptions about what kind of model the data follow with the more direct approach of allowing the data itself to reveal its underlying structure and model.”)

to be inverse to traditional statistics practice because these methods did not assume *a priori* idealized distributions of data as in classical statistics.²⁷ Similarly, academic work performed by Trevor Hastie, Robert Tibshirani, and Jerome Friedman provided the foundation for many of the algorithmic methods currently employed by data scientists to model data in order to quantifiably represent patterns in data, classify observations, or predict future events.²⁸ These algorithms either: (1) help elucidate structure in data when no outcome is known; or (2) predict the likelihood of an outcome when it is known.²⁹ The former is known as “unsupervised learning,” the latter is called “supervised learning.”³⁰ For example, when data scientists use algorithms to identify customer segments in historical sales data, this is an unsupervised learning problem.³¹ If the data scientists instead train algorithms to predict the likelihood that customers will purchase a given item, that is a supervised learning problem based on past purchase history.³² Regardless of the exact type of analysis, the goal of any good data science effort should be to inform decision making.³³

²⁷ *See id.* at § 1.1.2.1.

²⁸ *See generally* TREVOR HASTIE ET AL., THE ELEMENTS OF STATISTICAL LEARNING: DATA MINING, INFERENCE, AND PREDICTION xi–xii (2d ed., 12th prtg. 2017), https://web.stanford.edu/~hastie/ElemStatLearn/printings/ESLII_print12_toc.pdf [<https://perma.cc/K8KQ-UELD>] (explaining the authors’ efforts to adapt the fields of computer science and engineering to statistical analysis).

²⁹ *Id.* at 2.

³⁰ *Id.*

³¹ Semih Yagcioglu, *Classical Examples of Supervised vs. Unsupervised Learning in Machine Learning*, SPRINGBOARD BLOG (May 18, 2020), <https://www.springboard.com/blog/lp-machine-learning-unsupervised-learning-supervised-learning/> [<https://perma.cc/L92N-TRGH>].

³² Romain Warlop, *Machine Learning in a Nutshell – Part 2: Predicting Future Behaviour Based on Past Data, with Supervised Learning*, 55 THE TEA HOUSE (Feb. 3, 2018), <https://teahouse.fifty-five.com/en/machine-learning-in-a-nutshell-part-2-predicting-future-behaviour-based-on-past-data-with-supervised-learning/> [<https://perma.cc/8FWJ-LVH4>].

³³ *See* ANDREW FAST & JOHN ELDER, ELDER RESEARCH, THE TEN LEVELS OF ANALYTICS

[8] Generally in current practice, the data science process consists of four steps: (1) data exploration, (2) data preparation, (3) modeling (when AI/ML algorithms are trained on historical data), and (4) data visualization.³⁴ Data exploration is the process of exploratory analysis during which data scientists learn about the characteristics of a dataset by inspecting it graphically to see if any interesting features exist.³⁵ This is typically done by looking at plots of data to see how the data distribute visually, or how they may or may not correlate with one another.³⁶ Data preparation involves extracting data from its locations in raw storage databases, then transforming or summarizing the data in a new way to prepare it for analysis by a modeling algorithm.³⁷ Modeling involves passing the prepared dataset into a mathematical equation or algorithm and finding the optimal parameters that best “trains” the algorithm to identify relevant patterns in the given data.³⁸ Finally, the product of data science efforts frequently require visualization to convey important findings to an audience other than the data scientist who performed the analysis.³⁹ Such visuals commonly take the form of charts or dashboards that graphically

2–3 (2015) (ebook), http://www.miningyourownbusiness.com/wb/img/Elder_Research_eBook_The_Ten_Levels_of_Analytics.pdf [<https://perma.cc/7X45-32TR>].

³⁴ See PETE CHAPMAN ET AL., SPSS, CRISP-DM 1.0: STEP-BY-STEP DATA MINING GUIDE 12 (2000) [hereinafter CRISP-DM] <https://www.the-modeling-agency.com/crisp-dm.pdf> [<https://perma.cc/H45X-PXQ9>].

³⁵ See *id.* at 18.

³⁶ See NAT’L INST. FOR STANDARDS AND TECH., ENGINEERING STATISTICS HANDBOOK § 1.1.4 <https://www.itl.nist.gov/div898/handbook/eda/section1/eda14.htm> [<https://perma.cc/683Y-XCN2>] (explaining goals of good exploratory data analysis).

³⁷ CRISP-DM, *supra* note 34, at 20–21.

³⁸ See *id.* at 24.

³⁹ See generally Scott Berinato, *Visualizations That Really Work*, HARV. BUS. REV., June 2016, <https://hbr.org/2016/06/visualizations-that-really-work> [<https://perma.cc/Y8SU-QPCB>] (stating that, without visualization, understanding data that “comes at us with such overwhelming velocity, and in such volume” would be “an impossible slog”).

convey information about the data and expected outcomes.⁴⁰ This visual presentation of information is necessary for both data science-trained and lay audiences alike to make informed decisions based upon the evidence in data.

B. The “Big Data” Revolution

[9] The fundamental methods employed by data scientists have existed for decades. Yet, it has only been since the advent of massive computing power and cheap storage systems that people have been able to analyze large datasets efficiently and accurately.⁴¹ These technological changes in the 2000s sparked the “Big Data” revolution, producing the data science field that currently exists today.⁴² Notably, computational problems that were difficult and time consuming as recently as the mid-1990s can now easily be completed within weeks if not days thanks to high-performance computing.⁴³ Such technological changes, in conjunction with the Internet revolution of the 21st century, led businesses to demand new analytical capabilities to capitalize on the market opportunities in information.⁴⁴ “The crushing practical needs of businesses to extract knowledge from data that could be leveraged immediately to increase revenues required

⁴⁰ See *Data Visualization Beginner's Guide: a Definition, Examples, and Learning Resources*, TABLEAU, <https://www.tableau.com/learn/articles/data-visualization> [<https://perma.cc/3TB9-9JUG>] (explaining how best to visualize data); see also EDWARD R. TUFTÉ, *THE VISUAL DISPLAY OF QUANTITATIVE INFORMATION* 13 (2d ed. 2006) (stating “[g]raphics reveal data”).

⁴¹ David Donoho, *50 Years of Data Science, Presentation at Tukey Centennial Workshop*, Sept. 2015, at 5, <https://courses.csail.mit.edu/18.337/2015/docs/50YearsDataScience.pdf> [<https://perma.cc/U6QY-K5CL>]

⁴² See Andrew McAfee & Erik Brynjolfsson, *Big Data: The Management Revolution*, HARV. BUS. REV. (Oct. 2012), <https://hbr.org/2012/10/big-data-the-management-revolution> [<https://perma.cc/7BDX-TNQF>].

⁴³ See generally ALTERA, *ACCELERATING HIGH-PERFORMANCE COMPUTING WITH FPGAS* 4 (2007) (demonstrating possible computer hardware acceleration factors for various software application benchmarks using modern graphical processing units (GPUs)).

⁴⁴ See McAfee & Brynjolfsson, *supra* note 42.

new analytical techniques that enabled analysis of highly nonlinear relationships in very large data sets with an unknown distribution.”⁴⁵ As a result, data science has exploded rapidly into an industry of economic and practical significance.⁴⁶ For example, prior to 2010 “data science” was hardly a search term in Google.⁴⁷ Since then, however, its use has grown steadily, doubling in search interest in each subsequent year from 2010-2019.⁴⁸ A similar trend is visible in Google searches for data science as a field of study.⁴⁹

[10] The explosive growth of the data science industry is also reflected in changes within organizational or corporate structures. In 2012, only 12% of financial services, healthcare, and other large industrial firms reported appointing a Chief Data Officer.⁵⁰ By 2017, that number had increased to 55.9%.⁵¹ Moreover, in 2018, 97.2% of all respondents to the NewVantage Partners survey, an annual survey of the current state of data science in business, reported investing heavily in advanced analytics talent, projects, or technology.⁵² McKinsey Global Institute estimates that the global market for data science could be as much as \$15.4 trillion including traditional industries such as retail, transport and logistics,

⁴⁵ NISBET ET AL., *supra* note 24, at 11.

⁴⁶ See, e.g., MCKINSEY ANALYTICS, ANALYTICS COMES OF AGE 3 (2018).

⁴⁷ See Google Searches for Term “Data Science”, GOOGLE, <https://trends.google.com/trends/explore?date=all&geo=US&q=Data%20science> [<https://perma.cc/TB6D-VJ96>].

⁴⁸ *Id.*

⁴⁹ See Google Searches for Field of Study “Data Science”, GOOGLE, https://trends.google.com/trends/explore?date=all&q=%2Fm%2F0jt3_q3 [<https://perma.cc/EYS6-BGUX>].

⁵⁰ See NEWVANTAGE PARTNERS, BIG DATA AND AI EXECUTIVE SURVEY 2019 6, 14 (2019).

⁵¹ *Id.*

⁵² *Id.* at 4.

consumer packaged goods, and manufacturing.⁵³

[11] Such growth is not limited to the private sector. Increasingly, federal government agencies are funding the research and development of technologies and capabilities related to data science.⁵⁴ This is reflected in both major contract awards as well as in grant funding.⁵⁵ For example, the Department of Defense recently created a Joint Artificial Intelligence Center (JAIC) responsible for vetting AI/ML contracts over \$15 million, which suggests a sufficient number of contracts exist to warrant their own interdepartmental center for review.⁵⁶ Also recently, the Department of Health and Human Services split a \$49 million contract for automation services between 57 small and large businesses as part of an agency-wide effort to adopt AI/ML in their operations.⁵⁷ Most recently, the General Services Administration (GSA) began a community of practice for AI to support standardizing AI/ML processes and adoption across federal agencies. This ‘community of practice’ is an interagency working group composed of government data science experts who the GSA hopes will

⁵³ MICHAEL CHUI ET AL., NOTES FROM THE AI FRONTIER: INSIGHTS FROM HUNDREDS OF USE CASES 17–18, 20 (2018), <https://www.mckinsey.com/~media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Notes%20from%20the%20AI%20frontier%20Applications%20and%20value%20of%20deep%20learning/Notes-from-the-AI-frontier-Insights-from-hundreds-of-use-cases-Discussion-paper.pdf> [<https://perma.cc/7XEM-CP27>].

⁵⁴ See, e.g., Aaron Boyd, *HHS Splits \$49M AI, Automation Contract Evenly Between Small, Large Businesses*, NEXTGOV (May 31, 2019), <https://www.nextgov.com/emerging-tech/2019/05/hhs-splits-49m-ai-automation-contract-evenly-between-small-large-businesses/157390/> [<https://perma.cc/GVT2-BHNR>] (reporting on federal government contract award to fund robotic process automation tools).

⁵⁵ See, e.g., Tom Simonite, *The Pentagon Doubles Down on AI—and Wants Help from Big Tech*, WIRED (Feb. 12, 2019, 7:30 PM), <https://www.wired.com/story/pentagon-doubles-down-ai-wants-help-big-tech/> [<https://perma.cc/5YR4-R52R>] (highlighting Department of Defense’s recently created Joint Artificial Intelligence Center (JAIC)).

⁵⁶ *Id.*

⁵⁷ Boyd, *supra* note 54.

share and communicate best practices and successful efforts in AI/ML across traditional organization barriers.⁵⁸

[12] The explosive growth of the data science industry has created intense demand from business, government, academic, and even non-profit organizations for a class of professionals equipped with the knowledge and skills necessary to do data science work.⁵⁹ Masters' Degrees, certification programs, and executive training courses have multiplied to meet this burgeoning demand.⁶⁰ Most major universities now offer some form of a Master in Analytics or Masters in Data Science degree.⁶¹ Graduates of these programs currently command some of the highest starting salaries outside of the traditional professions, meaning data science talent is in exceptionally high-demand.⁶² Not surprisingly, in 2019 Forbes named Data Scientist “the hottest job” of the year for the fourth straight year.⁶³

⁵⁸ Steven Babitch, *GSA Launches Artificial Intelligence Community of Practice*, GSA BLOG (Nov. 5, 2019), <https://www.gsa.gov/blog/2019/11/05/gsa-launches-artificial-intelligence-community-of-practice> [<https://perma.cc/GV8G-3YFT>].

⁵⁹ Fayyad & Hamutcu, *supra* note 20, at 2.

⁶⁰ See Marc Parry, *Data Scientists in Demand*, THE CHRON. OF HIGHER EDUC. (Mar. 4, 2018), <https://www.chronicle.com/article/Colleges-Rush-to-Ride/242674> [<https://perma.cc/MYK7-6ZWH>] (discussing boom in data science programs at colleges and universities).

⁶¹ See *id.*

⁶² See *Data Scientist Salaries*, GLASSDOOR, https://www.glassdoor.com/Salaries/data-scientist-salary-SRCH_KO0,14.htm [<https://perma.cc/CXN2-E89Q>] (explaining that the national average salary for a Data Scientist is approximately \$115,000 in the United States and that salaries range from approximately \$85,000 to \$154,000); *Senior Data Scientist Salaries*, GLASSDOOR, https://www.glassdoor.com/Salaries/senior-data-scientist-salary-SRCH_KO0,21.htm [<https://perma.cc/A7UQ-MHLL>] (explaining that the national average salary for a Senior Data Scientist is approximately \$134,000 in the United States and that salaries range from approximately \$100,000 to \$181,000).

⁶³ Louis Columbus, *Data Scientist Leads 50 Best Jobs in America for 2019 According to Glassdoor*, FORBES (Jan. 23, 2019, 12:10 AM), <https://www.forbes.com/sites/louiscolombus/2019/01/23/data-scientist-leads-50-best-jobs-in-america-for-2019-according-to-glassdoor/?sh=2db41a177474> [<https://perma.cc/6GNN-SPQE>].

C. The Promise & Pervasiveness of Data Science

[13] Technologically, society has entered a new era in information with the rise of data science. Data science is driving changes across industry, academia, and the public sector.⁶⁴ Data science, specifically its encompassed deep-learning technologies of AI/ML, promises to revolutionize nearly any human endeavor.⁶⁵ This perception exists due to several high-profile successes of such algorithms performing tasks previously associated only with human achievement.⁶⁶ For example, Alphabet's AlphaGo algorithm recently defeated a human player in the Chinese board game Go, achieving a victory that even five years ago seemed unfathomable to computer scientists and expert players alike.⁶⁷ Relatedly, IBM's Watson artificial intelligence system successfully diagnosed a rare form of cancer that had evaded traditional oncological diagnosis.⁶⁸ High profile successes like these increase interest in and

⁶⁴ See Prasad Kothari, *Data Science is Changing the World for the Better: Here's How*, INSIDE BIG DATA (Apr. 14, 2020), <https://insidebigdata.com/2020/04/14/data-science-is-changing-the-world-for-the-better-heres-how/> [<https://perma.cc/JE55-MVFQ>].

⁶⁵ See Michael Evans, *The Machine Learning Revolution: How Artificial Intelligence Could Transform Your Business*, FORBES (Oct. 20, 2018, 11:15 AM), <https://www.forbes.com/sites/allbusiness/2018/10/20/machine-learning-artificial-intelligence-could-transform-business/?sh=d691320c6c3a> [<https://perma.cc/7EDB-TZBY>].

⁶⁶ See Sara Harrison, *AI May Not Kill Your Job – Just Change It*, WIRED (Oct. 31, 2019, 8:00 AM), <https://www.wired.com/story/ai-not-kill-job-change-it/> [<https://perma.cc/8VMF-482N>].

⁶⁷ See Hamza Shaban, *Google's AlphaGo Defeats World's Best Go Player – Again*, WASH. POST (May 26, 2017, 2:53 PM), <https://www.washingtonpost.com/news/innovations/wp/2017/05/26/googles-alphago-beats-the-worlds-best-go-player-again/> [<https://perma.cc/ZQ28-8DVJ>].

⁶⁸ Sam Brusco, *IBM's Watson Diagnosed a Rare Condition that Left Doctors Stumped*, MPO (Aug. 8, 2016), https://www.mpo-mag.com/contents/view_online-exclusives/2016-08-08/ibms-watson-diagnosed-a-rare-condition-that-left-doctors-stumped/#:~:text=According%20to%20Japanese%20NHK%20News,wasn't%20responding%20to%20treatment [<https://perma.cc/XS32-MP2X>].

demand for data-based solutions for previously insoluble problems.⁶⁹

[14] However, while these successes demonstrate the exciting potential of AI/ML, this success is limited in general applicability to other fields. An algorithm can achieve superhuman performance in a game like Go because it operates in a constrained universe of rules and outcomes in which the algorithm must make decisions (even if the universe is a complicated one).⁷⁰ Watson succeeded initially in diagnosing a rare form of cancer because data scientists trained it on extensive corpus of historical oncological treatments and outcomes related to that particular form of cancer.⁷¹ By contrast, an algorithm struggles to make decisions when operating in an open-ended universe, such as an urban environment.⁷² Autonomous vehicles are one example of this challenge. While humans and machines can both learn “the rules of the road,” machines lack the ability to infer the myriad unexpected hazards (or, in computer science terminology, “edge cases”) that arise around a road.⁷³ Data scientists must

⁶⁹ See Jeffrey D. Camm et al., *The Recession’s Impact on Analytics and Data Science*, MIT SLOAN MGMT. REV. (June 16, 2020), <https://sloanreview.mit.edu/article/the-recessions-impact-on-analytics-and-data-science/> [<https://perma.cc/WLJ4-KPPQ>].

⁷⁰ David Silver et al., *Mastering the Game of Go Without Human Knowledge*, 550 NATURE 354, 354 (Oct. 19, 2017) (explaining how AlphaGo learned to play Go by using reinforcement learning algorithm).

⁷¹ Eliza Strickland, *How IBM Watson Overpromised and Underdelivered on AI Health Care*, IEEE SPECTRUM (Apr. 2, 2019, 3:00 PM), <https://spectrum.ieee.org/biomedical/diagnostics/how-ibm-watson-overpromised-and-underdelivered-on-ai-health-care> [<https://perma.cc/5EAK-K9LT>] (acknowledging Watson’s overall performance in the clinical space—even in oncology— has lagged behind IBM’s lofty predictions significantly and has failed to generalize across regions).

⁷² See Symposium, *Safety Critical Systems Symposium*, Safety Critical Systems Club (2019), available at https://users.ece.cmu.edu/~koopman/lectures/Koopman19_SSS_slides.pdf [<https://perma.cc/94R2-AFMD>] (presentation of Prof. Philip Koopman outlining “edge cases,” which are unusual circumstances, occurring in the urban setting of a public road).

⁷³ See *id.* (describing edge cases, including illustrative examples of unexpected road users, such as a fighter jet taxiing on a public highway, and a person crossing a road in a chicken suit)

expose AI/ML algorithms to exact, discrete examples of different hazards in training data to “know” them in advance.⁷⁴ It is not possible for even the best data scientist (or team of data scientists) to envision *all* possible hazards that an autonomous vehicle may encounter when driving down a road, no matter how thoughtful or safety-minded.⁷⁵ Recent, high profile, fatal traffic accidents involving Tesla’s autopilot and Uber’s self-driving mode both resulted due to failure of the autonomous driving AI to recognize hazards that a normal human driver would have correctly identified.⁷⁶ The Tesla Model S, operating on autopilot, crashed into a parked fire truck.⁷⁷ Notably, “[t]he fire truck was deliberately stopped in the lane. It angled itself slightly so it would not look like it was actually using the lane, making it clear, to humans at least, that it was deliberately closing the lane.”⁷⁸ In the Uber case, its self-driving car fatally struck a

⁷⁴ See Philip Koopman et al., *Credible Autonomy Safety Argumentation*, SAFETY CRITICAL SYSTEMS CLUB, Feb. 2019, at 397 (“Rather, it is simply free of the bugs that the test suite knows how to find, leaving the system exposed to bugs that might involve only very subtle differences from the test suite.”).

⁷⁵ See *id.* at 395.

⁷⁶ See Tom Krisher, *3 Crashes, 3 Deaths Raise Questions About Tesla’s Autopilot*, ABC NEWS (Jan. 3, 2020), <https://abcnews.go.com/US/wireStory/crashes-deaths-raise-questions-teslas-autopilot-68045418> [<https://perma.cc/93MB-ZP9Z>] (reporting that Tesla’s autopilot driving system has played a role in a few fatal accidents); see also Richard Gonzales, *Feds Say Self-Driving Uber SUV Did Not Recognize Jaywalking Pedestrian In Fatal Crash*, NPR (Nov. 7, 2019), <https://www.npr.org/2019/11/07/777438412/feds-say-self-driving-uber-suv-did-not-recognize-jaywalking-pedestrian-in-fatal-> [<https://perma.cc/2C87-N2NP>] (reporting that a self-driving Uber collided with and killed a pedestrian when it did not recognize her).

⁷⁷ See Ethan Baron, *Tesla ‘on Autopilot’ Slams into Parked Fire Truck on California Freeway*, MERCURY NEWS (Jan. 22, 2018), <https://www.mercurynews.com/2018/01/22/tesla-on-autopilot-slams-into-parked-fire-truck-on-freeway/> [<https://perma.cc/EVU4-T45X>] (reporting that the Tesla Model S ran into the back of a firetruck parked at an accident).

⁷⁸ Brad Templeton, *NTSB Report on Tesla Autopilot Shows What Happened and It’s Not Pretty for FSD*, FORBES (Sept. 6, 2019), <https://www.forbes.com/sites/bradtempleton/2019/09/06/ntsb-report-on-tesla-autopilot-accident-shows-whats-inside-and-its-not-pretty-for-fsd/?sh=604d3da44dc5>. [<https://perma.cc/H6YP-XLX9>].

pedestrian walking a bicycle across a street; a hazard familiar to any human driver accustomed to driving in an urban environment.⁷⁹

[15] Deep-learning data science technologies offer exciting possibilities and are driving innovative pursuits, like NASA's Mars Perseverance Rover. However, it is data science's more mundane applications that is allowing the technologies to permeate everyday life. In this way, data science revolutionizes everything from journalism, to marketing, to civic governance.⁸⁰ Some data science's more visible applications include, but are not limited to: predictive policing used to prioritize routing and staffing for urban police departments;⁸¹ automated diagnostic assistants for radiological diagnosis;⁸² data-driven human resources solutions for screening job applicants;⁸³ self-driving vehicle technology;⁸⁴ and personal virtual assistants (e.g., Siri or Alexa) that incorporate advanced speech recognition algorithms.⁸⁵ Data science is

⁷⁹ See Phil McCausland, *Self-Driving Uber Car That Hit and Killed Woman Did Not Recognize That Pedestrians Jaywalk*, NBC NEWS (Nov. 9, 2019), <https://www.nbcnews.com/tech/tech-news/self-driving-uber-car-hit-killed-woman-did-not-recognize-n1079281> [<https://perma.cc/65DD-TBZA>] (reporting that the self-driving Uber hit the pedestrian as she was crossing the street with her bicycle).

⁸⁰ See DEEP INDEX, <https://deepindex.org/> [<https://perma.cc/3TGJ-8SNP>] (monitoring a wide variety of AI activities).

⁸¹ See WALTER L. PERRY, ET AL., RAND CORP., PREDICTIVE POLICING: THE ROLE OF CRIME FORECASTING IN LAW ENFORCEMENT OPERATIONS 14 (2013) (detailing how predictive policing can help police departments determine which areas need increased police patrol).

⁸² Ahmed Hosny et al., *Artificial Intelligence in Radiology*, 18 Nature Rev. Cancer 500 (Aug. 2018).

⁸³ Rebecca Heilweil, *Artificial Intelligence Will Help Determine if you get Your Next job*, VOX: RECODE (Dec. 12, 2019), <https://www.vox.com/recode/2019/12/12/20993665/artificial-intelligence-ai-job-screen> [<https://perma.cc/VEL9-EGMD>].

⁸⁴ *Self-Driving cars Explained*, UNION OF CONCERNED SCIENTISTS (Feb. 21, 2018), <https://www.ucsusa.org/resources/self-driving-cars-101> [<https://perma.cc/H3VQ-9QZD>].

⁸⁵ See Bernadette Johnson, *How Siri Works*, HOWSTUFFWORKS.COM (Feb. 6, 2013),

becoming a part of everyday life whether or not we realize it.

III. ISSUES WITH DATA SCIENCE IN CURRENT PRACTICE

A. The Problem with Data Scientists

[16] As data scientists apply automated AI/ML technologies to new sectors of society, there will hardly be a job, role, function, or industry left untouched by data science in the next decade.⁸⁶ However, this also means that the algorithmic models data scientists produce will be utilized further and further from the highly-numerate environments of their computer science origins. Such models stand to have increasingly broader impacts on society, both positive and negative.⁸⁷ Presently, however, data scientists are not required—either by law or by their profession—to consider such impacts.⁸⁸ There are no laws that explicitly regulate the practice of data science.⁸⁹ This means that neither data scientists nor their employers are held civilly (or, if applicable, criminally) liable for harm resultant from their AI/ML technologies.⁹⁰ While some existing laws might offer relief to

<https://electronics.howstuffworks.com/gadgets/high-tech-gadgets/siri1.htm>
[<https://perma.cc/VSU8-76MV>].

⁸⁶ See Nicolaus Henke et. al, *The Age of Analytics: Competing in a Data-Driven World*, McKinsey Glob. Inst., 1 (Dec. 2016) (“Data and analytics have altered the dynamics in many industries, and change will only accelerate as machine learning and deep learning develop capabilities to think, problem-solve, and understand language.”).

⁸⁷ See *id.*

⁸⁸ See Michael A. Walker, *The Professionalisation of Data Science*, 1 INT. J. DATA SCIENCE 7 (2015).

⁸⁹ See *id.* at 9–10.

⁹⁰ See, e.g., NAT’L TRANSP. SAFETY BD., *HWY18MH010*, VEHICLE AUTOMATION REPORT 7–8 (2019) (finding that Uber had not trained the autonomous vehicle model to recognize jaywalking pedestrians as a hazard, meaning that vehicle did not recognize the woman walking her bicycle across the road outside of crosswalk, thereby striking and killing her).

victims of bad, malicious, or just plain negligent data science, this is a patchwork solution.⁹¹ Data science is too significant an industry and its technologies too powerful for legislators to continue to ignore the people behind the machines.

[17] Government, however, is not solely to blame for the lack of oversight of data scientists. The data science profession itself lacks self-regulation.⁹² There is no standard training for one to become a data scientist, meaning competency varies across the field.⁹³ Moreover, there are no uniform competency requirements for practitioners, meaning there is neither quality control of the individuals doing data science work or the models they produce.⁹⁴ The data science profession also lacks a common code of ethical conduct for its practitioners.⁹⁵ This means that employers have no consistent basis for assessing—nor any grounds for assuming—ethical practice in the work produced by their data scientists. It also means that society cannot rely on data scientists to monitor their peers as there are no standards to which to hold one accountable.⁹⁶ “Where is the code of

⁹¹ See, e.g., Equal Credit Opportunity Act, 15 U.S.C. § 1691 (2020) (prohibiting creditors, who often use algorithmic models to inform lending decision, from discriminating against applicants in credit lending practices).

⁹² See Walker, *supra* note 88, at 7, 9.

⁹³ See *Data Science Certificates in 2020 (Are They Worth It?)*, DATAQUEST (July 6, 2020), <https://www.dataquest.io/blog/data-science-certificate/> [<https://perma.cc/GJZ6-RTPK>].

⁹⁴ See Michael Brooks, *GDPR Implications for Data Science*, SLALOM TECHNOLOGY (Feb. 27, 2019), <https://medium.com/slalom-technology/gdpr-implications-for-data-science-342229c62aea> [<https://perma.cc/4F3B-8RJK>].

⁹⁵ See Daphne Leprince-Ringuet, *Data Scientists are Used to Making up the Rules. Now They're Getting Some of Their Own*, ZDNET (July 27, 2020), <https://www.zdnet.com/article/data-scientists-are-creating-the-hidden-rules-of-the-world-but-how-do-we-know-they-are-up-to-the-job/> [<https://perma.cc/C79M-HCNQ>] (noting that “while organizations have been pulling together ethics committees and writing up white papers on the rules that should govern the use of data, not much [has been] done at the individual level” to regulate data scientists).

⁹⁶ See *id.*

ethics in the [data science] field for what gets built and what doesn't? To what would a young [data scientist] turn to [to make such decisions]? Who gets to use these sophisticated systems and who doesn't?"⁹⁷ Consequently, the lack of both external government regulation and internal professional regulation of data sciences makes the possibility of ethical quandaries and legal violations increasingly likely.

B. Common Legal & Ethical Issues in Data Science Practice

[18] Importantly, as the technological growth of data science continues to rapidly outpace the development of laws which ought to regulate it, numerous legal and ethical issues arise.⁹⁸ Data scientists have little guidance on how to address these issues in practice.⁹⁹ The majority of legal and ethical issues that data scientists face in everyday practice include, but are not limited to: (1) data privacy and protection; (2) informed consent; (3) bias (of both outcomes and data); and (4) a lack of data literacy in the general population.¹⁰⁰ The sections below unpack each of these issues in more detail and provide examples of the harm posed by the lack of professional regulation.

1. Data Privacy & Protection

⁹⁷ Singer, *supra* note 5.

⁹⁸ See *AI in 2018: A Year in Review*, AI NOW INSTITUTE (Oct. 24, 2018), <https://medium.com/@AINowInstitute/ai-in-2018-a-year-in-review-8b161ead2b4e> [<https://perma.cc/26A2-EPHF>] (showing timeline of AI news events, many of which also raised legal concerns, including Cambridge Analytica scandal, self-driving Uber car killing pedestrian, EU implementing GDPR, and Facebook security breach exposing 50 million users' information).

⁹⁹ See *id.*

¹⁰⁰ Hokke S, Hackworth NJ, Quin N, Bennetts SK, Win HY, Nicholson JM, et al., *Ethical Issues in Using the Internet to Engage Participants in Family and Child Research: A Scoping review*, PLOS ONE 13(9): e0204572 (1992) <https://doi.org/10.1371/journal.pone.0204572> [<https://perma.cc/47CK-4UU5>].

[19] Data privacy and protection is the most visible and pressing legal issue facing the data science profession. It is also the issue that governments seem most keen to address.¹⁰¹ In data science practice, data privacy is a question of whether people have the opportunity to consent to the collection and use of their information.¹⁰² This issue is visible partly due to media coverage of high-profile data breaches, and the political pressure that results as the public demands lawmakers hold companies who suffer leaks responsible for the consequences.¹⁰³ Yet, the question of data privacy and protection is not solely about high-profile data breaches. It is also about the constant collection of mundane but personal details (e.g., demographic information, purchase histories) by third parties for monetization.¹⁰⁴ For example, digital advertisers will go to extreme lengths to acquire, aggregate, and then analyze data on consumers' mortgages, places of employment, places of residence, and personal interests. They do this to reconstruct a digital "persona" that the advertisers can use to classify this consumer for making recommendations about future purchases.¹⁰⁵ Much of this data collection and aggregation happens in the background of an online interface without users' knowledge (beyond a tacit request to "Allow Cookies" when visiting a website).¹⁰⁶ At present this data collection occurs without users having the ability to understand how their data may or may not be used or resold, or to request that this information be deleted.¹⁰⁷ In short, users lack the ability

¹⁰¹ See, e.g., CAL CIV CODE §§ 1798.100(a)-(b), 1798.105(b), 1798.110, 1798.115, 1798.120(b), 1798.130, and 1798.135 (2020); General Data Protection Regulation 2016/679, art. 13-14, 2016 O.J. (L 119/1).

¹⁰² Louise Matsakis, *The WIRED Guide to Your Personal Data (And Who is Using It)*, WIRED (Feb. 15, 2019, 7:00 AM), <https://www.wired.com/story/wired-guide-personal-data-collection/> [<https://perma.cc/GNA7-TT66>].

¹⁰³ *Id.*

¹⁰⁴ *Id.*

¹⁰⁵ *See id.*

¹⁰⁶ *See id.*

¹⁰⁷ *See id.*

to provide informed consent regarding the collection, storage, and processing of their data. Notably, recent privacy-focused data regulation, including both the European Union’s General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), has sought to address such privacy issues by requiring data collectors to disclose what information they collect and how they intend to use it.¹⁰⁸ While these disclosures mandated in CCPA and GDPR are an important first step, they are just that: a first step. Because the data scientists who make use of these consumer data are not regulated themselves as practitioners, the requirements placed on companies subject to CCPA and GDPR presume an internal data governance structure that limits the use of data to the disclosed intended uses, as well as innate professionalism amongst data scientists to abide by these restrictions.¹⁰⁹ Neither assumption may hold in practice¹¹⁰, leading to the question of whether consumers know exactly what it is that they are consenting to.

2. Informed Consent

[20] In data science practice, informed consent means that individuals and entities who are represented in data, and whose data may be used for analytical purposes, actively permit—or have the opportunity to refuse—that their data be collected by an organization providing a product or service.¹¹¹ Software vendors and application creators (e.g., Apple and

¹⁰⁸ CAL. CIV. CODE §§ 1798.100(a)-(b) (amended 2020), 1798.105(b) (amended 2020), 1798.110 (amended 2020), 1798.115 (amended 2020), 1798.120(b) (amended 2020), 1798.130 (amended 2020), and 1798.135 (amended 2020); *see also* Regulation 2016/679, art. 13–14, 2016 O.J. (L 119) 41,42.

¹⁰⁹ *See* Michael Brooks, *GDPR Implications for Data Science*, MEDIUM.COM (Feb. 27, 2019), <https://medium.com/slalom-technology/gdpr-implications-for-data-science-342229c62aea> [<https://perma.cc/WS54-BQ4T>].

¹¹⁰ *See id.*

¹¹¹ *See* CAL. CIV. CODE § 1798.120(b) (amended 2020).

Google) frequently obtain consent through the use of End User License Agreements (EULAs). EULAs are contracts entered into between users and software vendors granting the user with license to use software, pending acceptance of terms established by the vendor (e.g., vendor's liability).¹¹² Online interfaces, including websites, social media, and email services, generally rely on Terms & Conditions of Service that broadly cover expected user behavior.¹¹³

[21] Increasingly, software vendors and online interfaces are collecting data from consumers without obtaining true informed consent by deliberately obfuscating privacy policies in absurdly long Terms & Conditions.¹¹⁴ CCPA and GDPR have had an impact by requiring such companies to provide plain language explanations of how customer data will be used, where it is stored, and for how long.¹¹⁵ GDPR goes further by requiring companies to provide European citizens with a pathway for having their data removed.¹¹⁶ However, even if customers consent to the use of their data for “processing,” most likely by advanced algorithms, it is questionable the degree to which these customers understand what that processing may actually entail.

[22] Informed consent issues extend beyond the Internet, however, as businesses and organizations seek to apply AI/ML technology that affects customer privacy, such as facial recognition, without notifying customers

¹¹² See also Seth Stevenson, *By Clicking on This Article You Agree to . . .*, SLATE (Nov. 17, 2014, 7:00 AM), <https://slate.com/technology/2014/11/end-user-license-agreements-does-it-matter-that-we-dont-read-the-fine-print-we-encounter-on-the-web.html> [<https://perma.cc/54QR-MFSV>] (explaining, in express language and in satire, EULAs).

¹¹³ Nicole O., *8 Common Issues with Terms and Conditions Agreements*, PRIVACY POLICIES (Jun. 08, 2020), <https://www.privacypolicies.com/blog/common-issues-terms-conditions> [<https://perma.cc/9RM3-K5ML>].

¹¹⁴ Matsakis, *supra* note 102.

¹¹⁵ CAL. CIV. CODE §§ 1798.100(a)–(b), 1798.105(b), 1798.110, 1798.115, 1798.120(b), 1798.130, and 1798.135 (2020); Council Regulation 2016/679, art. 13–14, 2016 O.J. (L 119) 3 (EC).

¹¹⁶ *Id.*

that the technology is in use and without giving them a meaningful opportunity to consent to the business or organization collecting and analyzing their personal image.¹¹⁷ In one high-profile example, Taylor Swift's security team used facial recognition to scan a concert crowd for stalkers without giving notice of the technology's use or obtaining informed consent.¹¹⁸ In another instance, an Australian shopping mall faced significant backlash when consumers were notified that stores were collecting images of shoppers and using facial recognition technology to predict their buying propensity without their informed consent.¹¹⁹

3. Bias

[23] Systematic algorithmic bias is another significant issue facing the data science field that has both legal and ethical implications.¹²⁰ Systematic algorithmic bias refers to outcomes that an algorithm replicates that are systematically less favorable to individuals within a

¹¹⁷ See, e.g., Brian Barrett, *Security News for This Week: Taylor Swift's Facial Recognition Scans Crowds for Stalkers*, WIRED (Dec. 15, 2018, 9:00 AM), <https://www.wired.com/story/taylor-swift-facial-recognition-security-roundup/> [<https://perma.cc/2N8P-TNMB>] (reporting that Swift's security team scanned unknowing fans faces while such fans watched concert highlight videos at kiosk).

¹¹⁸ *Id.*; Jay Stanley, *The Problem with Using Facial Recognition on Fans at a Taylor Swift Concert*, ACLU FREE FUTURE BLOG (Dec. 14, 2018, 5:15 PM), <https://www.aclu.org/blog/privacy-technology/surveillance-technologies/problem-using-face-recognition-fans-taylor-swift> [<https://perma.cc/8DSQ-J95Z>] (highlighting issues of notice and consent: "Security people are used to operating with secrecy, but this is a novel, controversial, and very powerful technology, and people have a right to know when they're being subjected to it.").

¹¹⁹ Luke Anscombe, *Westfield is Using Facial Detection Software to Watch Where You Shop*, NEWS.COM.AU (Oct. 19, 2017, 1:16 PM), <https://www.news.com.au/finance/business/retail/westfield-is-using-facial-detection-software-to-watch-how-you-shop/news-story/7d0653eb21fe1b07be51d508bfe46262> [<https://perma.cc/RJ9S-SWZH>].

¹²⁰ Karen Hao, *This is How AI Bias Really Happens and Why It's So Hard to Fix*, MIT TECH. REV. (Feb. 4, 2019), <https://www.technologyreview.com/s/612876/this-is-how-ai-bias-really-happensand-why-its-so-hard-to-fix/> [<https://perma.cc/E3QR-SDUU>].

particular group, and where there is no relevant difference between groups that justifies such harm.¹²¹ These negative outcomes often arise because the data used for building an algorithm does not sufficiently represent the population on whom the algorithm is subsequently applied.¹²² For example, consider a voice recognition algorithm (e.g., Apple's Siri virtual assistant)¹²³ that is trained exclusively on American English speakers. If this algorithm is subsequently trialed in Scotland, it is likely to have a high error rate, since none of the voices on which it was trained were Scots-English speakers.¹²⁴ The algorithm will not understand the people speaking to it because it does not recognize their pattern of speaking as English.

[24] While this hypothetical example may not have serious social ramifications, other manifestations of systematic algorithmic bias do.¹²⁵ Systematic algorithmic bias is especially problematic when businesses, governments, and other organizations rely on algorithms for reviewing resumes, predicting loan default likelihood, or even estimating criminal

¹²¹ Nicol Turner Lee et. al., *Algorithmic Bias Detection and Mitigation: Best Practices and Policies to Reduce Consumer Harms*, Brookings Institute (May 22, 2019), <https://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms/> [<https://perma.cc/8QNR-NWGW>].

¹²² *Id.*; see also Will Goodrum, Ph.D., *Picking Favorites: A Brief Introduction to Selection Bias*, Elder Research Blog (Jan. 19, 2018), <https://www.elderresearch.com/blog/selection-bias-in-analytics> [<https://perma.cc/XR87-RG3D>] (Stating that in this benign sense, systematic algorithmic bias is actually a manifestation of sampling bias that is well understood from classical statistics.).

¹²³ Erik Eckel, *Apple's Siri: A Cheat Sheet*, TechRepublic (Oct. 13, 2020), <https://www.techrepublic.com/article/apples-siri-the-smart-persons-guide/> [<https://perma.cc/6RLL-9RB5>].

¹²⁴ CNet, *It's Shite Being Scottish in a Smart Speaker World*, YOUTUBE (Mar. 1, 2018), <https://youtu.be/XQCHoKAq9xA> [<https://perma.cc/P9CK-WAJJ>] (illustrating bias in voice recognition due to underrepresentation of Scots-English speakers in data sets used to train smart speaker algorithms).

¹²⁵ See Goodrum, *supra* note 122.

recidivism because it can reinforce social patterns of discrimination.¹²⁶ In addition to biased data, systematic algorithmic bias can also result due to a lack of awareness on the part of the data scientists developing and training AI/ML algorithms. This occurs when the scientists are not from underrepresented groups and do not take care to ensure fair representation and mitigate discriminatory patterns.¹²⁷ Importantly, systematic algorithmic bias has drawn widespread attention in the data science field.¹²⁸ Groups like OpenAI, the NYU AI Now Institute, and the MIT Media Lab have gathered together AI stakeholders in an effort to devise both technological and ethical solutions to mitigate the problems that result from such bias.¹²⁹

[25] Systematic algorithmic bias poses not only ethical quandaries for federal and state governments relying on potentially discriminatory algorithmic decision-making, but also Constitutional questions. The Fourteenth Amendment’s Equal Protection Clause guarantees every person “equal protection of the laws.”¹³⁰ The issue of systematic algorithmic bias raises possible equal protection issues by applying algorithmic decision-making that discriminates between different classes of persons.¹³¹ The algorithms do this because they rely on biased data.¹³²

¹²⁶ See Hao, *supra* note 120; see also Lee et al., *supra* note 121.

¹²⁷ Michael Li, *Addressing the Biases Plaguing Algorithms*, HARV. BUS. REV. (May 13, 2019), <https://hbr.org/2019/05/addressing-the-biases-plaguing-algorithms> [<https://perma.cc/3CB7-8SVE>] (encouraging companies to “remain vigilant to keep bias out of their AI systems” and suggesting they do so by “incorporat[ing] anti-bias training alongside their AI and ML training” allowing them to “spot potential for bias in what they’re doing, and actively correct for it”).

¹²⁸ See Hao, *supra* note 120.

¹²⁹ See Lee et al., *supra* note 121.

¹³⁰ U.S. CONST. amend. XIV, § 1.

¹³¹ See Lee et al., *supra* note 121.

¹³² See Lee et al., *supra* note 121.

This is true whether the data scientist inputs historical data or data scraped from Internet webpages; the “garbage in, garbage out” problem persists.¹³³ Biased data input results in biased algorithms that make biased predictions. “For example, when algorithms in the criminal justice system rely upon data that contains racial bias, the machine learning algorithms that use this data to make predictions will inevitably reflect that racial bias.”¹³⁴ Regarding predictive policing specifically, “any algorithm that associates race and criminality will subsequently consider people of color and their neighborhoods more likely to be the possible perpetrators, victims, and sites of future crimes.”¹³⁵ As such, an equal protection challenge can arise when a data scientist trains an algorithm “on historical crime data or [web scraping Internet] searches because this information allows the algorithms to classify and target on the basis of race.”¹³⁶

[26] Yet, there is no law or regulation currently prohibiting data scientists from using such data in algorithmic decision-making because there are no standards for data collection, data use, or even data quality.¹³⁷ At a basic level, there exists a lack of transparency in decision making and oversight of data scientists and how their methods are being applied

¹³³ Elizabeth E. Joh, *Feeding the Machine: Policing, Crime Data, & Algorithms*, 26 WM. & MARY BILL RTS. J., 287, 294 (2017) (“[A]ny [algorithmic] decision is as good or as bad as the data relied upon by the program.”).

¹³⁴ *Id.*

¹³⁵ Renata M. O’Donnell, *Challenging Racist Predictive Policing Algorithms Under the Equal Protection Clause*, 94 N.Y.U. L. REV. 544, 558 (2019).

¹³⁶ *Id.* at 566–67 (laying out framework and arguments for equal protection challenge of biased predictive policing algorithms).

¹³⁷ See Mark MacCarthy, *Fairness in Algorithmic Decision-making*, BROOKINGS, (Dec. 6, 2019), <https://www.brookings.edu/research/fairness-in-algorithmic-decision-making/#:~:text=The%20Algorithmic%20Accountability%20Act%20of,the%20results%20of%20their%20assessments> [https://perma.cc/FXH6-C64E] (explaining possible laws and regulations that could be put in place regarding standards for data); see also S.1108, 116th Cong. (2019).

in different industries.¹³⁸

4. Lack of Data Literacy

[27] Data literacy is “the ability to read, write and communicate data in context, including an understanding of data sources and constructs, analytical methods and techniques applied.”¹³⁹ Data literacy is lacking in much of the United States general population. In a recent Census-wide survey conducted by the data visualization company Qlik, only 24% of business decision makers felt confident and comfortable in their ability to read, analyze, and argue from data.¹⁴⁰

[28] The general public’s lack of data literacy poses problems for data scientists in two ways. First, the lack of data literacy exacerbates aforementioned problems around data privacy and consent because people do not understand the full consequences of the algorithmic applications to which they are consenting.¹⁴¹ Even if consent is formally given, the

¹³⁸ See Matt Reany, *Big Data Desperately Needs Transparency*, KD NUGGETS BLOG (Mar. 2017), <https://www.kdnuggets.com/2017/03/big-data-needs-transparency.html> [<https://perma.cc/B4RP-KRAF>]; see also David Herman & J. Galen Buckwalter, *Transparency in Data Science: On Trusting Machines*, PAYOFF BLOG (Mar. 20, 2016), <https://medium.com/payoff/transparency-in-data-science-9a8778083b3> [<https://perma.cc/X59R-GTTY>] (“We believe every data scientist accepts the ethical responsibility to treat data as an extension of the person whose behavior created the information. Responsible data scientists ought to, along with physicians and psychologists, vow to do no harm to the person whose data they use.”).

¹³⁹ Kasey Panetta, *A Data and Analytics Leader’s Guide to Data Literacy*, GARTNER (Feb. 6, 2019), <https://www.gartner.com/smarterwithgartner/a-data-and-analytics-leaders-guide-to-data-literacy/> [<https://perma.cc/D3DM-2ZHN>].

¹⁴⁰ *Lead with Data—How to Drive Data Literacy in Enterprise*, QLIK (2018), https://www.qlik.com/us/bi/-/media/08F37D711A58406E83BA8418EB1D58C9.ashx?ga-link=datlitreport_resource-library [<https://perma.cc/EN4H-7NUS>].

¹⁴¹ See *Responsible AI Replies on Data Literacy*, SEMANTICS (June 8, 2018), <https://2018.semantics.cc/responsible-ai-relies-data-literacy> [<https://perma.cc/EX72-RX8S>] (“I appreciate that there are more and more discussions around data privacy and the importance of it. But at the same time, it is contradictory to see how people act when they talk about privacy and how little aware they are about what happens to their data.

consenting public may not fully understand how the company is intending to use their data, or how such use could impact their lives. Second, the general public's lack of data literacy has increased demand for data scientists to act as expert advisors to businesses, government agencies, non-profits, and other organizations on data matters.¹⁴² This is primarily due to the public's unrealistic expectations for technological performance.¹⁴³ Notably, as is common with any form of new or advanced technology,¹⁴⁴ AI/ML is currently feeding public anxiety about increasingly sophisticated and capable algorithms.¹⁴⁵ These concerns are generally unfounded due to

We have to wait and see whether citizens really become more cautious about whom they give their data to and in which way.” (quoting Elena Simperl)).

¹⁴² See Claudia Perlich, *Recruiting Data Scientists to Do Social Good*, HARV. BUS. REV. (Aug. 25, 2014), <https://hbr.org/2014/08/recruiting-data-scientists-to-do-social-good/> [<https://perma.cc/T6FW-KK52>].

¹⁴³ See generally Ben Ziomek, *Let's be realistic about our expectations of AI*, HELP NET SEC. (April 23, 2020), <https://www.helpnetsecurity.com/2020/04/23/leveraging-ai/> [<https://perma.cc/AY7D-RDP9>] (discussing the general public's unrealistic expectations of AI); Bob O'Donnell, *We Have Unrealistic Expectations of a Tech-Driven Future Utopia*, VOX (Jul. 25, 2017), <https://www.vox.com/2017/7/25/16026870/technology-advances-limits-ethics-vr-ai-autonomous-google-glass/> [<https://perma.cc/P2NS-298G>] (discussing limits on technology in regards to public perception).

¹⁴⁴ See, e.g., Mark Byrnes, *In 1954, Americans Were Told to Paint Their Houses to Increase Their Chances of Surviving an Atomic Bomb*, BLOOMBERG: CITYLAB (May 8, 2013), <https://www.bloomberg.com/news/articles/2013-05-08/in-1954-americans-were-told-to-paint-their-houses-to-increase-their-chances-of-surviving-an-atomic-bomb> [<https://perma.cc/U9EV-EFEP>] (demonstrating (now amusing, though peculiar) marketing exploitation of “The House in the Middle” from the beginning of the Atomic Age. There, the paint industry lobby tried to exploit the risks of nuclear attack by stoking fear in the general populace, claiming a “neglected,” unpainted house would not stand up to an attack).

¹⁴⁵ See Baobao Zhang & Allan Dafoe, *Artificial Intelligence: American Attitudes and Trends* 66, CTR. GOVERNANCE AI, FUTURE HUMANITY INST. UNIV. OXFORD (2019), https://governanceai.github.io/US-Public-Opinion-Report-Jan-2019/us_public_opinion_report_jan_2019.pdf [<https://perma.cc/2S8X-QGQV>]; see also, e.g., Jane Wakefield, *'Dangerous' AI Offers to Write Fake News*, BBC (Aug. 27, 2019), <https://www.bbc.com/news/technology-49446729> [<https://perma.cc/2Y5K-PS3X>] (offering one example of how AI can be misused).

the significant limitations present in AI/ML systems that consequently limit their general applicability.¹⁴⁶ Nonetheless, the disconnect between the public's understanding of AI/ML and the actual capabilities of AI/ML technologies has created a need for experts—whether to reassure wariness or reset wishful thinking—to advise and explain the consequences of applying data science technologies. Data scientists often fill this gap.¹⁴⁷ However, their suitability to do so is questionable given the variance in competency due to a lack of professional standards of practice. For this reason, data science professionals actually stand to undermine public trust.

[29] The 2020 International Baccalaureate exam results debacle is an example of what can happen when data illiterate decision makers rely on unregulated data scientists as experts. When the COVID-19 pandemic forced the International Baccalaureate Organization (IBO) board to cancel its year-end high school graduation exams, the IBO “opted for using [AI] to help set overall scores for high-school graduates based on students’ past work and other historic data.”¹⁴⁸ Notably, this data input included teacher-corrected final coursework as well as predicated grades provided by

¹⁴⁶ See Erik Brynjolfsson & Andrew McAfee, *The Business of Artificial Intelligence*, HARV. BUS. REV. (July 21, 2017), <https://hbr.org/cover-story/2017/07/the-business-of-artificial-intelligence> [<https://perma.cc/975Z-AUZ2>]. State-of-the-art AI image recognition systems can easily mistake animals for pastries in ways that are so immediately obvious to humans that the AI intelligence indeed seems ersatz. Of greater concern, however, are recent examples of so-called “adversarial AI,” where AI algorithms are trained to deliberately and maliciously upset the function of other AI systems, such as tricking an autonomous vehicle into thinking that a stop sign actually says the speed limit is 45 miles per hour by modifying road signs with stickers to fool the vehicle’s computer vision system. See, e.g., Will Knight, *How Malevolent Machine Learning Could Derail AI*, MIT TECH. REV. (Mar. 25, 2019), <https://www.technologyreview.com/s/613170/emtech-digital-dawn-song-adversarial-machine-learning/> [<https://perma.cc/63Z6-ZH7U>].

¹⁴⁷ See Brynjolfsson & McAfee, *supra* note 146.

¹⁴⁸ Theodoros Evgenio et al., *What Happens When AI is Used to Set Grades?*, HARV. BUS. REV. (Aug. 13, 2020), <https://hbr.org/2020/08/what-happens-when-ai-is-used-to-set-grades> [<https://perma.cc/XS8K-SMAR>].

teachers.¹⁴⁹ “The experiment was not a success.”¹⁵⁰ Critically, “[t]ens of thousands of students all over the world received grades that not only deviated substantially from their predicted grades but did so in unexplainable ways.”¹⁵¹ As a result, the IBO has received thousands of complaints from unhappy students and parents along with requests to appeal the grades.¹⁵² Yet, the IBO’s usual appeals process, which consists of having an independent reviewer regrade the student’s work, does not transfer as the complaints are with the algorithm’s assessment.¹⁵³ Additionally, “[s]everal governments have also launched formal investigations, and numerous lawsuits are in preparation, some for data abuse under EU’s GDPR.”¹⁵⁴ This example illuminates multiple issues in data science practice, including informed consent to bias. Yet, the data literacy issue is particularly striking because the IBO—due to a lack of data literacy—failed to appreciate the full ramifications of the work undertaken by these data scientists and the need for a revised appeals process that would allow for redress of student grievances.¹⁵⁵

[30] “The IBO’s experience obviously has lessons for deploying AI in many contexts—from approving credit, to job search, or policing. Decisions in all these cases can, as with the IB, have life altering consequences for the people involved.”¹⁵⁶ Yet, unless data scientists are

¹⁴⁹ *See id.*

¹⁵⁰ *Id.*

¹⁵¹ *Id.*

¹⁵² *Id.*

¹⁵³ *See id.*

¹⁵⁴ *Id.*

¹⁵⁵ *See* Evgeniou et al., *supra* note 148.

¹⁵⁶ *Id.*

subject to professional regulation, such life-altering scenarios will continue to occur and data scientists will bear no responsibility for the harm they have caused with their algorithms. Unless data scientists are held to the same level of fiduciary responsibility to their clients as their professional peers, questions of culpability in the case of harm will remain unresolved.

IV. REGULATORY MODEL: FIDUCIARY DATA SCIENCE

[31] Increasingly, data scientists are exerting greater influence over decision-making in government, business, academia, and civic life as leaders and executives turn to data to inform their decisions.¹⁵⁷ Data scientists should exercise this influence prudently. This is particularly critical given the knowledge asymmetry present between data scientists and those who consult them, and the power of AI/ML technologies that data science relies on.¹⁵⁸ Yet, as discussed, there are no existing laws that expressly regulate the practice of data science.¹⁵⁹ Consequently, there is no quality control of the individuals who practice data science or of the work they produce. The risk of public and private harms as the result of ignorant, negligent, malicious, or just plain bad data science practice is too great for lawmakers, as well as data science professionals, to allow the current unregulated regime to continue. Data science as a profession needs external government regulation to ensure quality and competency among practitioners and to incentivize the profession to regulate itself by developing best practices and formally adopting an ethical code of conduct. Moreover, like other specialized professionals working in fields characterized by asymmetries of information, such as law or medicine,¹⁶⁰

¹⁵⁷ See, e.g., Kashmir Hill, *Wrongfully Accused by an Algorithm*, N.Y. TIMES (June 24, 2020), <https://www.nytimes.com/2020/06/24/technology/facial-recognition-arrest.html> [<https://perma.cc/RQ9U-P87C>] (stating the use of faulty facial recognition led to the arrest of an innocent man).

¹⁵⁸ Alex Castrounis, *What is Data Science, and What Does a Data Scientist Do?*, INNOARCHITECH (Sep. 02, 2020), <https://www.innoarchitech.com/blog/what-is-data-science-does-data-scientist-do> [<https://perma.cc/M7LQ-ENRD>].

¹⁵⁹ See Leprince-Ringuet, *supra* note 95.

¹⁶⁰ See MODEL RULES OF PRO. CONDUCT PmbL. (AM. BAR ASS'N 2020); CODE OF

data scientists should be regulated as fiduciaries. The fiduciary relationship is the best way not only to ensure trust between data scientists and their clients, but also to protect the public.

A. Data Scientists Should Be Fiduciaries

[32] A fiduciary is “one who has special obligations of loyalty and trustworthiness toward another person. The fiduciary must take care to act in the interests of the other person.”¹⁶¹ Specifically, a fiduciary has two key duties: a duty of care and a duty of loyalty.¹⁶² The duty of care is the responsibility of the fiduciary to act competently and diligently in the interest of a client.¹⁶³ Its complement is the duty of loyalty: to keep client interests in mind and act in line with those interests.¹⁶⁴ Fiduciary relationships form as relations of dependence and trust between the fiduciary and the client.¹⁶⁵ Law, medicine, accountancy, certified financial planning, and chartered engineering are examples of existing professions that are either formally bound by a fiduciary duty or operate or are regulated in a fiduciary manner.¹⁶⁶ Fiduciary relationships are

MEDICAL ETHICS Pmbl. (AM. MEDICAL ASS’N 2016).

¹⁶¹ LEGAL INFORMATION INSTITUTE (LII) WEX DICTIONARY ONLINE: “FIDUCIARY DUTY,” https://www.law.cornell.edu/wex/fiduciary_duty [<https://perma.cc/P8YR-427F>].

¹⁶² *Id.*

¹⁶³ *Id.*

¹⁶⁴ *Id.*

¹⁶⁵ *Id.*

¹⁶⁶ *See, e.g.*, Restatement (Third) of the Law Governing Lawyers §49 (2011); Sande Buhai, *Lawyers as Fiduciaries*, 53 ST. LOUIS. U. L. J. 553, 554 (2009) (referring to the lawyer as “the quintessential fiduciary”); *Lockett v. Goodill*, 430 P.2d 589, 591 (Wash. 1967) (“The relationship of patient and physician is a fiduciary one of the highest degree.”); AMA COUNCIL ON ETHICAL AND JUD. AFF.S, CODE OF MEDICAL ETHICS: OPINION 10.015: THE PATIENT-PHYSICIAN RELATIONSHIP, <https://www.ama-assn.org/sites/ama-assn.org/files/corp/media-browser/code-of-medical-ethics-chapter-1.pdf> [<https://perma.cc/8SER-K6BW>]; *see also* Gabriel Lazaro-Munoz, *The*

relationships of trust that involve the use and exchange of information.¹⁶⁷ Clients entrust fiduciaries with sensitive and valuable information because they believe that doing so will ultimately be to their benefit and that the fiduciary has a duty to responsibly use such information.¹⁶⁸ Additionally, generally clients freely provide this information and accept the outcomes of the fiduciary expert's review as valid. "The question is not the form the information takes but how it is obtained and how it is used in the context of relations of dependence and trust" that secures it according to fiduciary duty.¹⁶⁹ This is the depth of relationship and responsibility that should be required of all data scientists.

1. Data Scientists are Professionals Offering Specialized Services and Expertise

[33] Like lawyers and physicians, data scientists are highly trained professionals offering specialized services and expertise to clients who depend on such to inform their decision-making.¹⁷⁰ Data scientists possess an advanced and unique combination of technical skills in computer programming, mathematics, and statistics well-beyond the level of the general public.¹⁷¹ Businesses, government agencies, and non-profits

Fiduciary Relationship Model for Managing Clinical Genomic "Incidental" Findings, 42 J.L. MED. & ETHICS 576, 576 (2014) (citing numerous cases where courts have recognized "the fiduciary nature of the physician-patient relationship").

¹⁶⁷ See LII, *supra* note 161.

¹⁶⁸ See Buhai, *supra* note 166, at 584.

¹⁶⁹ Jack M. Balkin, *Information Fiduciaries and the First Amendment*, 49 U.C. DAVIS L. REV. 1183, 1220 (2016).

¹⁷⁰ See, e.g., DELOITTE SERV.S: ADVANCED ANALYTICS (2020), <https://www2.deloitte.com/ie/en/pages/technology/solutions/emea-csf/advanced-analytics.html> [<https://perma.cc/S52L-F39H>] (Deloitte, the multinational consulting firm, is one example of a business offering specialized, expert data science services to inform client business decisions).

¹⁷¹ See, e.g., N.C. ST. U. INST. FOR ADVANCED ANALYTICS, Master of Science in Analytics Curriculum https://analytics.ncsu.edu/?page_id=123 [<https://perma.cc/3FYD->

all hire data scientists to provide expert counsel based on these skills, whether as in-house or as consultants.¹⁷² Moreover, the specialized services data scientists offer rely on the presumption that data scientists are able to accurately assess their client's data, "seeking patterns, correlations, trends, and other useful information," to make recommendations to guide decision-making.¹⁷³ Such services include training machine learning algorithms, building charts and graphs to convey meaning to non-experts from data, and preparing data for analysis.¹⁷⁴

[34] Also like lawyers and physicians, data scientists receive sensitive information from their clients that the client offers, because the clients believe doing so is to their benefit.¹⁷⁵ Such information could include personally identifiable information (e.g. health records), business financial information (e.g. sales revenue), or even trade secrets.¹⁷⁶ Yet, clients entrust this information to their data scientists because they believe the potential business or policy insights the data scientists can glean from

VJC4] (2020) (full list of curriculum includes such highly technical courses as Linear Algebra, Polynomial Regression, and Kernel Density Estimation among others).

¹⁷² *E.g.*, *Technology In Action*, MCGUIREWOODS, <https://www.mcguirewoods.com/client-tools/technology> [<https://perma.cc/BJ5F-3T2Z>] ("McGuireWoods uses data analytics to guide strategy and decision-making . . . Our lawyers and our technology team, including dedicated data analytics talent, collaborate to . . . examine large sets of data seeking patterns, correlations, trends and other useful information that will identify—even predict—clients' complex business problems quickly and efficiently.").

¹⁷³ *Id.*

¹⁷⁴ DELOITTE, *supra* note 170.

¹⁷⁵ *See generally* Balkin, *supra* note 169, at 1207, 1220–1, 1230–1 (discussing the expectations for different fiduciaries that manage sensitive personal information).

¹⁷⁶ *See, e.g.*, Jordan Harrod, *Health Data Privacy: Updating HIPPA to Match Today's Technology Challenges*, HARVARD SCI. IN THE NEWS BLOG (May 15, 2019), <http://sitn.hms.harvard.edu/flash/2019/health-data-privacy/> [<https://perma.cc/2V8A-EGFE>] (illustrating how data scientists may use protected health information in Figure 2).

such information is worth the risk of sharing this sensitive information.¹⁷⁷ Data scientists cannot do their work if the client is unwilling to share data.¹⁷⁸ Nor can businesses, governments, universities, non-profits, or other organizations benefit from data science if they are unwilling to share.¹⁷⁹

[35] The asymmetry of information present in the data scientist-client relationship, as well as the level of trust concerning information, are similar to those present in lawyer-client, physician- patient, and other professional fiduciary relationships.¹⁸⁰ However—unlike lawyers and physicians—data scientists presently owe no duties to their client beyond those outlined in the contract.¹⁸¹ The client places their trust in the data scientist entirely in good faith. Yet, the client does so at their own risk because data scientists are not currently regulated as fiduciaries.¹⁸²

2. The Theory of Information Fiduciaries

[36] Recognizing the fiduciary nature of the relationship between data scientists and their clients would establish a common standard of care among practitioners. This is not only ethically desirable, but it's also

¹⁷⁷ See Balkin, *supra* note 171, at 1194.

¹⁷⁸ See *Common Workplace Problems for Data Scientists, and How to Address Them*, DATAQUEST (Apr. 27, 2019) <https://www.dataquest.io/blog/data-science-problems-fix/> [<https://perma.cc/Z9PM-45WS>].

¹⁷⁹ *Id.*

¹⁸⁰ See *id.*; Sandra Feder, *Research by Stanford sociologist reveals how and why privileged defendants fare better in criminal court than non-privileged ones*, STANFORD SCH. OF HUMANITIES & SERV. (Dec. 08, 2020), <https://humsci.stanford.edu/feature/research-stanford-sociologist-reveals-how-and-why-privileged-defendants-fare-better> [<https://perma.cc/H8Z4-584G>].

¹⁸¹ See Balkin, *supra* note 169, at 1199.

¹⁸² See *id.* at 1216–17.

necessary to protect against technological abuses, as well as data scientists' misuse or mishandling of data. The characteristics of the data scientist-client relationship fits the fiduciary framework under the theory of 'information fiduciaries.'¹⁸³ An information fiduciary is "a person or a business who, because of their relationship with another, has taken on special duties with respect to the information they obtain in the course of the relationship."¹⁸⁴

[37] Yale law professor Jack M. Balkin recently has popularized the theory of information fiduciaries as a model for regulating data-based relationships as a means of reigning in such big technology companies as Facebook, Google, and Amazon.¹⁸⁵ Whereas Balkin's model advocates making these data-handling online service providers (OSPs) fiduciaries vis-a-vis their responsibility to act in the interests of end-users,¹⁸⁶ the model proposed in this article focuses on regulating not the corporate entity, but rather the individual employees. Another important distinction between OSPs and data scientists is that data scientists have a fiduciary responsibility to their clients, but not necessarily the end-users on whose information they rely.¹⁸⁷ Balkin's focus on the relationship between

¹⁸³ *See id.* at 1186.

¹⁸⁴ *Id.* at 1209.

¹⁸⁵ *See id.* at 1186.

¹⁸⁶ *See id.* at 1222, 1226. Notably, Balkin's primary reason for advocating for an information fiduciary approach is due to the significant vulnerability of end users "because online service providers have considerable expertise and knowledge and end users generally do not." This is in keeping with the generally recognized issue of information asymmetry between professionals and the general public, and the potential for harm that can result from this asymmetry. "[T]here are strong asymmetries of information between companies and end users. Online Service Providers operations, algorithms, and collection practices are mostly kept secret."; *Id.* at 1227. Critically, of greatest concern is the fact that this asymmetry of information exists in a framework largely bereft of oversight or regulation, and users are "largely dependent on the good will of these companies not to abuse their personal information."; *Id.* at 1227.

¹⁸⁷ *See Balkin, supra* note 169, at 1226.

companies and their customers misses this point entirely. Data scientists are incentivized to use information that they receive from their clients for the benefit of the client.¹⁸⁸ As such, the primary social relationship for the data scientist rests not with the end- user, but with their client. Consider an example from the private sector: a data scientist working at Facebook. In this relationship, Facebook is the data scientist's client, although there are stakeholders (i.e., Facebook users) who also are subject to consequences from the data scientist's practice.

[38] Regardless, the information fiduciary theory fits the data science profession as a regulatory model because of the asymmetry of information present in the data scientist-client relationship, as well as the level of trust concerning information. The data scientist-client relationship is like the relationships present between lawyers and their clients and physicians and their patients. As such, the data science profession should be regulated in the same way by imposing a fiduciary duty on data science practitioners.

B. Fiduciary Data Scientists are Necessary to a Robust Data Regulatory Scheme

[39] In the age of analytics, the intangible value found in data is beginning to equal or exceed the value of tangible assets for businesses.¹⁸⁹ As the federal government begins to regulate the collection, storage, and sale of data,¹⁹⁰ it takes significant steps towards protecting the public from the harmful consequences of data science practice. Yet, regulating data handling and sales offers only partial redress.¹⁹¹ Lawmakers must also

¹⁸⁸ See *id.* at 1205.

¹⁸⁹ DOUGLAS B. LANEY, INFONOMICS 207 GARTNER (2019).

¹⁹⁰ Gregory M. Kratofil, Jr., Elizabeth Harding, *Federal Privacy Legislation Update: Consumer Data Privacy and Security Act of 2020*, 10 NAT'L L. REV. 74 (Mar. 14, 2020), <https://www.natlawreview.com/article/federal-privacy-legislation-update-consumer-data-privacy-and-security-act-2020> [<https://perma.cc/QT66-VDRK>].

¹⁹¹ See Noah Ramirez, *Data Privacy Laws: What You Need to Know in 2020*, OSANO (Nov. 8, 2020), <https://www.osano.com/articles/data-privacy-laws> [<https://perma.cc/5ABC-VSXU>].

regulate the use and analysis of data as well as the individuals using or analyzing such data in order to fully address the legal implications of data science practice. Regulating data scientists as fiduciaries reflects the power of the profession and its ability to help or harm the public. Data scientists should be regulated as fiduciaries to ensure their practice will result in outcomes that maximize the potential benefit of AI/ML for society. Accordingly, fiduciary data science is a necessary component of a robust data regulatory scheme because it would (1) establish basic levels of competency for data science practitioners; (2) serve as a quality control measure, likely by creating a class of certified or licensed professionals able to provide data science services to clients, including audit; (3) establish a common set of best practices for data science; (4) establish a common code of ethical conduct; and (5) subject AI/ML decision-making to the same level of scrutiny as human decision-making.¹⁹²

1. Fiduciary Data Science Would Establish a Basic Level of Competency Among Practitioners

[40] Regulating data scientists as fiduciaries is necessary for a robust data regulatory scheme because there is no requirement that practicing data scientists possess or maintain a basic level of competency in AI/ML methodologies, tools, and technologies. As a result, there is no commonly agreed standard or curriculum for data science education, training, or certification.¹⁹³ Additionally, there is no continuing education requirement like in other powerful, expert professions, like law or medicine.¹⁹⁴ The lack of competency requirements, including continuing education, is particularly egregious in a field with such a volatile and ever-changing

¹⁹² See generally Ariel Dobkin, *Information Fiduciaries in Practice: Data Privacy and User Expectations*, 33 BERKELEY TECH. L.J. 1 (2018) (discussing the advantages and responsibilities of fiduciaries).

¹⁹³ But see MODEL RULES OF PROF'L CONDUCT (2020) (self-governing ethical code of conduct for lawyers), and CODE OF MEDICAL ETHICS (2020) (self-governing ethical code for physicians).

¹⁹⁴ See Data Scientist, COMPUTERSCIENCE.ORG (Jan. 13, 2020), <https://www.computerscience.org/careers/data-science/> [https://perma.cc/J9D4-7PAN].

state-of-the-art as data science. For example, natural language inference uses statistical algorithms to teach a computer to infer meaning from written text. The state of the art in natural language inference has advanced three times in the last year alone.¹⁹⁵ This means that if a data scientist began building a “state-of-the-art” natural language system for their client in January, the system’s performance would be superseded *three times over* by December, and the data scientist could be completely unaware. Notably, ensuring competent practitioners will help safeguard the general public from malpractice or negligence, and engender public trust in the data science profession.

2. Fiduciary Data Science Would Ensure Quality Control of Data Science Practice

[41] Additionally, regulating data scientists as fiduciaries would create a class of data scientists whose role would be to ensure quality control of data science practice through third-party audit. Specifically, these fiduciary data scientists would offer client services to audit models produced by other data scientists. This would be akin to the current practice in accountancy of auditing financials, both for the sake of tax compliance and also for shareholder assurance.¹⁹⁶ In accountancy, the chartered professionals who conduct audits are certified to the basic level of proficiency of their profession and are independent of their clients.¹⁹⁷ The government, specifically states, could regulate data scientists in the same way as licensure is a common form of state regulation of

¹⁹⁵ See, e.g., Sebastian Ruder, NLP PROGRESS, https://github.com/sebastianruder/NLP-progress/blob/master/english/natural_language_inference.md [<https://perma.cc/B4RZ-5PDS>].

¹⁹⁶ See, e.g., *Audit, Obtain Clarity, Quality and Trust in Financial Statements*, SC&H GROUP, <https://www.schgroup.com/services/audit/> [<https://perma.cc/RQZ5-T4KY>] (offering audit services for financial statements).

¹⁹⁷ See *Understanding a Financial Statement Audit*, PWC (Jan. 2013), <https://www.pwc.com/gx/en/audit-services/publications/assets/pwc-understanding-financial-statement-audit.pdf> [<https://perma.cc/BX4H-XQLU>].

professions.¹⁹⁸ Notably, the purpose of licensure as a state regulatory tool is to protect the public.¹⁹⁹ The state intends licensure to accomplish this goal by establishing minimum competency requirements that an individual must meet in order to practice a particular occupation or profession, thereby ensuring quality control.²⁰⁰ Similarly, fiduciary data scientists could be licensed and independent, responsible for providing an unbiased assessment of the assumptions, biases, and risks of algorithms produced by other data scientists to ensure that those algorithms adhere to those same standards of quality.

¹⁹⁸ See Kara Schmitt, *What is Licensure*, 1 Licensure Testing: Purposes, Procedures, and Practices 5 (James C. Impara ed., Buros Institute of Mental Measurements, University of Nebraska-Lincoln) (1995) (noting that licensure “is one of the forms of regulatory control states have over individuals wishing to practice certain occupations or professions”); see also VA. DEP’T OF PROF’L AND OCCUPATIONAL REGUL., <http://www.dpor.virginia.gov/ProfessionsAndOccupations/> [<https://perma.cc/FG74-2XYK>] (showing that Virginia uses licensure for regulating many professions such as medicine, law, auctioneers, and even professional wrestlers); N.Y. OFF. OF THE PROFESSIONS, <http://www.op.nysed.gov/prof/> [<https://perma.cc/V6JL-5JD2>] (showing that New York alone regulates over 50 occupations through licensure).

¹⁹⁹ See VA. STATE BAR, <https://www.vsb.org/site/about> [<https://perma.cc/8B9Z-XPTQ>] (stating that part of the mission of the Virginia State Bar is “to protect the public”); NEW YORK OFFICE OF THE PROFESSIONS, <http://www.op.nysed.gov/aboutop.htm#> [<https://perma.cc/LPN3-AG8D>] (noting that New York’s “unique system of professional regulation,” sets the regulatory authority for regulation within the state’s university education system and is “for public protection.”).

²⁰⁰ See VA. BD. OF BAR EXAM’RS., <https://barexam.virginia.gov/motion/motionrules.html> [<https://perma.cc/93DF-PSUJ>] (establishing minimum competency requirements for practicing law in Virginia); Va. Code. Ann. §54.1-2400 (authorizing state health regulatory boards to establish qualifications for medical licensure, including such qualifications “which are necessary to ensure competence and integrity to engage in the regulated professions.”); see also NAT’L SOC. OF ENG’RS, *100 Years of Engineering Licensure*, <https://www.nspe.org/resources/press-room/resources/100-years-engineering-licensure> [<https://perma.cc/973H-TTR6>] (celebrating a 100 years of licensure for professional engineers, noting that prior to licensure “anyone could work as an engineer without proof of competency.”).

3. Fiduciary Data Science Would Require the Profession to Establish Best Practices

[42] Currently, the data science profession lacks a set of commonly agreed best practices.²⁰¹ CRISP-DM is a widely known process amongst most data scientists, but data scientists have not adopted CRISP-DM as a universal standard for data science practice.²⁰² The lack of best practices for data science is problematic because it prevents the possibility of robust, reliable, and repeatable audit that would be necessary to enable independent quality control and unbiased assessment.²⁰³ For example, there is no universally agreed standard for what constitutes “high accuracy” for machine learning models, though a figure of 80% is often touted as sufficient.²⁰⁴ When dealing with extremely rare events (e.g., terrorist action, fraud) it is possible to achieve accuracies well in excess of 90% by always predicting that the event will not occur (but this model is obviously useless).²⁰⁵ Regulating data scientists as fiduciaries will incentivize the profession to establish a set of best practices for data science because such regulation would refer to and define those practices. Moreover, establishing best practices will help narrow the data literacy gap by helping data scientists to clearly communicate to the public about such established,

²⁰¹ See Philip J. Piety et al., *Educational Data Sciences – Framing Emergent Practices for Analytics of Learning, Organizations, and Systems*, LAK ‘14: PROCEEDINGS OF THE FOURTH INTERNATIONAL CONFERENCE ON LEARNING ANALYTICS AND KNOWLEDGE 193, 193 (March 2014), <https://dl.acm.org/doi/10.1145/2567574.2567582> [<https://perma.cc/235F-WE32>].

²⁰² See CRISP-DM, *supra* note 34.

²⁰³ See Piety et al., *supra* note 201.

²⁰⁴ See Jayawent N. Mandreker, *Receiver Operating Characteristic Curve in Diagnostic Test Assessment*, 5 J. THORACIC ONCOLOGY 1315, 1316 (2010) (discussing the area under the receiver operating characteristic curve (AUC), a common metric for accuracy in data science, and noting that a value of 0.8 (or 80%) is typically viewed as “good.”).

²⁰⁵ See Gary M. Weiss and Haym Hirsh, *Learning to Predict Extremely Rare Events*, AM. ASS’N FOR ARTIFICIAL INTELLIGENCE (2000), <https://storm.cis.fordham.edu/~gweiss/papers/aaai00ws.pdf> [<https://perma.cc/D5J8-P3WR>].

widely trusted methods.²⁰⁶

4. Fiduciary Data Science Would Require the Profession to Adopt a Code of Ethical Conduct

[43] A common code of ethical conduct for data scientists is necessary to guide practitioners to act ethically in their work. Professional codes of conduct are the norm in fiduciary professions. Law and medicine have codes of professional conduct that allow the profession to self-regulate practitioners.²⁰⁷ Presently, data scientists have not formally adopted any code of professional conduct, though several exist.²⁰⁸ The purpose of such codes is to ensure a uniform and ethical standard of practice within the profession.²⁰⁹ Such codes are essential to a fiduciary relationship, since they establish a clear standard of care to which all practitioners must adhere.²¹⁰ This is critical because data scientists make decisions everyday

²⁰⁶ See *Ethical Data Science*, OXFORD-MUNICH CODE OF CONDUCT: PROFESSIONAL DATA SCIENTIST, <http://www.code-of-ethics.org> [<https://perma.cc/P6TS-KT8X>].

²⁰⁷ See MODEL RULES OF PROF'L CONDUCT, *Preamble: A Lawyer's Responsibilities* (AM. BAR ASS'N 1983) ("The legal profession is largely self-governing" and explaining that "[t]o the extent that lawyers meet the obligations of their professional calling, the occasion for government regulation is obviated. Self-regulation also helps maintain the legal profession's independence from government domination."); *Code of Medical Ethics Preface & Preamble*, AM. MED. ASS'N., <https://www.ama-assn.org/about/publications-newsletters/code-medical-ethics-preface-preamble> [<https://perma.cc/F4QN-7WP4>]; see also *Code of Medical Ethics Overview*, AM. MED. ASS'N., <https://www.ama-assn.org/about/publications-newsletters/code-medical-ethics-preface-preamble> [<https://perma.cc/Z74K-B7XJ>] (emphasizing that the Code articulates "the values to which physicians commit themselves as members of the medical profession.").

²⁰⁸ See, e.g., *Code of Conduct*, OXFORD-MUNICH CODE OF CONDUCT: PROFESSIONAL DATA SCIENTIST, <http://www.code-of-ethics.org/code-of-conduct/> [<https://perma.cc/VVH4-QLVP>]; *Data Science Code of Professional Conduct*, DATA SCIENCE ASS'N., <https://www.datascienceassn.org/code-of-conduct.html> [<https://perma.cc/RU43-VPSM>].

²⁰⁹ See *id.*

²¹⁰ See *id.*

regarding AI/ML systems that have the potential to impact broad swathes of society.²¹¹ For example, data scientists training an algorithm to filter resumes for hiring managers will make assumptions about what resumes to include or exclude. This could impact large numbers of job seekers if that algorithm is found to produce biased outcomes when applied in different geographies or industries.²¹² Moreover, a common code of ethical conduct for data science also serves to protect data scientists themselves. Although fiduciary data scientists would have a primary duty to their clients, they would be governed by a broader ethical code of conduct. Should their client make requests of them that would violate this code, fiduciary data scientists would be empowered to refuse to perform such requests.²¹³

5. Fiduciary Data Science Would Establish Stricter Scrutiny for AI/ML Decision-making

[44] Finally, AI/ML decision making (whether automated or informed) should be subject to the same level of scrutiny as human decision making. Imposing fiduciary responsibilities on data scientists would ensure that AI/ML decision systems would be designed and built, as well as expertly audited on release with a careful and ethical approach. As demonstrated, data is used by data scientists to perform analyses that either result in or

²¹¹ See Nigel Davis & Sarah Clinch, *Pervasive Data Science: New Challenges at the Intersection of Data Science and Pervasive Computing*, IEEE PERSASIVE COMPUTING, 1 (2017); see, e.g., Eygenio et al., *supra* note 148.

²¹² See Miranda Bogen, *All the Ways Hiring Algorithms Can Introduce Bias*, HARV. BUS. REV. (May 6, 2019), <https://hbr.org/2019/05/all-the-ways-hiring-algorithms-can-introduce-bias> [<https://perma.cc/7GWJ-GWE2>]; see also Manish Raghavan et. al., *Mitigating Bias in Algorithmic Hiring: Evaluating Claims and Practices*, CONF. ON FAIRNESS, ACCOUNTABILITY, AND TRANSPARENCY 469 (2020), https://dl.acm.org/doi/pdf/10.1145/3351095.3372828?casa_token=cArAXBtLUd4AAA:AAA:bHd16zknxtTeb5dEMAXRITHDPEZ0rSb27RvltBN3HNC_47SE8GoRgesCIU_yeawvHbukmEfQOBy [<https://perma.cc/Y5PW-LHU7>].

²¹³ See, e.g., MODEL RULES OF PROF'L CONDUCT r. 3.3 (AM. BAR ASS'N 2020) (requiring lawyer to refuse client's request to knowingly "make a false statement of fact or law to a tribunal").

inform a decision. All decisions, whether algorithmically or human-driven, impact another person at some point. In the event of injury, harm, or wrongdoing, human decision-making is subject to documentation and scrutiny in the form of review and potentially litigation.²¹⁴ Algorithmic decision-making should be similarly subject to defense or prosecution. While it has been fashionable to refer to AI algorithms like deep neural networks as “black box” methods (i.e., the rationale behind a particular outcome from the algorithm is obscured from human understanding due to complexity),²¹⁵ this “interpretability gap” is becoming less and less acceptable.²¹⁶ Transparency, increased data literacy, and clarity concerning liability are key reasons for closing the interpretability gap.²¹⁷ If the government regulated data scientists as fiduciaries, then it would allow both private citizens and the state itself to hold accountable the data scientists who create AI/ML systems for outcomes of AI/ML decision making, thereby offering relief.

V. CONCLUSION

[45] The data science field is growing in impact in the private and public sectors, thanks to the enormous potential of AI/ML technologies to impact individuals and society. Until recently, AI/ML technology has remained largely unregulated.²¹⁸ However, high-profile failures of AI/ML

²¹⁴ See, e.g., NAT’L TRANSP. SAFETY BD., *supra* note 90, at 13; ‘*Inadequate Safety Culture*’, *supra* note 9; BBC, *supra* note 9.

²¹⁵ Cynthia Rudin & Joanna Radin, *Why Are We Using Black Box Models When We Don’t Need To? A Lesson From An Explainable AI Competition*, HARV. DATA SCI. REV. (Nov. 22, 2019), <https://hdr.mitpress.mit.edu/pub/f9kuryi8/release/5> [<https://perma.cc/W2RE-75F7>]; see also Will Kenton, *Black Box Model*, INVESTOPEDIA (Aug. 25, 2020), <https://www.investopedia.com/terms/b/blackbox.asp> [<https://perma.cc/TY72-XXGZ>].

²¹⁶ See Kenton, *supra* note 215.

²¹⁷ See Josh Bersin & Marc Zao-Sanders, *Boost Your Team’s Data Literacy*, HARV. BUS. REV. (Feb. 12, 2020), <https://hbr.org/2020/02/boost-your-teams-data-literacy> [<https://perma.cc/A5MT-YLFW>].

²¹⁸ See Mark MacCarthy, *AI Needs More Regulation, Not Less*, BROOKINGS (Mar. 9,

systems, coupled with documented bias, and large information asymmetries between data science practitioners and the public-at-large has led to increasing interest in the passage of laws to mitigate AI/ML risks.²¹⁹ Existing regulation focuses on the collection, use, and sale of the data itself, but not on the practitioners who make use of that data.²²⁰ If the social and ethical issues facing the use of AI/ML are to be resolved, the regulation of data scientists as fiduciaries will be necessary for the creation and preservation of a robust regulatory regime around data.

2020), <https://www.brookings.edu/research/ai-needs-more-regulation-not-less/> [<https://perma.cc/UKJ5-P4NL>].

²¹⁹ See Hao, *supra* note 8; 'Inadequate Safety Culture', *supra* note 9; Samuel, *supra* note 10.

²²⁰ See Michael Spencer, *Artificial Intelligence Regulation May Be Impossible*, FORBES (Mar. 2, 2019), <https://www.forbes.com/sites/cognitiveworld/2019/03/02/artificial-intelligence-regulation-will-be-impossible/?sh=2cb9bf3d11ed> [<https://perma.cc/2P2K-WQ3P>].