CONSUMER FINANCE AND AI: THE DEATH OF SECOND OPINIONS?

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People have come to rely on the advice of algorithms for all aspects of their lives, from mundane tasks like choosing the most efficient navigation route home to financial decisions regarding how to invest retirement savings. Because of the ubiquity of algorithms, people have become increasingly comfortable relying on them—a tendency known as automation bias. This Article presents an empirical study that explores automation bias in the area of consumer finance. The study confirms that when making consumer finance decisions, including making significant investment decisions, Americans significantly prefer following the recommendations of algorithms to those of human experts. Moreover, even after poor performance as a result of following an algorithm's advice—or even outright mistakes by the algorithm—consumers continue to favor algorithms to human experts. This result demonstrates that we view algorithms—especially those rooted in big data—as a superior authority.

Our increasing deference to algorithmic results is concerning because we are avoiding obtaining "a second opinion"—even when the first opinion comes from an algorithm that has made mistakes in the past. Although second opinions are costly, they are important—and even critical—in certain situations. By reducing the acceptability of seeking second opinions, our algorithm-dependent society is nudging us to tone down creativity, innovation and critical thinking, and instead to blindly rely on the new experts—the algorithms, whose biases are difficult to assess.

Second opinions do not necessarily need to be human-formulated opinions. In the era of big data and AI, different algorithms that are based on dissimilar data and assumptions can offer second opinions that might be more objective than human-formulated second opinions, which are affected by a human automation bias. As a conclusion, this Article argues that institutions and individuals should implement cultural changes by hyper-nudging users to seek second opinions, including AI-based opinions, and by requiring algorithmic auditing.

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Introduction

Imagine that you are about to take a taxi to the train station, where you plan to catch a train, which departs every few hours, and you are trying to estimate how long it will take to get to the station. Trying to be a sophisticated consumer, you check your traffic-information Waze GPS app on your smart phone,[1] which shows you an estimated travel time of fifty minutes using the app's recommended route. Since a fifty-minute drive would cause you to miss the train you had originally booked, you are trying to look for alternative routes on Waze, and the app shows you a different option with an estimated

1. "Waze incorporates traffic reports from drivers on the road into its mapping software, redirecting drivers away from delayed highways and on to side streets." David Schleicher, *How Land Use Law Impedes Transportation Innovation*, *in* Evidence and Innovation in Housing Law and Policy 38, 47 (Lee Anne Fennell & Benjamin J. Keys eds., 2017).

travel time of seventy minutes. Attempting to be a savvy consumer, and not realizing that Google acquired Waze several years ago and integrated it with Google Maps,[2] you exit the app and check Google Maps hoping for better results, but to your dismay, the predictions remain the same. Accepting your algorithmic destiny, you ask the taxi driver to take what seems to be the fastest option—the fifty-minute route—and also call the train company to pay for a change of reservation as you rebook the next train.

Imagine that instead of accepting the algorithmic results and modifying your reservation accordingly, you consulted with your taxi driver about the routes and the driver disagreed with the app's estimates, having just returned from the train station. Assume that the driver tells you what caused the traffic—a random street closure that will be open again in a few minutes. Having just been there, the driver can also tell you that the police officers standing by the street closure told him that after they reopen the street, traffic will move quickly in the route that currently shows up as the longer, seventy-minute ride. The driver is therefore positive that you can get to the station and to your originally booked train in thirty minutes or less if you take that other route. Confused by the different estimates, you are not sure what to do.

These dilemmas are the kind "considered by the judgment and decision-making literature" in connection with weighing opinions and taking advice.[3] This Article compares taking advice from human ex-

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2. *See* Stephen Edelstein, *Waze's Incident Reporting Feature Is Now Available on Google Maps*, DRIVE (July 2, 2018), http://www.thedrive.com/tech/21895/wazes-incident-reporting-feature-is-now-available-on-google-maps.

3. Christina A. Rader et al., *Advice as a Form of Social Influence: Informational Motives and the Consequences for Accuracy*, 11 SOC. & PERSONALITY PSYCHOL. COMPASS 1, 1 (2017). As discussed in the literature, "[i]n weighting opinions, people rely on cues to an advisor's accuracy. They take more advice from advisors who are more confident, experienced, accomplished, and trusted." *Id.* at 3 (first citing Jack B. Soll & Richard P. Larrick, *Strategies for Revising Judgment: How (and How Well) People Use Others' Opinions*, 35 J. EXPERIMENTAL PSYCHOL.: LEARNING, MEMORY & COGNITION 780, 797 (2009) (confident); then citing Nigel Harvey & Ilan Fischer, *Taking Advice: Accepting Help, Improving Judgment, and Sharing Responsibility*, 70 ORGANIZATIONAL BEHAV. & HUM. DECISION PROCESSES 117, 131 (1997) (experienced); then citing Ilan Yaniv, *Receiving Other People's Advice: Influence and Benefit*, 93 ORGANIZATIONAL BEHAV. & HUM. DECISION PROCESSES 1, 1 (2004) (accomplished); and then citing Janet A. Sniezek & Lyn M. Van Swol, *Trust, Confidence, and Expertise in a Judge-Advisor System*, 84 ORGANIZATIONAL BEHAV. & HUM. DECISION PROCESSES 288, 302–05 (2001) (trusted)). Similarly, people do not listen as much to others' advice when they themselves are more confident. *Id.* (citing Francesca Gino & Don A. Moore, *Effects of Task Difficulty on Use of Advice*, 20 J. BEHAV. DECISION MAKING 21, 31 (2007)). However, it is important to note that "confidence and trust are subjective and susceptible to distortion." *Id.*

perts to taking advice from algorithms—automatic rules that use numerical inputs to produce results—and explores the effects that algorithmic recommendations have on consumers' desire to get second opinions. In particular, it focuses on automation bias,[4] which results in a decreased desire to get second opinions despite the potential of second opinions to change decisions,[5] when those that solicited the second opinion have no fixed view regarding the advice they receive.[6]

This Article studies automation bias and second opinions by exploring two trends in consumer finance. The first trend is the passive outsourcing of decision-making processes to technology,[7] especially to big data algorithms.[8] As some scholars have argued, algorithms "automate aspects of [people's] lives that never used to be subject to the control of"[9] algorithms or artificial intelligence (AI), to the extent that people have basically "outsourced the daily experience of being human to algorithms and machines."[10] The second trend, which this Article demonstrates using an empirical survey experiment, is our perception of algorithms as superior experts that can always outdo human specialists. Moreover, the survey experiment shows that even after realizing that algorithms make mistakes, people still feel more comfortable using them again than a human expert.[11] These empirical results

4. Automation bias and its effects are regarded as, "[t]he impulse to follow a computer's recommendation flows from human 'automation bias'—the 'use of automation as a heuristic replacement for vigilant information seeking and processing.'" Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249, 1271–72 (2008) (quoting Linda J. Skitka et al., *Automation Bias and Errors: Are Crews Better than Individuals?*, 10 INT'L J. AVIATION PSYCHOL. 85, 85 (2000)).

5. *See* Michael Klausner, Geoffrey Miller & Richard Painter, *Second Opinions in Litigation*, 84 VA. L. REV. 1411, 1418 (1998).

6. *See id.* at 1419.

7. This is demonstrated in the emergence of technology that does not just "augment" human intellect and lives, but a technology that is meant to "automate and outsource our humanity." Evan Selinger, *Today's Apps Are Turning Us into Sociopaths*, WIRED (Feb. 26, 2014, 6:30 AM), https://www.wired.com/2014/02/outsourcing-humanity-apps (using the BroApp as an example, as it is a "clever relationship wingman" that "offers the promise of 'maximizing' romantic connection through 'seamless relationship outsourcing,'" and presumably helps achieve a Pareto optimal outcome).

8. *See generally* BRETT FRISCHMANN & EVAN SELINGER, RE-ENGINEERING HUMANITY (2018) (discussing the consequences of outsourcing decisionmaking to algorithms). As stated by Nicholas Carr, our "computer is becoming our all-purpose tool for navigating, manipulating, and understanding the world, in both its physical and its social manifestations." NICHOLAS CARR, THE GLASS CAGE: AUTOMATION AND US 12 (2014).

9. Christine Rosen, *Automation for the People?*, DEMOCRACY: J. IDEAS (2015), https://democracyjournal.org/magazine/35/automation-for-the-people/ (book review).

10. *Id.*; CARR, *supra* note 8, at 18.

11. *See infra* Part II.

are surprising, but not shocking: recent literature in sociology and psychology supports the notion that we no longer seek the guidance of traditional experts or professionals, but the guidance of those that we believe get the best results.[12] For example, the people aboard the USS Vincennes on July 3, 1988, illustrated their automation bias,[13] after trusting the vessel's computer system that recorded Iran Air Flight 655's passenger plane as an F-14 fighter aircraft, and as a result shot it down, leaving its 290 passengers dead, despite evidence available to the pilots beforehand that suggested the computer was wrong.[14]

As exemplified by the crew on the USS Vincennes, automation bias and its resulting outsourcing tendency are concerning. Commenting on people's growing reliance and dependence on algorithmic tools, Evan Selinger and Brett Frischmann argued:

> In the never-ending stream of comfortable, unchallenging personalized info-tainment there's little incentive to break off, to triangulate and fact check with reliable and contrary sources . . . . It is crucial for a resilient democracy that we better understand how these powerful, ubiquitous websites are changing the way we think, interact and behave.[15]

This Article finds that the combination of outsourcing decision-making to algorithms and perceiving algorithms as superior experts is associated with a decreased likelihood that an individual would seek second opinions in connection with algorithmic decisions. This Article refers to this disturbing phenomenon as "the death of the second opinion." While certain studies argue that in some contexts, people could demonstrate an "algorithmic aversion"[16] similar to "advice-taking

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12. *See* sources cited *infra* Part I.B.

13. *See* Peter M. Asaro, *Modeling the Moral User*, 28 IEEE TECH. & SOC'Y MAG. 20, 22–24 (2009); Mary L. Cummings, *Automation and Accountability in Decision Support System Interface Design*, 32 J. TECH. STUD. 23, 23 (2006); M.L. Cummings, *Creating Moral Buffers in Weapon Control Interface Design*, 23 IEEE TECH. & SOC'Y MAG. 28, 32 (2004).

14. Instead, all the people on board trusted it and authorized it to shoot. Chantal Grut, *The Challenge of Autonomous Lethal Robotics to International Humanitarian Law*, 18 J. CONFLICT & SECURITY L. 5, 14 (2013) ("The shooting down of Iran Air Flight 655 is a particularly outrageous example of automation bias, because of the wealth of evidence outside of the Aegis system which clearly indicated that the plane was civilian.").

15. Evan Selinger & Brett Frischmann, *Why It's Dangerous to Outsource Our Critical Thinking to Computers*, GUARDIAN (Dec. 10, 2016, 7:00 AM), https://www.theguardian.com/technology/2016/dec/10/google-facebook-critical-thinking-computers.

16. *See* Paul Michelman, *When People Don't Trust Algorithms*, MIT SLOAN MGMT. REV. (July 5, 2017), https://sloanreview.mit.edu/article/when-people-dont-trust-algorithms/ (first citing Berkeley J. Dietvorst et al., *Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err*, 144 J. EXPERIMENTAL

aversion,"[17] the death of the second opinion is concerning, given our

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PSYCHOL.: GEN. 114, 119–26 (2005); then citing Berkeley J. Dietvorst et al., *Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them*, 64 MGMT. SCI. 1155 (2018); and then citing Berkeley J. Dietvorst, People Reject (Superior) Algorithms Because They Compare Them to Counter-Normative Reference Points (Nov. 20, 2017) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2881503 [https://perma.cc/98N5-5VDB]). This research focused on a very specific aspect of humans versus algorithms in the following way. As Berkeley Dietvorst described in an interview conducted by Paul Michelman,

> [Experiment] participants' job was to complete a forecasting task, and they were incentivized to perform well. The better they performed, the more money they would earn in each experiment. There were two stages: first a practice round—for both humans and algorithms—and then a stage where participants were paid based on the quality of their performance. In the practice round, we manipulated what forecasts participants were exposed to. Some made their own forecasts and saw those of the algorithm. Some made only their own forecasts. Some saw only the algorithm's results. Some saw neither. So each group had different information about how well each forecasting option had performed during the practice round. For the second stage, participants could choose to forecast the results themselves or rely on the algorithm. The majority of participants who had *not* seen the algorithm's results from the first round chose to use it in the second round. However, those people who had seen the algorithm's results were significantly *less* likely to use it, even if it beat their own performance.

Id. The researchers thus concluded, "once people had seen the algorithm perform and learned that it was imperfect . . . they didn't want to use it" and went with their own predictions. Even though people too could have made a forecast that was imperfect, participants still were not less likely to use their own forecasts. Rather, they "saw that effect only for the algorithm." *Id.* The same researchers tried to understand how they could get people to use algorithms once they know that they were imperfect. "In these experiments, however . . . [s]ome participants were given the choice between using the algorithm as it existed or not at all. Other participants, if they chose to use the algorithm, could make some adjustments to it." *Id.* The study concluded,

> people were substantially more willing to use algorithms when they could tweak them, even if just a tiny amount. People may be unwilling to use imperfect algorithms as they exist—even when the algorithm's performance has been demonstrated superior to their own—but if they get any freedom to apply their own judgment through small adjustments, they are much more willing to use the algorithms.

Id.

17. Rader et al., *supra* note 3, at 1 (describing how past research has tested "how accurately people incorporate information from others" and explaining a study that used a literature review "to show that people have mixed success in fulfilling informational motives—they increase their accuracy through the use of advice, but not as much as they could."). The study by Rader et al. states,

> In part, people may discount advice because the reasons for their own answers are better understood or because they overestimate their own abilities. . . . However, people continue to egocentrically discount even when their own reasons are not accessible and when they believe advisors to be as skillful as themselves. . . . In sum, research . . . has shown that

rising dependence on algorithms.[18] Society relies on algorithms that constantly grow in sophistication and size,[19] particularly in the consumer finance area, where people interact with human experts that they may not fully trust or are not always comfortable taking advice from.[20] Yet the same people might view algorithms as more trustworthy because they are aimed at optimizing all decisions.[21] Therefore, algorithms are more commonly used now than ever before, due to the reduction in costs, need for scalability, and efficiency that results from automation, and at times have completely replaced human judgment.[22]

> people can improve accuracy by taking advice, but they rarely do so fully because of egocentric discounting.

Id. at 4 (citations omitted).

18. *See, e.g.*, Nicholas Carr, *Nicholas Carr: 'Are We Becoming Too Reliant on Computers?,'* GUARDIAN (Jan. 17, 2015, 4:00 PM), https://www.theguardian.com/books/2015/jan/17/nicholas-carr-are-we-becoming-too-reliant-on-computers.

19. *See, e.g.*, Thomas Burri, *Free Movement of Algorithms: Artificially Intelligent Persons Conquer the European Union's Internal Market*, *in* RESEARCH HANDBOOK ON THE LAW OF ARTIFICIAL INTELLIGENCE 537, 537 (Woodrow Barfield & Ugo Pagallo eds., 2018) ("explor[ing] the implications such AI entities have for the internal market of the European Union"); Tal Zarsky, *The Trouble with Algorithmic Decisions: An Analytic Road Map to Examine Efficiency and Fairness in Automated and Opaque Decision Making*, 41 SCI., TECH., & HUM. VALUES 118, 119 (2015).

20. A 2018 study conducted in the United States regarding the human experts and professionals that people trust the most and would probably be most comfortable following their recommendations, found that three out of the top five were healthcare professionals (nurses, doctors, and pharmacists). Interestingly enough, the other top two were grade school teachers and military officers, trusted with the safety and security of the people they serve. *See* Niall McCarthy, *America's Most and Least Trusted Professions [Infographic]*, FORBES (Jan. 4, 2018, 7:54 AM), https://www.forbes.com/sites/niallmccarthy/2018/01/04/americas-most-and-least-trusted-professions-infographic/#525dedda65b5. Similarly, a 2017 study conducted in the United Kingdom found that the top five most trusted professionals were nurses, doctors, teachers, professors, and scientists. *See* Niall McCarthy, *Politicians Rated the UK's Most Dishonest Profession*, STATISTA (Dec. 4, 2017), https://www.statista.com/chart/12106/politicians-rated-the-uks-most-dishonest-profession. The increased trust in these types of professionals might lead to weaker effects of the death of the second opinion where interactions with such professionals are taking place. In contrast, bankers, business executives, and even lawyers, for example, enjoy much lower trust levels. *Id.*

21. *See* Michelman, *supra* note 16 (quoting Professor Berkeley Dietvorst in stating that "[a] lot of others followed up Dawes's work and showed that algorithms beat humans in many domains—in fact, in most of the domains that have been tested"); Lee Rainie & Janna Anderson, *Code-Dependent: Pros and Cons of the Algorithm Age*, PEW RES. CTR. (Feb. 8, 2017), http://www.pewinternet.org/2017/02/08/code-dependent-pros-and-cons-of-the-algorithm-age.

22. *See* Carl Benedikt Frey & Michael A. Osborne, *The Future of Employment: How Susceptible Are Jobs to Computerisation?*, 114 TECHNOLOGICAL FORECASTING & SOC. CHANGE 254, 265 (2017) ("According to our estimate, 47% of total US employment is in the high risk category, meaning that associated occupations are potentially automatable over some unspecified number of years, perhaps a decade or two.").

This Article argues that even though algorithms may beat humans in some domains, people should not consider algorithms to be an ultimate and unquestionable authority. Second-guessing decisions, including ones made by algorithms, is critical for our deliberative democracy and our ability to disrupt, innovate, and think outside of the box. This Article also elaborates on the issue of how we define what we consider to be a "better" result when we seek a second opinion, and what values should be included in a decision-making process when we search for "the best result." Second opinions are extremely important and often are relied on for, *inter alia*, high-stakes decisions, decisions about which experts disagree and/or have many options, or situations in which the decision-maker is unhappy with the expert's opinion and is unqualified to sufficiently evaluate the quality of it.[23]

This Article proposes that second opinions do not need to be—and in some circumstances it might be better for them not to be—human-made opinions. In the era of big data and AI, different competing and relatively inexpensive algorithms which are based on dissimilar data and assumptions can also offer second opinions and introduce more options to users.[24] Thus, the Article argues that the new European Union's General Data Protection Regulation (GDPR)—which views fully automated decision-making processes as presumptively unfair and thus provides for the availability of human review of algorithmic results—may have missed the mark. Indeed, in some situations AI-based alternative options can provide more impartial second opinions because exposing human reviewers to algorithmic results could bias the GDPR-mandated reviewers, just like inadmissible evidence could bias jurors.[25] Moreover, given that AI algorithms can self-improve to the extent that even their own programmers might not be able to explain them, it might make sense to consider mandating crowd-sourced algorithm auditing using incentives such as bug bounties to properly assess the logic behind certain algorithmic decisions.[26]

23. *See* Klausner, Miller & Painter, *supra* note 5, at 1419.

24. *Cf. id.* at 1420 (arguing that the more it costs people to obtain second opinions, the less likely they are to seek one). It is important to note that in order for us to indeed know that these algorithms are based on different data and assumptions, we need more algorithmic transparency and accountability.

25. *See* Linda J. Demaine, *In Search of an Anti-Elephant: Confronting the Human Inability to Forget Inadmissible Evidence*, 16 GEO. MASON L. REV. 99, 100–10 (2008) (discussing the influence of evidence that jurors were not supposed to hear on the jurors, after judges instruct them to ignore it).

26. *See* Amit Elazari Bar On, *Bug Bounty Programs as a Corporate Governance "Best Practice" Mechanism*, BERKELEY TECH. L.J.: BLOG (Mar. 23, 2017), http://btlj.org/2017/03/bug-bounty-programs-as-a-corporate-governance-best-practice-mechanism. This Article regards bug bounty programs as:

Lastly, the Article calls for a cultural change in the way algorithms are perceived and suggests employing choice architecture and a hypernudging scheme to address some of the concerns in connection with the need to get a second opinion.

The Article is organized as follows. Part I provides background on our algorithmic society and how people became comfortable with algorithms, relying on them as experts, to which they outsource decision-making processes. This reliance is partly the result of it being convenient, as well as being economically rational.[27] Centering on the issue of authority and how it is perceived in legal, sociological, and psychological scholarship,[28] Part I also explores the role of algorithms as a preferred source of authority. In recent years, scholars have widely discussed algorithms' transparency and accountability[29] but

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> a relatively new strategy employed in the realm of cybersecurity. The policy has an increasing presence in the technology industry, as companies like Apple, Microsoft, Google, PayPal, and Facebook have utilized bug bounty programs to identify weaknesses in their systems. Essentially, bug bounties help "companies to make products more secure while [working] with hackers, many of whom would be looking for the vulnerabilities" in the system regardless.

Kiersten Denny, *Hacking Hollywood: The Entertainment Industry's Constant Concerns with Cybersecurity*, 18 FLA. ST. U. BUS. REV. 31, 50 (2019) (quoting Cassandra Kirsch, *The Grey Hat Hacker: Reconciling Cyberspace Reality and the Law*, 41 N. KY. L. REV. 383, 397 (2014)).

27. *See* Landon Thomas Jr., *At BlackRock, Machines Are Rising Over Managers to Pick Stocks*, N.Y. TIMES (Mar. 28, 2017), https://www.nytimes.com/2017/03/28/business/dealbook/blackrock-actively-managed-funds-computer-models.html.

28. *See* Charles Sanders Peirce, *How to Make Our Ideas Clear*, *in* 5 THE COLLECTED PAPERS OF CHARLES SANDERS PEIRCE 258, 258–68 (Charles Hartshorne & Paul Weiss eds., 1934); Catharine Pierce Wells, *Old Fashioned Postmodernism and the Legal Theories of Oliver Wendell Holmes, Jr.*, 63 BROOK. L. REV. 59, 65–70 (1997). Charles Peirce was a founder of the Pragmatism school of thought, which "represented a new way of looking at the world and an alternative way to understand the increasingly rapid development of science." Wells, *supra* at 63. As described by Catherine Wells, Peirce argued that every human being "seeks to find beliefs that are stable, that will not dissolve into doubts each time we confront a new experience." *Id.* at 68. As also described by Wells, Peirce "considers four distinct strategies for accomplishing this goal—the method of tenacity, the method of authority, the a priori method, and the method of science." *Id.* (citation omitted). Note that more recently, scholars have argued that the difference between the "method of authority" and the "method of science" may not be as absolute as Peirce thought. *See, e.g.*, DOUGLAS WALTON, APPEAL TO EXPERT OPINION: ARGUMENTS FROM AUTHORITY 5–6 (1997).

29. *See, e.g.*, N.Y. Univ. Info. Law Inst., *Algorithms and Accountability Conference*, NYU SCH. L. (Feb. 28, 2015), https://www.law.nyu.edu/centers/ili/AlgorithmsConference [https://perma.cc/35ZQ-XM47]; N.Y. Univ. Info. Law Inst., *Algorithms and Explanations*, NYU SCH. L. (Apr. 27, 2017), https://www.law.nyu.edu/centers/ili/events/algorithms-and-explanations [https://perma.cc/9YY6-9CRB]; *see also* NICHOLAS DIAKOPOULOUS, ALGORITHMIC ACCOUNTABILITY REPORTING: ON THE INVESTIGATION OF BLACK BOXES 2 (2014); Deven R. Desai & Joshua A. Kroll, *Trust But Verify: A Guide to Algorithms and the Law*, 31 HARV. J.L. & TECH. 2, 4–5 (2017)

have not thoroughly addressed people's view of algorithms as experts, or how and why we stopped second-guessing them.[30]

Part II demonstrates this view of algorithms as preferred authorities, which are extremely successful at convincing people.[31] This Part also describes a survey experiment, which was conducted on Amazon Mechanical Turks and found that people feel more comfortable taking the recommendations of algorithms over reputable human experts. Part II then explains how many people are likely to give up on second-

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(arguing that while the standard solution to the algorithmic transparency problems is a call for transparency, "the proposed solution will not work for important computer science reasons. . . . [G]eneral calls to expose algorithms to the sun or to conduct audits will not only fail to deliver critics' desired results but also may create the illusion of clarity in cases where clarity is not possible."); Katherine Noyes, *The FTC Is Worried About Algorithmic Transparency, and You Should Be Too*, PCWORLD (Apr. 9, 2015, 8:36 AM), http://www.pcworld.com/article/2908372/the-ftc-is-worried-about-algorithmic-transparency-and-you-should-be-too.html [https://perma.cc/N3Z2-5M3E] ("[E]ven if an algorithm is made explicit and can be inspected, the light it will shed on potential consequences may be minimal, particularly when the algorithm is complicated or performs operations on large sets of data that aren't also available for inspection."); Christian Sandvig et al., Auditing Algorithms: Research Methods for Detecting Discrimination on Internet Platforms 16 (May 22, 2014) (unpublished manuscript), http://www-personal.umich.edu/~csandvig/research/Auditing%20Algorithms%20--%20Sandvig%20--%20ICA%202014%20Data%20and%20Discrimination%20Preconference.pdf [https://perma.cc/PRE6-G79P] (using a "social scientific audit study" to examine platforms based on algorithms).

30. Recent scholarship that empirically studies people's view of algorithms as experts largely resides outside the field of consumer finance. *See, e.g.*, Jennifer M. Logg et al., *Algorithm Appreciation: People Prefer Algorithmic to Human Judgment* 10–13 (Harvard Bus. Sch., Working Paper No. 17-086, 2018), https://www.hbs.edu/faculty/Publication%20Files/17-086_610956b6-7d91-4337-90cc-5bb5245316a8.pdf (studying "the extent to which people are willing to adjust their estimates" in the context of "guess[ing] an individual's weight from a photograph," "forecast[ing] the popularity of songs on the upcoming week's Billboard Magazine Hot 100 Music Chart," and "predict[ing] how another person would judge a potential romantic partner"); Jennifer M. Logg, *Theory of Machine: When Do People Rely on Algorithms?* (Harvard Bus. Sch., Working Paper No. 17-086, 2017), https://dash.harvard.edu/bitstream/handle/1/31677474/17-086.pdf?sequence=1&isAllowed=y (describing eight experiments that study the circumstances and extent to which people rely more on algorithms than a human expert).

31. Somewhat relatedly, Aristotle wrote about persuasion and methods of informal reasoning, describing what makes one be seen as a convincing, effective authority. *See generally* ARISTOTLE, THE ART OF RHETORIC (H.C. Lawson-Tancred trans., Penguin 1991).

guessing their results, as doing so appears to be pointless[32] and logistically difficult.[33]

Part III focuses on the risks and challenges associated with not seeking a second opinion and instead passively outsourcing to[34] and relying upon algorithms.[35] First, we do not want to live in a society where algorithms inform individuals what the chances are for certain futures to materialize and the individuals passively embrace the predictions without second-guessing them. This could come at the cost of abandoning their hopes and dreams, and studies have shown a direct

32. Among the experts that people would find pointless to second guess are doctors, who enjoy much of the "institutional aura and the halo effect" that scientists receive, even though they, too, make mistakes in their diagnosis and decision-making processes. WALTON, *supra* note 28, at 247. A "2010 Gallup poll found 70 percent of Americans are confident in their doctor's accuracy, and only 29 percent feel the need to do their own research after receiving medical advice. But one in 20 Americans is subjected to diagnostic errors, according to a 2014 [federal] study . . . ." NerdWallet.com, *3 Times You Should Get a Second Opinion About Your Health*, FOX NEWS, http://www.foxnews.com/health/2014/09/26/3-times-should-get-second-opinion-about-your-health.html (last updated Oct. 27, 2015).

33. As Serge Egelman wrote in a fascinating Twitter thread on mistakes by automated fraud detection systems, the human employees not overriding the mistaken automated-systems' decisions, and their inability to do so:

> After multiple hourly calls to my bank to explain the problem, they said there's nothing [they] can do: their fraud detection algorithm will always lock the account after this number of transactions . . . [after multiple calls trying to explain to Amazon's support, the employees have said that] they've given up: it seems that their fraud detection algorithm interprets *any* purchase of gift cards on my account as fraud. . . . They conclude they cannot override the algorithm.

Serge Egelman (@v0max), TWITTER (Dec. 23, 2018, 11:47 AM), https://twitter.com/v0max/status/1076927245107777536?s=11 [https://perma.cc/R578-L4RE].

34. Current trends have historical antecedents. "[B]y the mid-nineteenth century, the man of science gave way to the scientist, representing a shift from gentlemanly vocation to profession." JOANNA WILLIAMS, ACADEMIC FREEDOM IN AN AGE OF CONFORMITY: CONFRONTING THE FEAR OF KNOWLEDGE 95 (2006) (internal quotation marks and citation omitted). As Thomas Haskell argues, "[p]recisely because there were truths that no honest investigator could deny, the power to make decisions had to be placed in the hands of experts whose authority rested on special knowledge rather than raw self-assertiveness, or party patronage, or a majority vote of the incompetent." THOMAS HASKELL, THE EMERGENCE OF PROFESSIONAL SOCIAL SCIENCE: THE AMERICAN SOCIAL SCIENCE ASSOCIATION AND THE NINETEENTH-CENTURY CRISIS OF AUTHORITY 87 (Johns Hopkins Univ. Press 2000) (1977). "What is it about modern society that causes men to rely increasingly on professional advice? Under what circumstances do men come to believe that their judgment, based on common sense and the customary knowledge of the community, is not adequate?" *Id*. at 28; *see* FRANK FUREDI, AUTHORITY: A SOCIOLOGICAL HISTORY 399 (2013).

35. Adrian Vermeule, *Second Opinions and Institutional Design*, 97 VA. L. REV. 1435, 1458 (2011) ("The main costs are the direct costs of obtaining a second opinion, the opportunity costs of delayed decision making, and the risk of indeterminacy if the two opinions differ." (emphasis omitted)).

correlation between a sense of hope and creativity.[36] Second, it is possible to succeed even when going against the odds. As data on successful startups show, more than nine out of ten startups will fail.[37] But, experiencing failures helps succeeding in the future.[38] And, even if one hopes, tries, and fails, there is still value in trying and failing.[39] Third, it is important to encourage people to dissent and second-guess results and decisions—even if "conformity is often a rational course of action."[40] Many people conform when they lack much information, and following others' provides the best available information about what should be done.[41] Such "widespread conformity deprives the public of information that it needs to have," and second-guessing helps maintain the sensation of democracy and free choice.[42] Fourth,

36. *See, e.g.*, Arménio Rego et al., *Are Hopeful Employees More Creative? An Empirical Study*, 21 CREATIVITY RES. J. 223, 223 (2009) ("Hope is potentially important for creativity at work because: (a) creativity requires challenging the *status quo* and a willingness to try and possibly fail . . . .").

37. *See, e.g.*, Erin Griffith, *Why Startups Fail, According to Their Founders*, FORTUNE (Sept. 25, 2014), http://fortune.com/2014/09/25/why-startups-fail-according-to-their-founders.

38. "Founders who have failed at a prior business have a 20 percent chance of succeeding versus an 18 percent chance of success for first time entrepreneurs." Matt Mansfield, *Startup Statistics—The Numbers You Need to Know*, SMALL BUS. TRENDS (Mar. 28, 2019), https://smallbiztrends.com/2016/11/startup-statistics-small-business.html.

39. As the British inventor James Dyson described, "Creativity is something we can all improve at . . . it is about daring to learn from our mistakes." Matthew Syed, *Viewpoint: How Creativity Is Helped by Failure*, BBC NEWS (Nov. 14, 2015), http://www.bbc.com/news/magazine-34775411 ("Organisations like Google, Apple, Dyson and Pixar have developed cultures that, in their different ways, create the conditions for empowering failure.").

40. Cass R. Sunstein, *Conformity and Dissent* 3 (Univ. of Chi. Law Sch., John M. Olin Law & Econ. Working Paper No. 164 (2d series), 2002), https://ssrn.com/abstract=341880 [hereinafter Sunstein, *Conformity and Dissent*]. As Sunstein argues, "[o]ne reason we conform is that we often lack much information of our own, and the decisions of others provide the best available information about what should be done." *Id.* (citing Joseph Henrich et al., *Group Report: What Is the Role of Culture in Bounded Rationality?*, *in* BOUNDED RATIONALITY: THE ADAPTIVE TOOLBOX 343, 344 (Gerd Gigerenzer & Richard Selten eds., 2002) ("Cultural transmission capacities allow individuals to shortcut the costs of search, experimentation, and data processing algorithms, and instead benefit from the cumulative experience stored in the minds (and observed in the behavior) of others.")).

41. *See* Henrich et al., *supra* note 40.

42. Sunstein, *Conformity and Dissent*, *supra* note 40. Scholars from multiple disciplines have questioned whether or not humans really have free will, how people make decisions, and whether people's decisions are actually merely illusions of their choice-making. *See generally* Phil Molé, *Zeno's Paradox and the Problem of Free Will*, 10 SKEPTIC 58 (2004). While these questions go beyond the scope of this Article (and were also at the center of an eight Academy Awards-winning movie in 2010, titled *Inception*), the importance of the sensation of democracy and free choice in our society is a key separate issue that this Article discusses. Therefore, this Article focuses

while automation may eliminate different types of jobs, it is not likely to replace jobs that rely on human traits that are tightly related to second-guessing and are hard for AI to replicate, such as innovation, creativity, social and emotional intelligence, critical thinking, and collaboration.[43] Fifth, the death of second opinions significantly impacts privacy. Finally, algorithms use opaque and often biased programmed reasoning that relies on data that is specifically or biasedly selected.

Part IV argues that two reforms are needed to maintain the benefits of the increasing human reliance on algorithmic decisions. First, we should require algorithmic decision-making tools to include user-friendly features that enable users to see what the algorithmic results they received were based on, and second (i.e., different) opinion alternatives. Attempting to achieve similar goals, algorithmic audits—an auditing process in which entities "open up their technology for evaluation"[44]—have recently become a beneficial and critical tool.[45] Second, we must nudge people to second-guess algorithmic results by employing choice architecture using behavioral psychological incentives, providing a "second opinion warning," and explaining that algorithmic results are based on automated processes that can never be neutral and that other experts might reach different conclusions. This includes other algorithms that may suggest different data and results, as algorithmic results do not represent a scientific singular truth. And, in order to make it more effective, the nudge process could be done using Karen Yeung's hypernudge concept, which is based on big data

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more on individuals' "signals[ ]about what is true and what is right," and how the desire to conform causes people to suppress their own preferences and choices, which can result in "significant social harm." Sunstein, *Conformity and Dissent*, *supra* note 39, at 6. Individuals might not even realize that there are other possible courses of actions to choose from. *See generally id.* Moreover, "[w]hen groups become caught up in hatred and violence, it is . . . [usually the] product of the informational and reputational influences . . . ." *Id*. at 5; *see also* Cass R. Sunstein, *Why They Hate Us: The Role of Social Dynamics*, 25 HARV. J.L. & PUB. POL'Y 429 (2002).

43. Lee Rainie & Janna Anderson, *The Future of Jobs and Jobs Training*, PEW RES. CTR. (May 3, 2017), http://www.pewinternet.org/2017/05/03/the-future-of-jobs-and-jobs-training.

44. Jessi Hempel, *Want to Prove Your Business Is Fair? Audit Your Algorithm*, WIRED (May 9, 2018, 8:00 AM), https://www.wired.com/story/want-to-prove-your-business-is-fair-audit-your-algorithm.

45. "By opting-in to an audit, many businesses believe they're getting early insight into tools that will eventually be required by regulators. In 2016, Obama's White House called on companies directly to audit their algorithms." *Id.*; *see* EXEC. OFFICE OF THE PRESIDENT, BIG DATA: A REPORT ON ALGORITHMIC SYSTEMS, OPPORTUNITY, AND CIVIL RIGHTS (2016), https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/2016_0504_data_discrimination.pdf.

algorithms knowing when and in what ways to nudge individuals.[46] Similarly, we should educate people to triangulate information[47] by consulting different sources of information they agree and disagree with and checking those against, preferably neutral, third party information. These recommendations are aimed at increasing knowledge and the ability to determine what is true, and that helps us maintain a sense of freedom. Promoting these goals, and also protecting people from unfair usages of data, are among the objectives of the GDPR, which came into effect across all European Union member states in May 2018.[48] This Article argues that the GDPR serves as an example to help ensure that any requested human intervention or review is effective and unbiased, and remove human prejudices in favor of automated decisions.

I.
IN ALGORITHMS WE TRUST?

A. *Rational People in an Algorithmic Culture*

> The next time you hear someone talking about algorithms, replace the term with "god" and ask yourself if the meaning changes. Our supposedly algorithmic culture is not a material phenomenon so much as a devotional one, a supplication made to the computers people have allowed to replace gods in their minds, even as they simultaneously claim that science has made us impervious to religion.
>
> —Ian Bogost[49]

Algorithms have become "powerful and consequential actors in a wide variety of domains."[50] They are ubiquitous in "search engines, online news, education, markets, political campaigns, urban planning cases, welfare benefits, and public safety"[51] related issues. They determine stock prices, assess espionage cases, rank movie ratings, create

46. Karen Yeung, '*Hypernudge': Big Data as a Mode of Regulation by Design*, 20 INFO., COMM. & SOC'Y 118, 119 (2017).

47. *See* VINCENT F. HENDRICKS & PELLE G. HANSEN, INFOSTORMS: HOW TO TAKE INFORMATION PUNCHES AND SAVE DEMOCRACY 139 (2014).

48. Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the Protection of Natural Persons with Regard to the Processing of Personal Data and on the Free Movement of Such Data, and Repealing Directive 95/46/EC, 2016 O.J. (L 119) 1 [hereinafter GDPR].

49. Ian Bogost, *The Cathedral of Computation*, ATLANTIC (Jan. 15, 2015), http://www.theatlantic.com/technology/archive/2015/01/the-cathedral-of-computation/384300 [https://perma.cc/AA6T-3FWV].

50. Malte Ziewitz, *Governing Algorithms: Myth, Mess, and Methods*, 41 SCI., TECH., & HUM. VALUES 3, 5 (2016).

51. *Id.*

medical diagnoses and music recommendations, impact criminal sentencing, and even play an incremental role in gambling.[52] This list of algorithm uses suggests an almost universal "relevance of algorithms."[53] Contributing to their popularity is the fact that computers today are fast enough to run large-scale neural networks at a relatively low cost,[54] so with lower technological and financial barriers to entry, sophisticated algorithms and AI tools are now available to big companies like Google, Amazon, and Apple as well as to smaller-scaled businesses and startups. And, in most cases, especially in the context of consumer finance,[55] the algorithmic results are so accurate and efficient that it is economically rational to rely on them, and extremely convenient to outsource decision-making to them.[56]

As I discuss in a chapter I coauthored in the *Research Handbook on the Law of Artificial Intelligence*, aside from occasional unpleasant occurrences, where less than ideal determinations such as the denial of a loan are the algorithmic systems' fault:[57]

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52. *Id.* (citing CHRISTOPHER STEINER, AUTOMATE THIS: HOW ALGORITHMS TOOK OVER OUR MARKETS, OUR JOBS, AND THE WORLD (2012)).

53. *See generally* Tarleton Gillespie, *The Relevance of Algorithms*, *in* MEDIA TECHNOLOGIES: ESSAYS ON COMMUNICATION, MATERIALITY, AND SOCIETY 167 (Tarleton Gillespie, Pablo Boczkowski & Kirsten Foot eds., 2014).

54. DANIEL D. GUTIERREZ, INSIDEBIGDATA, INSIDEBIGDATA GUIDE TO DEEP LEARNING & ARTIFICIAL INTELLIGENCE 2 (2017) (on file with the N.Y.U. Journal of Legislation and Public Policy).

55. Francesco D'Acunto, Nagpurnanand Prabhala & Alberto G. Rossi, *The Promises and Pitfalls of Robo-Advising* 19 (CESifo Working Paper Series, Paper No. 6907, 2018), https://ssrn.com/abstract=3122577 (finding that for all investors, robo-advising positively impacts and lowers, even if it does not completely eliminate, pervasive behavioral biases).

56. *See* Nizan Geslevich Packin & Yafit Lev-Aretz, *On Social Credit and the Right to Be Unnetworked*, 2016 COLUM. BUS. L. REV. 339, 369 (2016) [hereinafter Packin & Lev-Aretz, *On Social Credit*].

> In general, rational actions and beliefs are defined as 'guided by reason, principles, fairness, [or] logic;' irrational decisions and beliefs are not. The definition appears to be fairly straightforward. Yet past decades have seen countless disagreements among scholars from different schools of thought as to what it means for individuals to behave in a rational way. The neoclassical economic theory builds upon the foundational assumption that economic individuals are rational maximizers of utility. In a world of 'perfect competition,' . . . economic individuals are presumed to all be somewhat similar, never err, and avoid any information costs. As a result, the model predicts that resources are always and instantly directed to their highest value use.

Id. (citations omitted). Time and money, being scarce resources, are things that people always need, and thus outsourcing decision-making processes to highly effective and efficient algorithms might just be an extremely rational thing to do.

57. *See* Desai & Kroll, *supra* note 29, at 2. Desai and Kroll list additional examples of these kinds of situations, such as:

> Across various industries, [AI] systems successfully cut costs, streamline processes, and produce valuable predictions. Artificial Intelligence is used by companies like Amazon and Google to fight malware. Indeed, in each of these companies, '[t]rained on hundreds of millions of files, the neural network learns to detect more threats and then uses its experience to predict new attacks.' The same logic is capitalized on in financial trading, where many trading firms use proprietary learning algorithms to predict and execute trades at high speeds and high volume . . . . AI also guides investments by hedge funds, informs investment strategies in asset management, helps detect money laundering and fraud, and offers alternative and arguably better risk prediction for potential borrowers . . . . AI is used in healthcare for different purposes such as mining medical records, designing treatment plans, diagnosing patients through analyzing physicians' free-form text notes in electronic health records, and predicting wait times for patients in emergency department waiting rooms.[58]

Similarly, AI algorithms are used in setting bail,[59] sentencing,[60] and to automatically detect and prevent disorderly and criminal activities.[61] Sophisticated algorithms also impact personnel decisions, and

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> Someone is denied a job. A family cannot get a loan for a car or a house. Someone else is put on a no-fly list. A single mother is denied federal benefits. None of these people knows why that happened other than the decision was processed through some software. Someone commandeers a car, controls its brakes, and even drives away. A car company claims its cars have low emissions, but in fact its cars pollute significantly. A voting machine is supposed to count votes accurately, but no one can tell whether the count is correct. A car's battery seems not to have a good range, so its software is updated, but no one knows whether the update has fixed the problem or is compliant with government regulations. Searches for black-sounding names yield ads suggestive of arrest records.

Id.

58. Nizan Geslevich Packin & Yafit Lev-Aretz, *Learning Algorithms and Discrimination*, *in* RESEARCH HANDBOOK ON THE LAW OF ARTIFICIAL INTELLIGENCE 89–90 (Woodrow Barfield & Ugo Pagallo eds., 2018) [hereinafter *Learning Algorithms*] (citations omitted).

59. *See* Shaila Dewan, *Judges Replacing Conjecture with Formula for Bail*, N.Y. TIMES (June 26, 2015), http://www.nytimes.com/2015/06/27/us/turning-the-granting-of-bail-into-a-science.html.

60. *See* Sonja B. Starr, *Evidence-Based Sentencing and the Scientific Rationalization of Discrimination*, 66 STAN. L. REV. 803, 809 (2014) ("'Evidence-based sentencing' (EBS) refers to the use of actuarial risk prediction instruments to guide a judge's sentencing decision."); Anna Maria Barry-Jester, Ben Casselman & Dana Goldstein, *Should Prison Sentences Be Based on Crimes that Haven't Been Committed Yet?*, FIVETHIRTYEIGHT (Aug. 4, 2015), https://fivethirtyeight.com/features/prison-reform-risk-assessment.

61. *See generally* Michael L. Rich, *Machine Learning, Automated Suspicion Algorithms, and the Fourth Amendment*, 164 U. PA. L. REV. 871 (2016); Sameer Shah, Aayoush Sharma, Raghav Angra, Nitin Singh et al., *Automated Vigilance Assistance*

have been used to suggest who to hire, fire, give a raise to, and what talent to develop, among other decisions.[62] Search and recommendation engines use machine learning algorithms to analyze user activity and determine consumption behavior.[63] Driverless cars, which are currently undergoing development, employ learning systems that likewise gather and analyze information about the car owner and their environment.[64] Finally, AI has made advancements in a range of markets and fields of research, from providing alternatives to traditional legal advice,[65] forecasting the weather and defending against asteroid threats,[66] to predicting and marketing meals.[67]

System with Crime Detection for Upcoming Smart Cities (SAE Int'l, Technical Paper No. 2017-01-1726, 2017), https://doi.org/10.4271/2017-01-1726.

62. *See* David H. Autor, *Why Are There Still So Many Jobs? The History and Future of Workplace Automation*, 29 J. ECON. PERSP. 3, 3 (2015); Richard Berriman & John Hawksworth, PwC, *Will Robots Steal Our Jobs? The Potential Impact of Automation on the UK and Other Major Economies*, UK ECON. OUTLOOK 30 (Mar. 2017), https://www.pwc.co.uk/economic-services/ukeo/pwcukeo-section-4-automation-march-2017-v2.pdf [https://perma.cc/HPG6-LT5W]; Jeanne Meister, *The Future of Work: The Intersection of Artificial Intelligence and Human Resources*, FORBES (Mar. 1, 2017, 9:20 AM), https://www.forbes.com/sites/jeannemeister/2017/03/01/the-future-of-work-the-intersection-of-artificial-intelligence-and-human-resources/#6d75932c6ad2.

63. *Learning Algorithms*, *supra* note 58, at 90.

64. *Id.*

65. *See* Stephanie Mlot, *AI Beats Human Lawyers at Their Own Game*, GEEK (Feb. 26, 2018, 1:30 PM), https://www.geek.com/tech/ai-beats-human-lawyers-at-their-own-game-1732154 (discussing a new study that suggests that artificial intelligence makes better lawyers than humans do, when LawGeex, an artificial intelligence LegalTech startup "pitted 20 experienced attorneys against a three-year-old algorithm trained to evaluate contracts," and the algorithm proved to be more effective and accurate). According to Deloitte, about 100,000 legal jobs are going to be automated in the next two decades, and thirty-nine percent of legal jobs can be automated. *See Deloitte Insight: Over 100,000 Legal Roles to Be Automated*, LEGAL IT INSIDER (Mar. 16, 2016, 10:28 AM), https://www.legaltechnology.com/latest-news/deloitte-insight-100000-legal-roles-to-be-automated. McKinsey Global Institute believes that twenty-three percent of legal professionals' jobs could be automated. Steve Lohr, *A.I. Is Doing Legal Work. But It Won't Replace Lawyers, Yet*, N.Y. TIMES (Mar. 19, 2017), https://www.nytimes.com/2017/03/19/technology/lawyers-artificial-intelligence.html (citing JAMES MANYIKA ET AL., MCKINSEY GLOBAL INST., A FUTURE THAT WORKS: AUTOMATION, EMPLOYMENT AND PRODUCTIVITY (2017), https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Digital%20Disruption/Harnessing%20automation%20for%20a%20future%20that%20works/MGI-A-future-that-works_Full-report.ashx [https://perma.cc/G9NM-F849]). Similarly, scholars have recently argued that the immediate implementation of emerging legal technology would result in an estimated decline of lawyers' hourly charges by thirteen percent. *See* Dana Remus & Frank Levy, Can Robots Be Lawyers? Computers, Lawyers, and the Practice of Law 46 (Nov. 27, 2016) (unpublished manuscript), https://ssrn.com/abstract=2701092 or http://dx.doi.org/10.2139/ssrn.2701092.

66. GUTIERREZ, *supra* note 55, at 8–9.

67. *See* Alicia Kelso, *Ghost Kitchens, AI and POS Systems: Restaurant Tech Providers Predict Top 2020 Trends*, FORBES (Jan. 2, 2020, 10:03 AM), https://

B. *The Search for the Ultimate Authority: Algorithms Are the New Experts*

Experts often possess more data than judgment.

—Colin Powell[68]

The consequences of the recent prevalence of algorithms and automated decision-making tools have resulted in numerous academic discussions, many of which focused on the scale of algorithmic processes—"sorting, filtering, searching, prioritizing, recommending, [and] deciding"—with only a few reflecting on the "social role" of algorithms.[69] This is to be expected, since "algorithmic processes take on increasing weight and responsibility."[70] Accordingly, even in the context of autonomous cars—an AI tool that has been met with great doubt and skepticism—recent studies have shown that when autonomous cars have "talked" to their users and explained their driving-decisions, the human passengers listened and trusted the algorithms to a much greater extent.[71] Armed with this realization, scholars have argued that algorithms "have the capacity to shape social and cultural formations and impact directly on individual lives,"[72] serve as "pathways through which capitalist power works,"[73] signify "rules of rationality [that] replaced the self-critical judgments of reasons,"[74] function as "an interpretative key of modernity,"[75] and even "acquire

www.forbes.com/sites/aliciakelso/2020/01/02/ghost-kitchens-ai-and-pos-systems-restaurant-tech-providers-predict-top-2020-trends/#59936181474d.

68. Colin L. Powell, My American Journey 102 (1995).

69. David Beer, *The Social Power of Algorithms*, 20 Info., Comm. & Soc'y 1, 3 (2017).

70. *Id.*

71. See an interview in Hebrew with Jack West, chief engineer at Intel and the Israeli Mobileye's autonomous cars project, at Tal Shahaf, *When the Autonomous Car Talks to the Passengers—They Believe It*, Globes (July 28, 2018), https://www.globes.co.il/news/article.aspx?did=1001247741#utm_source=social [https://perma.cc/SX8Z-T7Q3] (Jack West, in an interview about building trust between passengers and their autonomous cars, talks about how when the car describes every single decision it makes to the passengers it is driving, the passengers trust it and believe in the accuracy of its decisions).

72. David Beer, *Power Through the Algorithm? Participatory Web Cultures and the Technological Unconscious*, 11 J. New Media & Soc'y 985, 994 (2009) (citing Scott Lash, *Power After Hegemony: Cultural Studies in Mutation?*, 24 Theory, Culture & Soc'y 55 (2007)).

73. Lash, *supra* note 72, at 71 (emphasis omitted).

74. Lorraine Daston, *How Reason Became Rationality*, MPIWG, http://www.mpiwg-berlin.mpg.de/en/research/projects/DeptII_Daston_Reason (last visited Feb. 1, 2020).

75. Paolo Totaro & Domenico Ninno, *The Concept of Algorithm as an Interpretative Key of Modern Rationality*, 31 Theory, Culture & Soc'y 29, 30 (2014).

the sensibility of truth."[76] Indeed, in an era that has been nicknamed the "age of the algorithm,"[77] users, activists, and policy makers are worried "that individual autonomy is lost in an impenetrable set of algorithms."[78]

For a wealth of reasons, people choose to rely on algorithms as they decide daily about matters—big or small—in their lives. As the use of algorithms becomes cheaper and more common in many areas of life, more and more users that benefit from using algorithms view their results as absolute truths and assign to the algorithms the institutional aura and halo effect that qualified experts have as a source of authority.[79] Part III discusses the problematic aspects of adopting such an approach toward algorithms. However, in order to better understand this human approach, several questions need to be explored first, such as: what kinds of issues do people care about when they search for experts and expertise, and what is the relation between the expert and the expertise? How do theories regarding professionals, scientists, skilled labor, knowledge, power, occupational groups, and rational actors fit in, and are skill and mastery more important than credentials and rituals of legitimation?[80] How is embodied expertise transformed

76. Kevin Slavin, *How Algorithms Shape Our World*, TED (July 2011), http://www.ted.com/talks/kevin_slavin_how_algorithms_shape_our_world.html (follow "Transcript" hyperlink).

77. Christopher Kelty, Assistant Prof., Rice Univ., Lecture at the RLG 2003 Annual Meeting: Qualitative Research in the Age of the Algorithm: New Challenges in Cultural Anthropology (May 5, 2003), http://worldcat.org/arcviewer/1/OCC/2007/08/08/0000070504/viewer/file1384.html [https://perma.cc/UJ6Z-WZGB].

78. EXEC. OFFICE OF THE PRESIDENT, BIG DATA: SEIZING OPPORTUNITIES, PRESERVING VALUES 10 (2014), https://obamawhitehouse.archives.gov/sites/default/files/docs/big_data_privacy_report_may_1_2014.pdf [hereinafter EXEC. OFFICE OF THE PRESIDENT, BIG DATA: SEIZING OPPORTUNITIES] ; Ziewitz, *supra* note 50, at 4.

79. *See* WALTON, *supra* note 28, at 5–9, 188 (discussing science as the modern authoritarianism).

80. *See, e.g.*, ANDREW ABBOTT, THE SYSTEM OF PROFESSIONS: AN ESSAY ON THE DIVISION OF EXPERT LABOR 2 (1988) (analyzing "the system of professions as a whole"); MAX WEBER, THE VOCATION LECTURES 17, 40 (David Owen & Tracy B. Strong eds., Rodney Livingstone trans., 2004) (discussing "science as a vocation" and "politics as a vocation"); HARRY COLLINS & ROBERT EVANS, RETHINKING EXPERTISE 11–12 (2009) (developing a "realist theory of expertise" based on a classification of different forms of expertise and "meta-expertise"); Dominic Boyer, *Thinking Through the Anthropology of Experts*, 15 ANTHROPOLOGY ACTION 38, 39 (2008) ("linking expertise to skill, competence, attention and practice"); E. Summerson Carr, *Enactments of Expertise*, 39 ANN. REV. ANTHROPOLOGY 17, 18–19 (2010) (basing its claims on the "simple premise that expertise is something people do rather than something people have or hold . . . expertise requires the mastery of verbal performance, including—perhaps most importantly—the ability to use language to index and therefore instantiate already existing inner states of knowledge"). *See generally* THE PHILOSOPHY OF EXPERTISE (Evan Selinger & Robert P. Crease eds., 2006) (collecting fifteen essays on the philosophy of expertise that cover a wide range of philosophical sub-specialties,

into bureaucratic structure or systematic forms of management and audit? Lastly, what kinds of empirical, critical, and philosophical work have been done in these domains, and does information technology and algorithms have a place in this discourse?[81]

This Article does not and cannot fully answer all of these questions, but it does introduce and address several issues that are relevant in the context of big data algorithms and having automated decision-making tools as potential authorities. Therefore, providing some background about society's perception of experts and their authority, based on sociology theories, seems like a key starting point.

Sociologist Gil Eyal compares the sociology of professions with experts and expertise, and believes that "the sociology of professions" has been mainly a "sociology of experts."[82] The word "profession" derives from the Latin *profiteri*, which means to declare aloud. It was also used as "the term for the vows or public declarations taken upon entering a religious order," but has become the foundation for the word "professor," which generally means a high-ranked teacher, and "professional."[83] Following a similar rationale, interestingly, the main word to describe someone who is not knowledgeable is a layman, which is generalized from the old contrast between laymen and clerics. *Layis* from the Latin *laicus* means not of the clergy and is derived from the Greek *laikos,* which means "of the people."[84]

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including the problem of trust, from the perspectives of experts and consumers of expertise); Gil Eyal & Larissa Buchholz, *From the Sociology of Intellectuals to the Sociology of Interventions*, 36 ANN. REV. SOC. 117 (2010).

81. *See, e.g.*, HUBERT L. DREYFUS & STUART E. DREYFUS, MIND OVER MACHINE: THE POWER OF HUMAN INTUITION AND EXPERTISE IN THE ERA OF THE COMPUTER 79 (1986) (arguing that the difficulty for computers to develop a "commonsense understanding" of the "human form of life" explained the slow rate of progress in AI research up to the 1980s); RICHARD SENNETT, THE CRAFTSMAN 8–11 (2008). *See generally* HUBERT L. DREYFUS, WHAT COMPUTERS STILL CAN'T DO: A CRITIQUE OF ARTIFICIAL REASON (1992) (criticizing AI and its abilities); Nick Seaver, *The Nice Thing About Context Is that Everyone Has It*, 37 MEDIA, CULTURE & SOC'Y 1101 (2015); Chloe Aiello, *Elon Musk Admits Humans Are Sometimes Superior to Robots, in a Tweet About Tesla Delays*, CNBC, https://www.cnbc.com/2018/04/13/elon-musk-admits-humans-are-sometimes-superior-to-robots.html (last updated Apr. 17, 2018, 1:28 PM); Clifford Atiyeh, *Toyota—of All Companies—Defends Drivers, Says It Won't Build a Fully Autonomous Car*, CAR & DRIVER (Sept. 10, 2014), https://www.caranddriver.com/news/toyota-defends-drivers-says-it-wont-build-a-fully-self-driving-car.

82. *See generally* Gil Eyal, *For a Sociology of Expertise: The Social Origins of the Autism Epidemic*, 118 AM. J. SOC. 863 (2013).

83. *Id.* at 869.

84. "In Christian Latin, laicus, from Greek Laikos 'of the people', applies to the generality of Christians as distinct from the clergy." Richard Sharpe, *Hiberno-Latin Laicus, Irish Láech and the Devil's Men*, 30 ÉRIU 75, 75 (1979).

Reviewing earlier scholarship, Eyal writes that "the sociology of professions typically treated expertise as an attribution [that] experts possessed by virtue of recognition granted by significant others . . . ."[85] However, a trend of "replac[ing] the sociology of professions with the more comprehensive and timely sociology of expertise,"[86] has started to take place. The word "expertise" "derives from the Latin root *experiri*, 'to try,' and typically means know-how, the capacity to get a task accomplished better and faster because one is more experienced, 'tried.'"[87] Some believe that an advantage of the term "expertise" is that it enables society to "distinguish between experts and expertise as requiring two distinct modes of analysis that are not reducible to one another": experts are 1) "the actors who make claims to jurisdiction over a task by 'professing' their disinterest, skill, and credibility," and 2) operated historically in an "organizational form: credentialing, licensing, and the formation of professional associations and lobbying outfits."[88] In other words, expertise is "the sheer capacity to accomplish [a] task better and faster."[89] Eyal regards expertise "as a network linking together agents, devices, concepts, and institutional and spatial arrangements," and describes how the term "expertise" is more relevant now and more recent than the term "expert."[90]

As conventional and recognized professions began to change in the 1960s, so did the meaning and use of "expert."[91] After the amount

85. Eyal, *supra* note 82, at 870 (citing COLLINS & EVANS, *supra* note 80, at 2).
86. *Id.* at 863.
87. *Id.* at 869.
88. *Id.* at 863, 869–70.
89. *Id.* at 869.
90. *Id.* at 863, 869.
91. *Id.* at 869. Also conducting research on experts and cultures of expertise, Dominic Boyer has written that since the 1950s and 1960s, "commentary on the social figure of 'the expert' began to appear routinely within ethnography." Boyer, *supra* note 80, at 38. Although "experts have come to receive increasingly prominent billing in the ethnography of modernity," she believes that "the theorization of exactly who or what counts as 'expert' continues to be underdeveloped" and that "we need to move beyond signaling the presence of experts and towards grappling with what kinds of persons they are." *Id.* at 39. Boyer suggests that "we define an expert as an actor who has developed skills in, semiotic-epistemic competence for, and attentional concern with, some sphere of practical activity." *Id.* Further, "by linking expertise to skill, competence, attention and practice, it becomes clear that there is no human being who is not 'expert' in some fashion." *Id.* Steven Brint also focuses on this change, and analyzes somewhat critically the concept of the profession. STEVEN BRINT, IN AN AGE OF EXPERTS: THE CHANGING ROLE OF PROFESSIONALS IN POLITICS AND PUBLIC LIFE 202–03 (1994). Brint stresses above all that there has been a fundamental shift in reality: from a social trusteeship role of the classic modern professions to the expert professionalism of an ever broader and far more diversified stratum of knowledge-based occupations. *Id.* at 203–05. He also discusses the changing roles of professions in advanced capitalist societies. *Id.*

of candidates for expert status rose and the "basis of their claims became more heterogeneous," people started using the term "expertise" in order to dechipher whether a claim was legitimate or not.[92] Over the last few decades, some sociologists have advocated for a "substantivist" approach to expertise that differentiates true experts from others based on the potential experts' embodied and implicit mastery of a background set of rules and practices, and argue that they can treat expertise as a fundamental skill that only some have.[93] Other scholars have argued that it is not clear if sociologists can even make such determinations without "themselves becoming embroiled in a controversy about their own expertise."[94]

Another interesting aspect of such a substantive approach is that it can be seen as "a spirited defense of human experts against" AI and expert systems invading into the human experts' jurisdiction.[95] Indeed, under the sociology of expertise there is no longer the question of who has jurisdiction and control over the task. The issue can instead be couched as

> if—as the substantive approach emphasizes—any rule-like performance is only explicable by reference to a 'background of practices' that are its 'condition of possibility,' then a full explication of expertise must explore indeed this background of practices and the social, material, . . . and conceptual arrangements that serve as its conditions of possibility.[96]

This analysis ideally should include the complex make-up of the expertise, but doing so may be hard as it is difficult to decode this make-up once the algorithmic black box process is completed and the expertise is developed and embodied in an expert.[97] This is especially true in connection with AI and expert systems.

Even though AI technologies have not reached human-like capabilities of cognitive thinking, AI (as distinguished from human) experts have gained considerable traction in recent years.[98] Intelligent

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92. *See Eyal*, *supra* note 82, at 869.

93. *Id.* at 870–73 (citations omitted).

94. *Id.*

95. *Id.* at 871.

96. *Id.*

97. *Id.* As for the black box process, "[c]hallenging algorithm-driven vetting and screening protocols under due process claims means demanding answers about the 'black box' processes that may flag individuals as potential risks or threats." Margaret Hu, *Algorithmic Jim Crow*, 86 FORDHAM L. REV. 633, 692 (2017).

98. *See, e.g.*, Cade Metz, *When the A.I. Professor Leaves, Students Suffer, Study Says*, N.Y. TIMES (Sept. 6, 2019), https://www.nytimes.com/2019/09/06/technology/when-the-ai-professor-leaves-students-suffer-study-says.html (explaining a study "conducted by researchers at the University of Rochester" that "found that over the

computer systems use "intelligent agents" that are programmed to carry out tasks and achieve certain outcomes.[99] Moreover, where intelligent agents have "machine learning" capabilities, these agents learn from data sets on which algorithms can be run to accomplish a prescribed goal.[100] In an unfamiliar environment, the agents will draw upon their data sets for optimal results and continue to fine-tune their behavior over time based on the results that have accumulated.[101] Unlike traditional statistical techniques that begin by "specify[ing] a mathematical equation" that "express[es] an outcome variable as a function of selected explanatory variables" to be subsequently applied to the data, "machine learning is nonparametric in that it does not require the researcher to specify any particular form of a mathematical model in advance."[102] Instead, it is the data that directs "how information contained in input variables is [positioned] to forecast the value of an output variable."[103]

The integration of a "nonparametric focus" with the algorithmic learning process has led to outperforming standard statistical techniques and generated extremely reliable and statistically efficient predictions.[104] Given that machine learning is not dependent on existing knowledge and the identification of the connection between variables, it is much more versatile and "can be applied to a broader range of questions and offer better forecasts compared with those based on human judgment or statistical alternatives."[105] Machine learning systems can also quickly adapt to modifications and developments: when

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last 15 years, 153 AI professors in North American universities left their posts for industry. An additional 68 moved into industry while retaining part-time roles with their universities. . . . In 2018 alone, 41 professors made the move").

99. *See* STUART J. RUSSELL & PETER NORVIG, ARTIFICIAL INTELLIGENCE: A MODERN APPROACH 4 (2d ed. 2003) (noting that these programs are designed "to achieve the best outcome or, when there is uncertainty, the best expected outcome").

100. Alan L. Schuller, *At the Crossroads of Control: The Intersection of Artificial Intelligence in Autonomous Weapon Systems with International Humanitarian Law*, 8 HARV. NAT'L SECURITY J. 379, 404 (2017).

101. *See* RUSSELL & NORVIG, *supra* note 99, at 54 (defining machine learning as "a process of modification of each component of the agent to bring the components into closer agreement with the available feedback information, thereby improving the overall performance of the agent").

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

103. *Id.* at 1156–57 (citing RICHARD A. BERK, STATISTICAL LEARNING FROM A REGRESSION PERSPECTIVE 13 (2008)).

104. *Learning Algorithms*, *supra* note 58, at 88 (citing Coglianese & Lehr, *supra* note 102, at 1157–58).

105. *Id.* at 88–89.

provided with new information, learning algorithms can "begin searching for new patterns" and thereby refine prior predictions.[106]

Big data algorithms' unique learning and connection-finding capabilities are especially attractive to businesses operating in the area of consumer finance, which is the focus of the empirical study described in Part II.[107] The consumer finance field thus serves as an example of an area in which big data algorithms are seen as experts and their predictions are perceived almost like objective scientific truths.

II.
BEAT THE EXPERT: MAN AGAINST THE MACHINE—AN EMPIRICAL STUDY

Building upon the sociological analysis of algorithms' growing role in our society and the increasing human dependence on them as summarized in Part I, I conducted a two-part empirical experiment in the consumer finance area. First, I compared consumers' approach toward algorithms with human experts when seeking a recommendation. Second, I examined people's willingness to return to the algorithms—as opposed to the human experts—as a guiding authority, after the individual learns about mistakes that the algorithms or the human experts made in their prior recommendations. To test my hypothesis that people feel more comfortable with algorithms than with human experts, at least in this context, I explored responses to a survey experiment that I designed and conducted on Amazon Mechanical Turk. Amazon Mechanical Turk is "a crowdsourcing marketplace that makes it easier for individuals and businesses to outsource their processes and jobs to a distributed workforce who can perform these tasks virtually."[108] In the experiment, 800 U.S.-based survey respon-

106. *Id*. at 89.

107. Financial service businesses have always relied on algorithms for many of the services that they offer, such as securities trading, financial predictions, and credit scoring determinations. But new smart algorithms offer many more possibilities, tools, and most importantly, accurate and cost-effective results. *Id.* at 100; *see also* Adam Satariano, *Silicon Valley Hedge Fund Takes on Wall Street with AI Trader*, BLOOMBERG (Feb. 6, 2017, 7:00 AM), https://www.bloomberg.com/news/articles/2017-02-06/silicon-valley-hedge-fund-takes-on-wall-street-with-ai-trader?cmpid=socialflow-facebook-markets&utm_content=markets&utm_campaign=socialflow-organic&utm_source=facebook&utm_medium=social (citing ALAN MCINTYRE ET AL., ACCENTURE, BANKING TECHNOLOGY VISION 2017, at 22 (2017), https://www.accenture.com/_acnmedia/pdf-47/accenture-banking-technology-vision-2017.pdf).

108. *See* AMAZON MECHANICAL TURK, https://www.mturk.com/ (last visited Nov. 7, 2019). It should be noted, however, that the Mechanical Turk's survey takers might

dents were asked to rate how likely they are to feel comfortable following the recommendation of an algorithm versus a human expert when investing their money.

The experiment included two vignettes, which "are simulations of real events which can be used in research studies to elicit subjects' knowledge, attitudes, or opinions according to how they state they would behave in the hypothetical situation depicted."[109] Using different vignettes allows for information to be collected simultaneously and from a large number of subjects—the 800 survey respondents—while manipulating a couple of variables "at once in a manner that would not be possible in observation studies."[110] The main vignette was the comparison between an algorithm functioning as an expert and a human expert. Therefore, half of the survey respondents received questions in which they were told that they received recommendations from an algorithm, while the other half received questions in which they were told that they received recommendations from a human expert. The other vignette was the level of investments that people were given and made. The objective of this second vignette was to check whether a lower or higher level of investment (skin-in-the-game) would impact survey respondents' preferences regarding the algorithmic versus the human expert's recommendations.

Therefore, about half of the survey respondents received a question asking them about investing fifteen percent of their funds, while the other half received a question asking them to invest sixty percent of their funds. In total, there were four versions of the same question presented to four different groups of survey respondents. The first group had a human expert with a recommendation to invest fifteen percent of the funds; the second group had a "reputable online automated investment advisor" (i.e., an algorithmic expert) with a fifteen percent investment recommendation; the third group had a human expert with a sixty percent investment recommendation; and the last

not perfectly represent the wider population in some respects, because the group of survey takers is comprised of people who are tech-savvy enough to be able to sign up online and earn money by taking online surveys on the platform. This might indicate they are already more likely to trust an algorithm than the wider population.

109. Dinah Gould, *Using Vignettes to Collect Data for Nursing Research Studies: How Valid Are the Findings?*, 5 J. CLINICAL NURSING 207, 207 (1996).

110. *Id.* An observation study is defined as a study where "individuals are observed or certain outcomes are measured. No attempt is made to affect the outcome (for example, no treatment is given)." *Definition of Observational Study*, NAT'L CANCER INST., https://www.cancer.gov/publications/dictionaries/cancer-terms/def/observational-study (last visited Feb. 13, 2020).

group had "an algorithmic expert" with a sixty percent investment recommendation.[111]

The results show that the survey respondents felt more confident that they got the best recommendation possible from an algorithmic expert than a reputable human expert.[112] Indeed, to determine whether and how having an algorithm or a human expert influences the comfort levels in following the recommendation for the lower as well as the high level of investment, I ran an OLS regression (regressing the dependent variable, post-recommendation comfort level, on all re-

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111. The question was phrased in the following ways:

> 1. You decide to invest 15% of your savings in the stock market. You find a reputable stockbroker, who makes investment recommendations. How confident are you that you got the best recommendation possible for your investment?
> 2. You decide to invest 60% of your savings in the stock market. You find a reputable stockbroker, who makes investment recommendations. How confident are you that you got the best recommendation possible for your investment?
> 3. You decide to invest 15% of your savings in the stock market. You find a reputable online automated investment advisor, who makes investment recommendations. How confident are you that you got the best recommendation possible for your investment?
> 4. You decide to invest 60% of your savings in the stock market. You find a reputable online automated investment advisor, who makes investment recommendations. How confident are you that you got the best recommendation possible for your investment?

The answers were given on a 1–5 Likert-style scale, "a psychometric scale commonly involved in research using questionnaires." *Likert Scale*, ScienceDirect, https://www.sciencedirect.com/topics/psychology/likert-scale (last visited Mar. 1, 2020). For example: 1) Extremely positive; 2) Very positive; 3) Moderately positive; 4) Slightly positive; 5) Not at all positive.

112. It should be noted that the survey experiment intentionally did not provide additional information regarding the human expert, although legally speaking there are differences among the different types of potential experts. Specifically, a "broad variety" exists of financial advisors that can either

> directly or indirectly sell personalized financial advice to the retail market. . . . The person providing personalized investment advice can be a stockbroker, registered investment advisor, insurance salesperson, confidence artist, lawyer, some other financial professional or some combination of the foregoing. . . . While not much research has been done on the differences in outcomes under different regimes, one recent study found that the kind of advice investors receive may be partially determined by the regulatory regime governing its provision. Three significant types of financial advisors now play a major role in dispensing personalized investment advice and influencing retail capital allocation decisions: (i) brokers or stockbrokers; (ii) insurance salespeople or producers; and (iii) registered investment advisers. Importantly, many financial advisors now operate within all three roles at the same time.

Benjamin P. Edwards, *Conflicts & Capital Allocation*, 78 Ohio St. L.J. 181, 212–13 (2017).

spondents who answered the questions on investing fifteen percent of their funds and the same for those answering the questions about investing sixty percent of their funds, N = 404 respondents; N = 373 respondents for the low and high levels of investment). The regression included the following controls: age, gender, socioeconomic status (whether they classify themselves as upper, middle or lower class), having some college education, race, and political ideology (liberal/conservative).

The results suggest that there is a statistically significant relationship showing the preference of the algorithmic expert. To confirm, I also ran an equal variance two-tailed t-test,[113] to compare the means of the two groups (respondents choosing algorithmic versus human expert) in regard to the level of comfort with adopting the recommendation. The t-value indicated a statistically significant relationship.[114] The respondents' age, gender, socioeconomic status, race, political ideology, and whether they had some college education did not play a part in explaining the difference in the responses, as they were not found to be statistically significant. This was also true regardless of the level of investments (fifteen percent or sixteen percent of the funds).[115]

In a follow-up question, the survey respondents were asked about how likely they were to use the same expert they had used before—algorithmic or human—despite having learned that the expert's first

113. "A 'two-sample t-test' compares two sample means to 'generalize about a difference between the two respective population means.'" Terrill Pollman & Judith M. Stinson, *IRLAFARC! Surveying the Language of Legal Writing*, 56 ME. L. REV. 239, 266 (2004) (citing R. MARK SIRKIN, STATISTICS FOR THE SOCIAL SCIENCES 271 (2d ed. 1999)).

114. *See infra* Appendix, Table 1. The t-test calculated a p-value of 0.00. Assuming that preferences as to algorithmic or human experts had no effect, this means that the likelihood of seeing the observed difference (or a greater difference) is 0.00%.

115. *See infra* Appendix, Table 1. Interestingly enough, "[n]otwithstanding the tendency of those trained in economics to view opportunity costs as equivalent to actual expenditures, modern social science research has confirmed the reality of . . . 'endowment effect' (the tendency to value already possessed goods more than prospective acquisitions)." O Centro Espirita Beneficiente Uniao Do Vegetal v. Ashcroft, 389 F.3d 973, 1016 (10th Cir. 2004), *aff'd and remanded sub nom.*, Gonzales v. O Centro Espirita Beneficente Uniao do Vegetal, 546 U.S. 418 (2006) (McConnell, J., concurring); *see also* James K. Beggan, *On the Social Nature of Nonsocial Perception: The Mere Ownership Effect*, 62 J. PERSONALITY & SOC. PSYCHOL. 229, 230 (1992); Russell B. Korobkin, *The Endowment Effect and Legal Analysis*, 97 NW. U. L. REV. 1227, 1228 (2003); Richard Thaler, *Toward a Positive Theory of Consumer Choice*, 1 J. ECON. BEHAV. & ORG. 39, 43–47 (1980). In this Article's experiment, there are some clear issues with the endowment effect that are harder to resolve in the design of the experiment, but this effect should nonetheless be kept in mind.

recommendation resulted in a thirty percent loss.[116] The answers to this question also showed a statistically significant difference in favor of the algorithmic expert.[117] Despite their disappointment, people still felt more comfortable following the algorithm's investment recommendation than that of the human expert. Put differently, individuals indicated a stronger willingess to rely on the algorithmic expert a second time despite learning that its recommendations can prove wrong.[118]

III.
THE DEATH OF THE SECOND OPINION

A. Outsourcing Individuals' Decisions

The results of the survey experiment correspond with the qualitative data and recent years' scholarship regarding how society increasingly relies on algorithms as experts and places great faith in them.[119] Moreover, studies have shown that some people do this while even ignoring their own self-critical judgments because they have such faith in algorithms as an authority.[120]

But it is not just an increased faith in algorithms that people demonstrate. As time goes by, more people and businesses opt to outsource decision-making and work processes to algorithms.[121] In general, outsourcing is the practice of using an outside entity or party to

116. The question was phrased in the following way: "The recommendation regarding the investment did not turn out as successful as you had hoped, going down 30% in value. How likely are you to use the same service again?" The answers were once again given on a 1–5 Likert scale: 1) Extremely likely; 2) Very likely; 3) Moderately likely; 4) Slightly likely; 5) Not at all likely.

117. *See infra* Appendix, Table 2 (showing the output for those who initially chose the algorithmic advice). The t-test calculated a p-value of 0.14. Assuming that learning that the algorithmic expert's recommendations can prove wrong had no effect, the likelihood of seeing the observed difference (or a greater difference) is 0.14%.

118. *See infra* Appendix, Table 2.

119. For example, certain post-2008 studies have argued that the "financial regulators delegated or outsourced to [unsuccessful algorithms] the responsibility of regulating a wide range of risk transfers in the economy—from consumer finance to global financial markets," and blamed this outsourcing to algorithms as the cause of the subprime mortgage market crisis or at least a factor that has "exacerbated the crisis." Erik F. Gerding, *Code, Crash, and Open Source: The Outsourcing of. Financial Regulation to Risk Models and the Global Financial Crisis*, 84 WASH. L. REV. 127, 129–30 (2009) (stating also that "[b]y outsourcing, financial regulation placed great faith in the new technology").

120. *See* Daston, *supra* note 74; Totaro & Ninno, *supra* note 75; EXEC. OFFICE OF THE PRESIDENT, BIG DATA: SEIZING OPPORTUNITIES, *supra* note 78.

121. *See* Coglianese & Lehr, *supra* note 102, at 1147 ("As machine learning's use expands across all facets of society, anxiety has emerged about the intrusion of algorithmic machines into facets of life previously dependent on human judgment.").

perform a specific type of work as an alternative to completing all needed work or assignments within the firm and without any external help. Outsourcing is often driven by expertise and cost-of-labor advantages, but it also generates agency risks because another party is the one making decisions, which impact the life quality or wealth of the outsourcing entity.[122]

In recent years, as technology continues to advance and offer more possibilities, academics have started arguing that humans let algorithms run their lives,[123] follow algorithms' decisions blindly, and have even developed a "religious, devotional culture around algorithms, where algorithms might as well be God," or at least "infallible science."[124]

There is a reason that scholars have referred to the human ability of "exerting thoughtful, independent judgment" as a "mental muscle" and a skill that must be constantly developed.[125] There is a body of empirical research that shows that people's passive reliance on algorithms and related technology changes us as humans in many respects, including biologically. For example, some scholars have maintained that navigating with GPS devices results in the creation of a diminished, conceptual appreciation of landscape,[126] "hinders the development of cognitive maps," and leads to a reduced "reconstruction and memory of the environment" in which an individual is commuting and

122. *See* George S. Geis, *Business Outsourcing and the Agency Cost Problem*, 82 NOTRE DAME L. REV. 955, 972–73, 977–82 (2013). Businesses outsource to stay competitive in the modern economy. Robert Malone, *Beyond Outsourcing to Smartsourcing*, FORBES (Aug. 11, 2006, 11:00 AM), http://www.forbes.com/2006/08/11/smartsourcing-outsourcing-business-improvement-cx_rm_0811smart.html. Outsourcing helps save money, improve efficiency, effectiveness and expertise, and can create a competitive advantage. *See* RICHARD BAILY, CONTENT AND RECORDS MANAGEMENT: THE BUSINESS CASE FOR TRANSFORMATIVE OUTSOURCING 2 (2008), http://www.xerox.com/downloads/usa/en/t/TL_whitepaper_records_management_Rich_Baily.pdf [https://perma.cc/87PZ-RUBW] (profitability, efficiency, effectiveness, expertise); Richard C. Insinga & Michael J. Werle, *Linking Outsourcing to Business Strategy*, 14 ACAD. MGMT. EXECUTIVE 58, 59 (2000) (competitive advantage). Therefore, many "American firms contract with third-party vendors to perform" outsourced work for them. *See* Meredith Johnson Harbach, *Outsourcing Childcare*, 24 YALE J.L. & FEMINISM 254, 255 (2012).

123. *See, e.g.*, Solon Barocas et al., Governing Algorithms: A Provocation Piece 3 (Mar. 29, 2013) (unpublished manuscript), https://www.ssrn.com/abstract=2245322 (explaining that some see algorithms to be "powerful entities that govern, judge, sort, regulate, classify, influence, or otherwise discipline the world").

124. Desai & Kroll, *supra* note 27, at 5.

125. Selinger & Frischmann, *supra* note 15; *see* FRISCHMANN & SELINGER, *supra* note 8.

126. *See* Hayden Lorimer & Katrin Lund, *Performing Facts: Finding a Way Over Scotland's Mountains*, 51 SOC. REV. 130, 141 (2003).

driving around.[127] "GPS navigation units have been identified as" the type of technological devices that necessitate "less skill and attention, by providing orientation and navigation as a commodity, with instant availability, ubiquity, safety, and ease of use, resulting in loss of engagement with the environment and others."[128] In 2017, researchers published similar reports about how humans' over-reliance on technology could cause brain regions to switch off, which was the case when experiments' participants passively "followed the instructions given to them."[129]

Even without focusing on biological issues such as undesired brain changes, there is no doubt that over-reliance on algorithms without having the ability to understand how they work is a serious problem.[130] As mentioned above, scholars have widely discussed the critical importance of algorithmic transparency and accountability to understand their processes better.[131] Yet, thus far, the literature has not acknowledged or addressed the situations where lack of transparency and accountability is not the problem, instead the toning down of the human desire to get a second opinion—even when one is not happy with an algorithmic decision—is the problematic issue. Indeed, many people are likely to give up the idea of getting a second opinion to

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127. Gilly Leshed et al., In-Car GPS Navigation: Engagement with and Disengagement from the Environment 1 (Apr. 5, 2008) (unpublished manuscript), http://www.cs.cornell.edu/~tvelden/pubs/2008-chi.pdf (citing Gary E. Burnett & Kate Lee, *The Effect of Vehicle Navigation Systems on the Formation of Cognitive Maps*, *in* TRAFFIC AND TRANSPORT PSYCHOLOGY: THEORY AND APPLICATION 407, 416–17 (Geoffrey Underwood ed., 2005)).

128. *Id.* (first citing ALBERT BORGMANN, TECHNOLOGY AND THE CHARACTER OF CONTEMPORARY LIFE: A PHILOSOPHICAL INQUIRY (1984)); then citing Claudio Aporta & Eric Higgs, *Satellite Culture: Global Positioning Systems, Inuit Wayfinding, and the Need for a New Account of Technology*, 46 CURRENT ANTHROPOLOGY 729, 744–45 (2005)).

129. *Over-Reliance on GPS Could Cause Brain Regions to Switch Off*, NEW ATLAS (Mar. 22, 2017), https://newatlas.com/gps-spatial-direction-ucl/48529. In addition,

> researchers found that there was a spike in hippocampal and prefrontal cortex activity when volunteers navigated and entered new streets on their own. This shot up even further when the number of navigational options increased when participants were in an area with several street segments. In contrast, no additional activity was detected when they simply followed the instructions given to them . . . .

Id.

130. *See generally* Desai & Kroll, *supra* note 29.

131. *See, e.g.*, DIAKOPOULOUS, *supra* note 29; Noyes, *supra* note 29 (discussing the limitations of solutions focused on creating greater transparency); Sandvig et al., *supra* note 29, at 17 ("The question at issue [is not] whether we would expect algorithm providers to be good or evil, but what mechanisms we have available to determine what they are doing. . . . Rather than regulating for transparency or misbehavior, we find this situation argues for 'regulation toward auditability.'").

compete with algorithms' results, because doing so may seem pointless given the institutional aura and the halo effect that algorithms have as an almost scientifically proven source of authority.[132] An example in the consumer finance area of consumers failing to seek second opinions was recently published in the context of seeking a good rate and then taking out a mortgage.[133] As further explained below, while it might be cost-effective to passively rely on algorithms' decisions, there are several major risks and challenges associated with our society increasingly doing so.

B. Risks and Challenges

1. Turning Imagination into Innovation

There are many instances in which individuals or entities hoping to improve their chances of success in whatever it is they are trying to achieve can find themselves in situations where seeking a second opinion can be useful.[134] In general, getting a second opinion is a good idea. As described in the context of bicameral legislatures, "[a] second

132. *See* Kia Rahnama, *Science and Ethics of Algorithms in the Courtroom*, 1 U. ILL. J.L. TECH. & POL'Y 169, 186 (2019) ("Unique problems in communicating the uncertainty of the science of algorithms and potentially unhealthy boundary work implications significantly raises the possibility that the use of algorithms in the courtroom will not be constrained by healthy public input. ").

133. *See* Alexei Alexandrov & Sergei Koulayev, *No Shopping in the U.S. Mortgage Market: Direct and Strategic Effects of Providing Information* 1–2, 13 (Consumer Fin. Prot. Bureau Office of Research, Working Paper No. 2017-01, 2018), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2948491. "Mortgage interest rates and loan terms can vary considerably across lenders. Despite this fact, many homebuyers do not comparison shop for their mortgages. . . . [According to the study,] failing to comparison shop for a mortgage costs the average homebuyer approximately $300 per year and many thousands of dollars over the life of the loan." *Know Before You Owe: Mortgage Shopping Study*, CONSUMER FIN. PROT. BUREAU (May 15, 2018), https://www.consumerfinance.gov/data-research/research-reports/know-before-you-owe-mortgage-shopping-study/.

134. *See* Richard Bayliss, *Second Opinions*, 296 BRIT. MED. J. 808, 808–09 (1988); David A. Hyman, *A Second Opinion on Second Opinions*, 84 VA. L. REV. 1439 (1998) (discussing how often second opinions are sought and how useful they can be as a solution addressing lawyer–client agency problems); Klausner, Miller & Painter, *supra* note 5; Wolfgang Pesendorfer & Asher Wolinsky, *Second Opinions and Price Competition: Inefficiency in the Market for Expert Advice*, 70 REV. ECON. STUD. 417, 417 (2003) (analyzing the advantages of getting second opinions and demonstrating that only with pre-determined rates and consumers having the ability to get various opinions, can a reliable second-best result materialize where consumers' welfare is maximized; assuming, however, that low skilled experts deliver an incorrect diagnosis); Miklos Sarvary, *Temporal Differentiation and the Market for Second Opinions*, 39 J. MARKETING RES. 129, 129–30 (2002) (studying situations in which "portfolio analysts do not actively solicit consumer business" and only offer consumers special second-opinion services when consumers reach out to them in "problematic situations," and examining "competing firms' pricing strategies in private information

chamber, regardless of its level of expertise and wisdom, constitutes such a quality-control mechanism" that both encourages lawmakers to proceed more carefully in the first instance and also helps to "discover mistakes after they have been committed."[135] Similarly, "[t]he very idea of a 'second opinion' implies that opinion givers are expressing judgments rather than preferences about the question at hand. . . . [A]dditional opinions might produce better answers."[136]

Moreover, the desire to get a second opinion is closely related to creativity, innovation, adaptability, collaboration and critical thinking,[137] which are all traits that as a society we want to nurture and

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markets" and under what terms firms will "specialize in selling second opinions to their clients").

135. GEORGE TSEBELIS & JEANNETTE MONEY, BICAMERALISM: POLITICAL ECONOMY OF INSTITUTIONS AND DECISIONS 40 (1997).

136. Vermeule, *supra* note 35, at 1442. Vermeule also argues that "many institutional structures, rules and practices have been justified as mechanisms for requiring or permitting decision-makers to obtain second opinions," and gives examples such as "judicial review of statutes or of agency action, bicameralism, the separation of powers, and the law of legislative procedure." *Id.* at 1435.

137. *See* Joseph Tanega & Andrea Savi, *Central Clearing Counterparties for OTC-Users: A Theoretical Framework: Methodological Limits of the Recent Macro-Prudential Initiatives*, 13 N.Y.U. J.L. & BUS. 825, 867–68 (2017) (analyzing the best approach to financial regulation and advocating for always seeking additional new, different solutions). Further,

> [a] uniform regulatory system thereby limits innovation and prevents the competition between different solutions to problems. . . . By using trial and error, a complex system receives information about what does not work and can endogenously improve itself. Stressors, randomness, and volatility are the conditions required to develop an anti-fragile system immune to large-scale unpredictable and irregular events of massive consequence. Uniform systems lack the ability to learn from their imperfections and to test new solutions. An efficient . . . regime, therefore, should promote the diversity and the adoption of heterogeneous models . . . .

Id. (internal quotation marks and citations omitted). For further discussion of this link, see Sapna Kumar, *Life, Liberty, and the Pursuit of Genetic Information*, 65 ALA. L. REV. 625, 644 (2014) (discussing how Congress had acknowledged the correlation between second opinions and innovation in the context of issuing gene patents, requiring the U.S. Patent and Trademark Office to examine and report on the "impact that the lack of independent second opinion testing has had on patient care and on innovation"); Orly Lobel, *The Law of the Platform*, 101 MINN. L. REV. 87, 160 (2016) (discussing the business model of the platform economy and the design of an ideal regulatory and governance regime for it, by stressing the importance of getting different opinions and the significance of "experimenting with different solutions to encourage innovation"); Christopher S. Yoo, *Protocol Layering and Internet Policy*, 161 U. PA. L. REV. 1707, 1725 (2013) (focusing on protocol layering, which is considered to be one of the bases of the Internet's success, and arguing that innovation can happen faster if we enable experimenting with different solutions and options); CPR Inst. for Dispute Resolution, *New Relationships Between Mediation and Arbitration Topics Include Creative Solutions and Lawyering, In-House Counsels' Views, and More. . .*, 19 ALTERNATIVES TO HIGH COST LITIG. 213, 217 (2001) ("Besides different maintain.[138] Writing about second opinions, Professor Adrian Vermeule explains that innovative, enthusiastic, and critical thinking processes in connection with a second opinion can provide a thoughtful check on "hot deliberation."[139] Similarly, according to Vermeule, it is also ideal to seek a second opinion because as "it may be desirable . . . to diversify the pool of opinion givers by introducing different professions or different bodies."[140] Yet our algorithmic-dependent society may be unintentionally nudging individuals to tone down these traits, as the more we think of algorithms as the most effective experts, the more we simply opt to passively rely on technology or outsource their decision-making to algorithms.

2. *Rooting for the Underdog, Heuristics and the American Dream*

Algorithms are often able to produce accurate results, but it is still important to encourage people to try and get second opinions even if getting a different result is not very likely. There are several reasons for this. First, it feels much better to win as David than it does as Goliath. When asked about this issue in empirical studies, people repeatedly demonstrate the "favorite-long-shot bias" heuristic, which "describes the long-standing empirical regularity that betting odds provide biased estimates of the probability of a horse winning: long shots are overbet whereas favorites are underbet."[141] This bias is the

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solutions, Menkel-Meadow said that creativity can take the form of new legal processes to reach the solutions . . . . More common than developing new solutions or processes . . . is the 'development, refinement and incremental change of already existing ideas.'").

138. *See, e.g.*, WORLD ECON. FORUM, THE FUTURE OF JOBS: EMPLOYMENT, SKILLS AND WORKFORCE STRATEGY FOR THE FOURTH INDUSTRIAL REVOLUTION 21 (2016) (including among the most needed skills by 2020: "Critical thinking"; "Creativity"; "Coordinating with Others"; "Emotional Intelligence"; and "Judgment and Decision-making"); Paul Petrone, *The Skills Companies Need Most in 2019—and How to Learn Them*, LINKEDIN (Jan. 1, 2019), https://learning.linkedin.com/blog/top-skills/the-skills-companies-need-most-in-2019—and-how-to-learn-them (stating that among the top five "soft skills" companies are looking for most are "Creativity"; "Adaptability"; and "Collaboration").

139. Vermeule, *supra* note 35, at 1451.

140. *Id.* at 1454.

141. Erik Snowberg & Justin Wolfers, *Explaining the Favorite-Longshot Bias: Is It Risk-Love or Misperceptions?*, 118 J. POL. ECON. 723, 723 (2010). A study by Jimmy Frazier and Eldon Snyder posed a hypothetical scenario to college students: two teams were competing in a series of games for some undisclosed type of sports, and the first team was "highly favored" to beat the second team. Jimmy A. Frazier & Eldon E. Snyder, *The Underdog Concept in Sport*, 8 SOC. SPORT J. 380, 383 (1991). The study examined which team the students would want to root for, and found that eighty-one percent of the students rooted for the less-likely-to-win team. *Id.* at 384. In a study by Joseph Vandello and Nadav Goldschmeid, and as summarized by Daniel Engber, Vandello and Goldschmeid "found that two-thirds of all voters in the 2004 presiden-

result of the "availability heuristic": people make judgments about probability based on the data that comes most easily to mind.[142] People also tend to identify the underdogs with the long shots and assign them certain traits as a result, such as having more heart.[143]

Second, failures are often thought to teach us much more than successes, and practically speaking, might contribute to a future success. For example, as data on successful startups show, more than nine out of ten startups will fail.[144] But that very same failure helps those who lived through it to succeed in the future.[145] Understanding that failure is a part of life and making it socially accepted gives innovators the social permission to chase their dreams and develop their ideas. Likewise, the American Dream is based on a similar ideal, which is that each person has the opportunity to pursue his or her own idea of happiness and to succeed, even if it is going to be a long shot.[146]

3. *Maintaining the Sensation of Free Choice*

Encouraging people to get a second opinion helps maintain the sensation of free choice.[147] It enables people to have their voices heard

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tial election described their preferred candidate as the 'underdog.' A follow-up four years later revealed that presidential candidates were deemed more likable after being characterized as an 'underdog' by someone else." Daniel Engber, *The Underdog Effect*, SLATE (Apr. 30, 2010, 6:27 PM), https://slate.com/technology/2010/04/why-do-we-love-to-root-for-the-underdog.html [https://perma.cc/9CLJ-GAVR]; *see* Joseph Vandello & Nadav Goldschmied, *The Advantage of Disadvantage: Underdogs in the Political Arena*, 31 BASIC & APPLIED SOC. PSYCHOL. 24, 27–30 (2009).

142. Vandello & Goldschmied, *supra* note 141, at 25.

143. *See* Joseph A. Vandello, Nadav P. Goldschmied & David A.R. Richards, *The Appeal of the Underdog*, 33 PERSONALITY & SOC. PSYCHOL. BULL. 1603, 1609–11 (2007). As summarized by Daniel Engber, the study by Vandello, Goldschmied and Richards showed that "[a]s a rule, the underdogs were characterized as having less 'talent' and 'intelligence' than the favorites but more 'hustle' and 'heart.' That was true even when subjects viewed the same video clip with the labels reversed." Engber, *supra* note 141.

144. *See* Griffith, *supra* note 37.

145. *See* Mansfield, *supra* note 38.

146. Kimberly Amadeo, *What Is the American Dream? The History That Made It Possible*, BALANCE, https://www.thebalance.com/what-is-the-american-dream-quotes-and-history-3306009 (last updated Dec. 14, 2019).

147. Whether or not free will is actually an illusion is a different story. *See* Shaun Nichols, *Is Free Will an Illusion?*, SCI. AM. (Nov. 1, 2011), https://www.scientificamerican.com/article/is-free-will-an-illusion/. Similarly, as some scholars have argued, it matters less that individuals' choices actually make them unhappy or have less efficient results. *See generally* JON ELSTER, SOUR GRAPES: STUDIES IN THE SUBVERSION OF RATIONALITY (1985) (subverting traditional concepts of rational choice by studying forms of irrationality, and describing the conditions that undermine rationality of preference formation); Amos Tversky & Daniel Kahneman,

and to feel as if they have choices and options, even if they are silly, impractical, or a longshot, and that is important. Recent research suggests that individuals are hardwired to desire autonomy[148]—the ability to make choices according to one's own free will.[149] For example, research shows that altruistic actions cause good feelings when done out of choice.[150]

Furthermore, scholars such as Cass R. Sunstein have argued that "for deliberative democracy to work, citizens must be in a position to consider a range of options."[151] Arguing that the explosion of algorithms, machine learning, and AI alters individuals' capacity to govern themselves, Sunstein states that his largest plea is for "an architecture of serendipity—for the sake of individual lives . . . innovation, and democracy itself."[152] "When people have multiple options and the liberty to select among them," Sunstein argues, they have freedom of choice, which is very significant.[153] He quotes Milton Friedman, who emphasized that people should be "free to choose."[154] But freedom

Judgment Under Uncertainty: Heuristics and Biases, 185 SCI. 1124, 1131 (1974) (discussing "three heuristics that are employed in making judgments under uncertainty," and finding they "lead to systematic and predictable errors").

148. Julie Beck, *People Want Power Because They Want Autonomy*, ATLANTIC (Mar. 22, 2016), https://www.theatlantic.com/health/archive/2016/03/people-want-power-because-they-want-autonomy/474669/.

149. Philipp Hacker, *Nudging and Autonomy: A Philosophical and Legal Appraisal*, *in* RESEARCH METHODS IN CONSUMER LAW: A HANDBOOK 77, 77 (Hans-W. Micklitz, Anne-Lise Sibony & Fabrizio Esposito eds., 2018) (describing individual autonomy as "a concept deeply interwoven with the ideal of deliberate and rational agency since Aristotle's discussion in Book III of the *Nicomachean Ethics*").

150. As described by Alex Lickerman,

> According to another study, altruism does not just correlate with an increase in happiness; it actually causes it—at least in the short term. When psychologist Sonja Lyubomirsky had students perform five acts of kindness of their choosing per week over the course of six weeks, they reported a significant increase in their levels of happiness relative to a control group of students who didn't.

ALEX LICKERMAN, THE UNDEFEATED MIND: ON THE SCIENCE OF CONSTRUCTING AN INDESTRUCTIBLE SELF 28–29 (2012) (emphasis omitted).

151. Angelia R. Wilson, *#Republic: Divided Democracy in the Age of Social Media, by Cass R. Sunstein*, TIMES HIGHER EDUC. (Mar. 9, 2017), https://www.timeshighereducation.com/books/review-republic-cass-sunstein-princeton-university-press#survey-answer [https://perma.cc/6WHU-GEUR] (book review) (citing CASS R. SUNSTEIN, #REPUBLIC: DIVIDED DEMOCRACY IN THE AGE OF SOCIAL MEDIA (2017)). For example, Sunstein argues, "[i]n short, aspirations for deliberative democracy sharply diverge from the ideal of consumer sovereignty—that is, a future in which, in Gates's words, 'you'll be able to just see what you're interested in, and have the screen help you pick.'" SUNSTEIN, *supra* at 134.

152. SUNSTEIN, *supra* note 151, at 5.

153. *Id.* at 11.

154. *Id.*

requires far more than that. Sunstein advocates for certain background conditions that would enable people to expand their own learning abilities and talks about "circumstances that are conducive to the free formation of preferences and values."[155]

Similarly, Paul Schwartz wrote that data collection "creates a potential for suppressing a capacity for free choice: the more that is known about an individual, the easier it is to force his obedience."[156] According to this view, big data algorithms are problematic given the size of their databases and methods of operations.[157] This is especially true when smart machine learning features learn and target the users' preferences, personality traits, and behavior patterns.

4. *Certain Human Features Are Difficult to Replicate*

Studies have shown that the human traits which algorithms cannot easily replicate are the same ones that may relate to wanting to get a second opinion—creativity and innovation,[158] critical thinking, collaboration,[159] social and emotional intelligence,[160] and the ability to adapt and learn new skills.[161]

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155. *Id.* at 4–5, 11.

156. Paul M. Schwartz, *Privacy and Participation: Personal Information and Public Sector Regulation in the United States*, 80 IOWA L. REV. 553, 560 (1995).

157. *Id.* ("[T]otalitarian regimes in Eastern Europe relied on information gathering and data storage to weaken the individual capacity for critical reflection and to repress any social movements outside their control.").

158. *See* Lauri Donahue, *A Primer on Using Artificial Intelligence in the Legal Profession*, JOLT DIG. (Jan. 3, 2018), https://jolt.law.harvard.edu/digest/a-primer-on-using-artificial-intelligence-in-the-legal-profession. Donahue, who is the Director of Legal Content at LawGeex, an artificial intelligence LegalTech startup that is transforming legal operations, gives creativity as an example of a trait that artificial intelligence cannot do, such as writing creatively in a Supreme Court brief. *Id.*

159. Referencing some of the collaboration and social features of human beings, Sunstein mentions "real world interactions" as the kind of thing that often force people to deal with more options and scenarios, many of which are not available when relying on algorithms. SUNSTEIN, *supra* note 151, at 11–12.

160. *See* Toby Walsh, *Will Robots Bring About the End of Work?*, GUARDIAN (Oct. 1, 2017, 2:00 AM), https://www.theguardian.com/science/political-science/2017/oct/01/will-robots-bring-about-the-end-of-work ("[T]he most important human traits will be our social and emotional intelligence."); Donahue, *supra* note 158 (arguing that negotiation is something that is hard for artificial intelligence to replicate).

161. James Bessen, *The Automation Paradox*, ATLANTIC (Jan. 19, 2016), https://www.theatlantic.com/business/archive/2016/01/automation-paradox/424437. Bessen argues that "[l]earning new skills is a significant social challenge as well. My research suggests that the jobs that get transferred to other occupations tend to be predominantly low-pay, low-skill jobs, so the burdens of automation fall most heavily on those least able and least equipped to deal with it." *Id.* This means that individuals that can adapt quickly and learn new skill sets are more likely to be working in those new roles, as it takes time to train AI to do something different and new.

The recent story of Captain Sully, who landed an aircraft safely onto the partially frozen Hudson River near Manhattan on January 15, 2009, after both engines were disabled by a bird strike, saving the lives of all 155 people aboard,[162] is a good example of the importance of human judgment and critical thinking. Captain Sully had to make a quick decision on his feet of where and how to land the plane, based on his estimate of his own abilities, and decided to land it on the river. Landing on the river is something that an algorithm would not and could not have decided to do, as it was not one of the programmable options. Nevertheless, that decision, which was completely outside of the box, ended up saving all of the passengers' lives.

Sully's story demonstrates how human decision-making and judgment are critical cognitive processes that cannot be replicated by algorithms, which are only programmed to consider and compare options that seem plausible, rather than extreme, out-of-the-box solutions such as landing a plane on a somewhat frozen river. Algorithms can pick up and process all the technical information while applying different measurements and data, but they cannot experience an event and wonder about its potential consequences. AI works better in more familiar and repeated situations, but in new settings with less ordinary conditions, humans can perform more promptly and appropriately. We might rely to some extent on algorithms, but should not regard it as a superior replacement to human critical and innovative thinking.

5. *Algorithms and Biases: Scrapping the "Black Box"*

As AI becomes more common in different services and products, many hope that algorithmic decision-making will eliminate the subjectivity and cognitive biases inherent in human decision-making.[163] These views, however, ignore the basic fact that algorithms are humanly devised. As such, their design involves human mental models and inevitably human biases. Even if they are well-intentioned, companies risk using erroneous or abusive algorithmic design that generates biased inferences and subsequently discriminatory outcomes against minority groups.

162. Susan Hay, *Sully: The Untold Story of US Airways Flight 1549*, GLOBAL NEWS (Sept. 7, 2016, 3:26 PM), https://globalnews.ca/news/2926225/sully-the-untold-story-of-us-airways-flight-1549.

163. Laura Hudson, *Technology Is Biased Too. How Do We Fix It?*, FIVETHIRTYEIGHT (July 20, 2017), https://fivethirtyeight.com/features/technology-is-biased-too-how-do-we-fix-it/ (explaining how algorithms were supposed to free us from our unconscious mistakes).

a. Trusting Online Data

We should not blindly and automatically trust internet sources and tools, as they are not always reliable or correct.[164] Especially as they are prone to data cleaning processes, which are more common in the context of social media data, in addition to occasional outages, random mistakes, and information gaps.[165] The existence of these issues, as well as data loss, which can happen when data is deleted or ruined because of problems in storing it, transmitting it, or processing it, creates doubts regarding the ability of online information to represent an objective truth. But what is even more concerning is that such errors, random outages, and losses in online datasets and sources can create much bigger problems when various datasets are combined and used together.[166]

An additional problematic issue relates to the fact that whenever an algorithm is designed, decisions regarding what data will be used must always take place. It is impossible to include all the data available "out there," and some sort of decisionmaking process regarding which sources of data to collect, mine, examine and use is required. "After all, data mining can forever reflect and maintain the preconceptions of former decision-makers or mirror the widespread biases that exist in society."[167] As explained by Solon Barocas and Andrew Selbst: "[e]ven in situations where data miners are extremely careful, they can still affect discriminatory results with models that, quite unintentionally, pick out proxy variables for protected classes."[168] Notable examples to this include "Flickr's auto-tagging of online photos label pictures of black men as 'animal' or 'ape,' or when researchers determine that Google search results for black-sounding names are more likely to be accompanied by ads about criminal activity than search results for white-sounding names."[169]

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164. *See Learning Algorithms*, *supra* note 58, at 91.

165. *Id.*; Amey Varangaonkar, *How to Effectively Clean Social Media Data for Analysis*, PACKT (Dec. 26, 2017, 12:00 AM), https://hub.packtpub.com/clean-social-media-data-analysis-python/ (explaining that "[d]ata cleaning and preprocessing is an essential—and often crucial—part of any analytical process" and some advanced cleaning procedures include grammar checking, spelling correction and storing).

166. *Learning Algorithms*, *supra* note 58, at 91.

167. *Id.*

168. Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CALIF. L. REV. 671, 675 (2016).

169. Lauren Kirchner, *When Big Data Becomes Bad Data*, PROPUBLICA (Sept. 2, 2015, 12:23 PM), https://www.propublica.org/article/when-big-data-becomes-bad-data; *see also Learning Algorithms*, *supra* note 58, at 92; Alex Hern, *Flickr Faces Complaints over 'Offensive' Auto-Tagging for Photos*, GUARDIAN (May 20, 2015, 4:49 AM), https://www.theguardian.com/technology/2015/may/20/flickr-complaints-

This issue is "especially concerning in the context of gathering information on individuals from social networks and platforms."[170] First, many individuals "live their entire lives outside the social networking realm."[171] Second, those who do "participate actively in social networks, and share information online regularly, [ ]do not necessarily exhibit equal qualitative and quantitative practices of information sharing."[172] Lastly, "datasets can be manipulated or limited, which makes blindly relying on such information problematic. Moreover, due to certain datasets' volume, there is always the risk of finding irrelevant or bogus correlations with statistical significance that shows no noteworthy connection between the variables."[173]

b. Ambiguity and Due Process[174]

Machine-learning algorithms are known for being extremely accurate, but this precision comes with an interpretive cost, which is the reason such algorithms have been referred to as "black box" systems.[175]

A good illustration that helps explain how machine learning works is the categorization of handwritten digits. Algorithms are able to learn particular geometric traits of handwritten digits, which makes it easier for them to interpret the digits that these shapes are meant to be. Yet it is difficult to know with certainty which particular characteristics an unsupervised AI algorithm is specifically relying on while conducting its interpretation and determination process. Machine-learning algorithms turn a series of inputs to a series of outputs by perfecting a performance criterion, however, that is the maximum that analysts are capable of understanding in terms of the algorithms actions.[176] Algorithmic users are not truly able to tell which particular relationships between variables factor into the algorithm's categorization, or at which stage.[177] Similarly, algorithmic users also cannot "establish how exactly the algorithm puts together different associations

offensive-auto-tagging-photos; Lauren Kirchner, *When Discrimination Is Baked into Algorithms*, ATLANTIC (Sept. 6, 2015), https://www.theatlantic.com/business/archive/2015/09/discrimination-algorithms-disparate-impact/403969.

170. *Learning Algorithms*, *supra* note 58, at 92.

171. Packin & Lev-Aretz, *On Social Credit*, *supra* note 56, at 381–82.

172. *Learning Algorithms*, *supra* note 58, at 92.

173. *Id.*

174. For more on this topic, see *id*. at 92–93.

175. *See, e.g.*, Leo Breiman, *Statistical Modeling: The Two Cultures*, 16 STAT. SCI. 199, 199 (2001).

176. *See Learning Algorithms*, *supra* note 58, at 92–93.

177. *See id.* at 91–92.

to yield its categorizations."[178] Hence, the "black box" metaphor, because analysts cannot look inside a black box to determine how specific transformation occurs or explain the associations with the same instinctive and fundamental language commonly used in typical statistical modeling.[179]

Programmers understand that the phrase "garbage in, garbage out" reflects how wrong, discriminatory or biased outputs are usually the result of inputting and using wrong, discriminatory or biased information.[180] Historically, bias in the data or in the coding process was easier to spot, if one was interested in doing so.[181] Yet unsupervised machine learning algorithms operate autonomously,[182] and choose, study and assess factors from a large pool of data in ways that do not always make sense or seem clear to those trying to interpret the process from the outside.[183] Having no algorithmic transparency makes it much more challenging to determine if systems are biased.

As data collection and AI predictions have become part of our everyday routine, the lack of certainty and minimal accountability that such methods and processes offer have started to cause more concern. Automated decision-making systems can negatively impact individuals' lives in many arbitrary and discriminatory ways, such as by unfairly calculating low credit scores. Yet the formulas of many of the algorithms that impact peoples' very livelihood remain secretive and are often almost impossible to reverse-engineer.[184] "The process is technologically opaque—the code usually remains unrevealed, and also substantively tricky to [specifically] understand—and outsiders" have no capability of figuring out what kinds of information were

178. *Id.* at 92.

179. *See, e.g.*, FRANK PASQUALE, THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION (2015).

180. *Algorithms and Bias: What Lenders Need to Know*, WHITE & CASE (Jan. 20, 2017), https://www.whitecase.com/publications/insight/algorithms-and-bias-what-lenders-need-know.

181. *See Learning Algorithms*, *supra* note 58, at 91–92.

182. *See* PETER FLACH, MACHINE LEARNING: THE ART AND SCIENCE OF ALGORITHMS THAT MAKE SENSE OF DATA 3 (2012); *see also* Packin & Lev-Aretz, *supra* note 171, at 348–49.

183. *See* Packin & Lev-Aretz, *On Social Credit*, *supra* note 56, at 348–49 (explaining that machine-learning algorithms can produce discriminatory results that will be hard to detect and explain, yet we will not have visibility into the nontraditional data, and even if we did, it would not be possible to make sense of the automated process, correct errors, or explain the reasons for the results).

184. *See Learning Algorithms*, *supra* note 58, at 93. On the significance of transparency and accountability in algorithms in the context of "search engine bias," see Oren Bracha & Frank Pasquale, *Federal Search Commission? Access, Fairness, and Accountability in the Law of Search*, 93 CORNELL L. REV. 1149, 1159, 1167–79 (2008).

even collected, what types of correlations are targeted, and what risks or potential issues "are factored into the algorithmic predictions."[185]

Those levels of opaqueness "can disguise biased, discriminatory, or [even plainly unfavorable] results from supervision until negative results become viable and clear."[186] The confidentiality shields businesses and public sector bodies from public disapproval, as entities never want to be known as discriminatory. There is also a real intellectual property interest that businesses want to protect. After all, exposing a business's algorithms to public criticism also means, *de facto*, sharing the intellectual property interests with competitors. "The secretive nature of algorithmic decisions harms due process both ex-ante—by enabling un-scrutinized [collection] and exploration of data—and ex-post—by precluding users from second-guessing" decisions that are harmful, as studying and scrutinizing the decision-making process is not a viable option.[187] Hence, the private nature of algorithmic decisions frustrates oversight and accountability.

Given the importance of accountability, scholars have been seeking for ways to unlock the black box. Additionally, regulators have begun to require, to the extent possible, any meaningful information about the logic of automated decisions and about the way the algorithms that made them were initially designed.[188] Current laws already require explanation of decision-making processes, and enabling those

185. *Learning Algorithms*, *supra* note 58, at 93.

186. *See* Packin & Lev-Aretz, *On Social Credit*, *supra* note 56, at 348–49.

187. *Learning Algorithms*, *supra* note 58, at 93.

188. While some regulators have taken action, creating laws such as the GDPR, *supra* note 48, thus far, academics have attempted to analyze the issue more than regulators have. *See*, *e.g.*, Kiel Brennan-Marquez, *"Plausible Cause": Explanatory Standards in the Age of Powerful Machines*, 70 VAND. L. REV. 1249, 1258–59, 1267–73 (2017) (drawing contrast between explanation and prediction); Pauline T. Kim, *Data-Driven Discrimination at Work*, 58 WM. & MARY L. REV. 857, 901 (2017) (stating that "[r]equiring data transparency, auditing for accuracy, and substantively regulating downstream uses of data are important steps in ensuring the fair use of data," but arguing that "these types of interventions cannot fully address the risk," and calling for an employment discrimination standard of whether an adverse action was "because of" protected class membership); Andrew D. Selbst, *Disparate Impact in Big Data Policing*, 52 GA. L. REV. 109, 123 (2017) ("[I]t is especially important that police understand their tools' capacity for discriminatory outcomes and vigilantly guard against them. Predictive policing systems operate in different ways, depending on the type of data they collect and what they seek to achieve."); *see also* Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 18–27 (2014); Joshua A. Kroll et al., *Accountable Algorithms*, 165 U. PA. L. REV. 633, 697–98, 704–05 (2017).

impacted by automated determinations to be able to understand them.[189]

Similarly, accountability is not a new concept in privacy law. It was introduced as a basic data protection principle in the Organization for Economic Co-operation and Development's (OECD) 1980 Guidelines Governing the Protection of Privacy and Transborder Flows of Personal Data, which were adopted September 23, 1980.[190] Since then, the accountability concept has been included in numerous data protection laws.[191] Accountability-based data protection laws typically require a proactive and systematic approach to data protection and mandate the implementation of appropriate data protection measures, and management programs.[192]

One of the most discussed laws in this context is the GDPR, which enables individuals to "access 'meaningful information about

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189. *Learning Algorithms*, *supra* note 58, at 94–95. Examples of such laws include the Fair Credit Reporting Act, 15 U.S.C. §§ 1681–1681x (2018), and the Equal Credit Opportunity Act, 15 U.S.C. §§ 1691–1691f (2018), which mandate different levels of explanations and accountability. *Learning Algorithms*, *supra* note 58, at 94–95.

190. Org. for Econ. Co-operation & Dev. [OECD], Recommendation of the Council Concerning Guidelines Governing the Protection of Privacy and Transborder Flows of Personal Data, OECD Doc. C(80)58/FINAL (Sept. 23, 1980), https://www.oecd.org/internet/ieconomy/oecdguidelinesontheprotectionofprivacyandtransborderflowsofpersonaldata.htm, amended by OECD Doc. C(2013)79 (July 11, 2013).

191. *Learning Algorithms*, *supra* note 58, at 94–95; *see, e.g.*, *Accountability and Governance*, INFO. COMMISSIONER'S OFF., https://ico.org.uk/for-organisations/guide-to-data-protection/guide-to-the-general-data-protection-regulation-gdpr/accountability-and-governance/ (last visited Feb. 2, 2020) ("Accountability is one of the data protection principles.").

192. *See, e.g.*, OFFICE OF THE PRIVACY COMM'R OF CANADA ET AL., GETTING ACCOUNTABILITY RIGHT WITH A PRIVACY MANAGEMENT PROGRAM (2012), https://www.priv.gc.ca/media/2102/gl_acc_201204_e.pdf. This document outlines what it believes are the "best approaches for developing a sound privacy management program." *Id.* at 2. The Office of the Privacy Commissioner of Canada, and the Offices of the Information and Privacy Commissioners of Alberta and British Columbia, have worked together to create a summary with the "goal of providing consistent guidance on what it means to be an accountable organization":

> Accountability in relation to privacy is the acceptance of responsibility for personal information protection. An accountable organization must have in place appropriate policies and procedures that promote good practices which, taken as a whole, constitute a privacy management program. The outcome is a demonstrable capacity to comply, at a minimum, with applicable privacy laws. Done properly, it should promote trust and confidence on the part of consumers, and thereby enhance competitive and reputational advantages for organizations. The concept of accountability appears straightforward, but constructing a privacy management program within an organization takes careful planning and consideration across disciplines and job functions.

Id. at 1.

the logic' of automated decisions."[193] Under the GDPR's accountability principle, controllers must create, and constantly update, "appropriate technical and organizational measures" to guarantee and be able to show that data processing is conducted in compliance with the GDPR.[194]

c. Reinforcing Social Biases

While people typically "think about algorithms in the same way [they] think about law—as a set of abstract principles manifesting rational objectives"—this is not exactly the case.[195] In reality, big data algorithms often convert cultural stigmas into empirically certifiable data sets, while incorporating discriminatory measures.[196] An example of one such measure is zip codes, which disclose much more information about people than their mere geographical location, and often serve as a signal of individuals' race or national origin.[197] Therefore, in a world of algorithmic decision-making, where disparate variables become progressively harder to unravel, we will need to re-evaluate "which variables qualify as sensitive [given] their connection to race, gender, or other conventionally-protected classes."[198] Once we identify these factors, "we would want to intensify the need for oversight, as there are [nuanced measures] that can be effectively disguised behind numerous proxies and discriminatory design, adopted by the algorithms' creators."[199]

The fact that algorithms are biased by nature should not be surprising. It has already been several decades since the political scien-

193. Andrew D. Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085, 1100 n.89 (quoting GDPR, *supra* note 48, arts. 13(2)(f), 14(2)(g), 15(1)(h)).

194. *See* GDPR, *supra* note 48, art. 24(1).

195. Sonia K. Katyal, *Private Accountability in the Age of Artificial Intelligence*, 66 UCLA L. REV. 54, 58 (2019). For more on this topic, see *Learning Algorithms*, *supra* note 58, at 95–97.

196. Anya Prince & Daniel Schwarcz, *Proxy Discrimination in the Age of Artificial Intelligence and Big Data*, IOWA L. REV. (forthcoming) (manuscript at 4) ("This big data revolution raises numerous complex challenges for anti-discrimination regimes. Perhaps most obviously, improperly designed algorithms or errant data can disproportionately harm discrete subsets of the population. But even correctly programmed algorithms armed with accurate data can reinforce past discriminatory patterns.").

197. *Id*. at 1 ("[W]hen a firm intentionally sought to discriminate against members of a protected class[, it could do so] by relying on a proxy for class membership, such as zip code.").

198. *Learning Algorithms*, *supra* note 58, at 95.

199. *Id.* at 95–96; *see* Prince & Schwarcz, *supra* note 196, at 3 (discussing in general how big data and AI "are revolutionizing the ways in which firms, governments, and employers classify individuals" using proxies).

tist, Langdon Winner, published his controversial thesis about how technology is always created, by design, with a specific agenda.[200] Winner's most famous example of this focused on the segregationist agenda embodied in the design of the New York States' bridges over parkways on Long Island, and in particular their low height, which was intended to prevent public buses from passing.[201] "One consequence was to limit access of racial minorities and low-income groups to Jones Beach, Moses' widely acclaimed Public Park."[202] Winner cautioned, however, that negative consequences of specific technological designs can also be unintentional, like the failure to offer accommodations for disabled people, that has been the result of a "long-standing neglect."[203]

Algorithms, much like bridges, can also be designed in a discriminatory way,[204] because of an input bias, a training bias, or a programming bias.[205] The discriminatory impact of any of these biases is often seen in one of the two following ways: (i) predictive formulas that result in "self-fulfilling prophesies" targeting particular groups of people given the algorithms' reliance on historic data that can be used as "non-blatant proxies" for a protected class;[206] or (ii) when "classes of individuals with little-to-no digital footprint may find themselves structurally excluded from opportunities that rely on predictive data-driven decisions."[207]

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200. LANGDON WINNER, THE WHALE AND THE REACTOR: A SEARCH FOR LIMITS IN AN AGE OF HIGH TECHNOLOGY 19–39 (1986).

201. *Id.*; *see also Learning Algorithms*, *supra* note 58, at 91.

202. WINNER, *supra* note 200, at 23.

203. *Id.* at 25.

204. *See, e.g.*, Mark Burdon & Paul Harpur, *Re-Conceptualising Privacy and Discrimination in an Age of Talent Analytics*, 37 U.N.S.W. L.J. 679, 680 (2014) ("[D]iscriminatory decisions can now also be founded on random attributes generated through endless correlations of predictive patterns . . . . For example the web browser an applicant used to upload their job application or when and where an employee has their lunch . . . ."); Kate Crawford & Jason Schultz, *Big Data and Due Process: Toward a Framework to Redress Predictive Privacy Harms*, 55 B.C. L. REV. 93, 99–101 (2014) (describing how big data can be used to "circumvent antidiscrimination enforcement mechanisms" in the real estate industry and credit loan industry); Graham Greenleaf Am, *Foreword: Abandon All Hope?*, 37 U.N.S.W. L.J. 636, 636–38 (2014) (discussing literature on the discriminatory use of big data in law enforcement and in the employment context); Robert Sprague, *Welcome to the Machine: Privacy and Workplace Implications of Predictive Analytics*, 21 RICH. J.L. & TECH. 1, 35–41 (2015) (describing how the use of predictive analytics may perpetuate systemic discrimination).

205. *See, e.g.*, *Learning Algorithms*, *supra* note 58, at 96.

206. Timothy M. Snyder, *You're Fired! A Case for Agency Moderation of Machine Data in the Employment Context*, 24 GEO. MASON L. REV. 243, 256–57 (2016); *see Learning Algorithms*, *supra* note 58, at 96.

207. Snyder, *supra* note 206, at 257.

d. *Seduction by Algorithms and Algorithmic Discrimination*[208]

In a society where more and more people are passively outsourcing their decision and choice-making processes to algorithms for various reasons, including that they feel more comfortable following algorithms' recommendations than those of human experts, seduction by algorithms should be something to be mindful of.

For example, discussing the rise of the "digital regulator," Rory Van Loo argued that "[i]n the decades leading up to the 2008 financial crisis, lenders paid brokers to steer home buyers toward costlier loans. Policymakers embrace today's algorithms [such as travel websites] as market guardians, rather than recognizing them as possible digital reincarnations of yesterday's market predators."[209]

Somewhat relatedly, the disparate impact doctrine has long been considered an important yet a controversial development in antidiscrimination law.[210] It has "been seen as beginning where intentional discrimination ends," and has been used in specific cases, such as seniority systems, and written exams that preserved prior intentional discrimination rather than serving a "broad theory of equality."[211] Practitioners have used the doctrine in lawsuits related to employment decisions, housing, and credit.[212] It enables proof of discrimination without the need to prove intent, given "the difficulty of proving intentional discrimination," especially in situations where evidence of explicit bias or spitefulness is missing.[213]

Advocates have used the disparate impact doctrine under Title VII of the Civil Rights Act of 1964 ever since the 1971 *Griggs v. Duke Power Co.*[214] landmark Supreme Court decision, seeking to ap-

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208. *Learning Algorithms*, *supra* note 58, at 97–100.

209. Rory Van Loo, *Rise of the Digital Regulator*, 66 DUKE L.J. 1267, 1272, 1328 (2017).

210. *See*, *e.g.*, *Learning Algorithms*, *supra* note 58, at 97. The disparate impact doctrine "allows challenges to employment or educational practices that are nondiscriminatory on their face but have a disproportionately negative effect on members of legally protected groups." D. Frank Vinik, *Disparate Impact*, BRITANNICA, https://www.britannica.com/topic/disparate-impact (last visited Feb. 17, 2020).

211. Michael Selmi, *Was the Disparate Impact Theory a Mistake?*, 51 UCLA L. REV. 701, 701 (2006); *see Learning Algorithms*, *supra* note 58, at 97.

212. *Learning Algorithms*, *supra* note 58, at 97.

213. Selmi, *supra* note 211, at 701, 706; *Learning Algorithms*, *supra* note 58, at 97.

214. 401 U.S. 424, 431–32 (1971). The U.S. Supreme Court "unanimously approved of the theory in the context of statutory employment discrimination claims." Selmi, *supra* note 211, at 702. The *Griggs* court ruled that it was illegal for the power company to use in hiring or promotion decisions items such as intelligence test scores and high school report cards—as those were proven to disproportionately favor white applicants and essentially disqualified people of color—to make, even if there was no intention to discriminate, especially since the power company could not show how

ply and extend it to the civil rights context,[215] and fight discrimination.[216] In fact, the doctrine has been so widely known that some criticize it now, arguing that it results in employers relying on quotas for hiring purposes, just to avoid disparate impact charges.[217] Likewise, some argue that Congress passed the Civil Rights Act of 1991, in order to reinforce the doctrine's goals.[218]

Nevertheless, the disparate impact doctrine is far from being bullet proof.[219] Violations of Title VII cases that are based on the disparate impact doctrine often fail because of the business necessity defense.[220] However, "[t]he overarching issue continues to be whether the term 'necessity' in the business necessity defense literally requires that the discriminatory practice be essential to the continued viability of the business, or whether it requires something less."[221]

As automation replaces humans as decision-makers in employment, housing, and credit determinations, we must understand if the disparate impact doctrine should apply to algorithmic bias.[222]

It is therefore unclear in what other areas of law the disparate impact doctrine could be applied, even if those relying on it would be successful in meeting the required burden,[223] which might be especially hard to do when using algorithms. Such a burden includes having the plaintiffs show: (i) a particular and identifiable system or policy; (ii) a statistically remarkable deviation in treatment among

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using these items as prerequisites was needed for hired employees to perform their jobs. *Learning Algorithms*, *supra* note 58, at 97; *Griggs*, 401 U.S. at 431–432.

215. *See* Washington v. Davis, 426 U.S. 229, 246–47 (1976). The *Washington v. Davis* court "refused to extend the theory to constitutional claims, holding instead that intentional discrimination is required to establish a violation of the Equal Protection Clause." Selmi, *supra* note 211, at 702; *see Washington*, 426 U.S. at 247–48.

216. *See*, *e.g.*, *Learning Algorithms*, *supra* note 58, at 97–98.

217. *See, e.g.*, Hugh Steven Wilson, *A Second Look at* Griggs v. Duke Power Company*: Ruminations on Job Testing, Discrimination, and the Role of the Federal Courts*, 58 VA. L. REV. 844, 873 (1972) ("[E]mployers may use privately imposed quotas to avoid" disparate impact liability); *Learning Algorithms*, *supra* note 58, at 97. *But see* Ian Ayres & Peter Siegelman, *The Q-Word as Red Herring: Why Disparate Impact Liability Does Not Induce Hiring Quotas*, 74 TEX. L. REV. 1487, 1489 (1996) ("[F]ar from producing hiring quotas that induce employers to discriminate in favor of minorities, disparate impact liability may actually induce hiring discrimination against minorities (and other protected groups).").

218. Ayres & Siegelman, *supra* note 217, at 1521.

219. *See*, *e.g.*, *Learning Algorithms*, *supra* note 58, at 98–100.

220. *See generally* Susan S. Grover, *The Business Necessity Defense in Disparate Impact Discrimination Cases*, 30 GA. L. REV. 387 (1996).

221. *Id.* at 387.

222. *See* Kirchner, *supra* note 169. This is especially the case given the minimal impact and success that the doctrine has had outside the scope of the written employment tests in recent years. *See Learning Algorithms*, *supra* note 58, at 98–100.

223. *See*, *e.g.*, *Learning Algorithms*, *supra* note 58, at 98–99.

protected groups and other groups; and (iii) a correlation between the inconsistency and the system or policy, as just showing the disparity is not enough.

Plaintiffs, therefore, might have a very hard time proving disparate impact cases when dealing with algorithms for several reasons. First, recent court decisions indicate that plaintiffs now face a stricter set of standards when identifying the policy or system that result in disparate impact,[224] emphasizing that a one-time decision does not equal a policy.[225] Therefore, a one-time decision, which is often the case when dealing with algorithmic decision-making, is trickier to challenge. And as machine learning algorithms constantly improve and evolve, most decisions might as well be a "one-time decision."[226]

Second, plaintiffs might face a higher standard for proving direct causation where random, multiple, often unknown factors impact the decision-making process.[227] The Court also stated that a "robust causality requirement" can and is likely to protect "defendants from being held liable for racial disparities they did not create."[228] This focus on "robust causality" will probably exclude decisions made by machine learning algorithms from the scope of the disparate impact doctrine's liability, as defendants could show that their algorithms just followed present methods of systemic bias against minorities.

Lastly, even if plaintiffs can meet the burden required to prove disparate impact,[229] defendants might still be able to avoid liability by demonstrating "business necessity," exhibiting a legitimate interest that is protected by their system.[230] They do this by showing how their policy was relevant to their business goals.[231] After the defendant employer shows business necessity, the burden shifts back to the plaintiffs, who need to suggest a different method that could achieve the same business goals, without causing a disparate impact.[232] This is difficult to do when dealing with algorithmic decision-making processes, which are opaque, secretive, and complex by design, even

224. *Id.*
225. *Id.*
226. *Id.*
227. *Id.*
228. Tex. Dep't of Hous. & Cmty. Affairs v. Inclusive Cmties. Project, 135 S. Ct. 2507, 2523 (2015) (internal citation omitted); *Learning Algorithms*, *supra* note 58, at 99.
229. For the familiar burden-shifting framework of disparate impact analysis, see Ricci v. DeStefano, 557 U.S. 557, 579 (2009).
230. *See*, *e.g.*, *Learning Algorithms*, *supra* note 58, at 99.
231. *See, e.g.*, *Ricci*, 557 U.S. at 587.
232. *See, e.g.*, *Learning Algorithms*, *supra* note 58, at 99.

if the plaintiffs understand the processes well enough to be able to present an alternative, discriminatory method.

IV.
A Cultural Change and Pushing for Critical Thinking via Choice Architecture

There are many significant advantages to individuals' daily lives that are the result of our human reliance on algorithms. Nevertheless, as described above, the challenges and risks are substantial, too.

A. The EU GDPR—Not a Savior

The GDPR offers users certain safeguards as a result of its view of fully automated decision-making being presumptively unfair.[233] The GDPR provides in Article 22(3) that "where automated decision-making is contractually necessary or consensual, certain safeguards for data subjects must apply, including 'at least the right to obtain human intervention on the part of the controller, to express his or her point of view and to contest the decision.' "[234] Recital 71 is non-binding and

> includes a tweak on the safeguards in Article 22(3), by specifying that safeguards for data subjects "should include specific information to the data subject and the right to obtain human intervention, to express his or her point of view, [and] to obtain an explanation of the decision reached after such assessment and to challenge the decision.[235]

However, the human tendency to perceive algorithms as a superior authority can circumvent Article 22's intended safeguards for two main reasons.[236] First, it could bias human reviewers examining results of automated decision-making systems in favor of the original algorithmic results that the human intervention was meant to keep in

233. *See* GDPR, *supra* note 48.

234. Andrew D. Selbst & Julia Powles, *Meaningful Information and the Right to Explanation*, 7 Int'l Data Privacy L. 233, 234–35 (2017) (quoting GDPR, *supra* note 48, art. 22(3)).

235. *Id.* at 235. As Selbst and Powles conclude, a "right to explanation, is therefore, neither endorsed nor limited by the discussion of safeguards in the text" of Article 22 of the GDPR. *Id.* at 237.

236. Some have been skeptical from the get-go about the protection that Article 22 actually affords to data subjects. *See, e.g.*, Sandra Wachter, Brent Mittelstadt & Luciano Floridi, *Why a Right to Explanation of Automated Decision-Making Does Not Exist in the General Data Protection Regulation*, 7 Int'l Data Privacy L. 76, 76 (2017). Others believe differently. *See generally* Bryce Goodman & Seth Flaxman, *European Union Regulations on Algorithmic Decision-Making and a "Right to Explanation,"* 38 AI Mag. 50 (2017).

check.[237] Believing that algorithms are more accurate and reliable than human experts would encourage humans to follow the algorithmic recommendations even if there is evidence supporting a different conclusion. Indeed, this was the case with the Iran Air Flight 655.[238]

Second, studies about evidentiary instructions—instructions given to jurors when courts wish for them to disregard inadmissible evidence—might be useful to examine in connection with the GDPR's human reviewers, given the human difficulty to ignore or forget irrelevant information after being exposed[239] to it when making decisions. At trial, evidentiary instructions come in two forms: an "instruction to disregard," which "tells jurors to ignore particular evidence to which they have been exposed,"[240] and a "limiting instruction," which "tells jurors not to use a particular piece of evidence to draw a certain [conclusion], although they are free to use the evidence in other ways."[241] But despite their intended goal, evidentiary instructions are still widely believed to be ineffective.[242]

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237. "[T]he 'naive assumption' that Justice Jackson famously criticized—the assumption 'that prejudicial effects can be overcome by instructions to the jury'—is an assumption that, in truth, has remarkably little currency." David Alan Sklansky, *Evidentiary Instructions and the Jury as Other*, 65 STAN. L. REV. 407, 410 (2013) (quoting Krulewitch v. United States, 336 U.S. 440, 453 (1949) (Jackson, J., concurring)). Justice Jackson is also quoted for criticizing this assumption in other cases. *See, e.g.*, Bruton v. United States, 391 U.S. 123, 129 (1968); Jackson v. Denno, 378 U.S. 368, 388 n.15 (1964); *see also* Note, *The Limiting Instruction—Its Effectiveness and Effect*, 51 MINN. L. REV. 264, 267 (1966) ("[M]any learned jurists and scholars . . . entertain no doubt that limiting instructions are useless.").

238. *See supra* note 14 and accompanying text.

239. *See, e.g.*, Andrew J. Wistrich, Chris Guthrie & Jeffrey J. Rachlinski, *Can Judges Ignore Inadmissible Information? The Difficulty of Deliberately Disregarding*, 153 U. PA. L. REV. 1251, 1251–52 (2005). As Wistrich et al. find, "[s]kepticism about the ability of jurors to ignore inadmissible information is widespread. Empirical research confirms that this skepticism is well-founded." *Id.* at 1251. Similarly, the study also finds that judges have a hard time forgetting information that they should, as it is irrelevant or inadmissible. *Id.*; *see also* Univ. of N.C. at Chapel Hill, *The Memories You Want to Forget Are the Hardest Ones to Lose*, SCIENCEDAILY (Aug. 16, 2007), www.sciencedaily.com/releases/2007/08/070815105026.htm [https://perma.cc/MPW7-DR3S] (finding, *inter alia*, that it is especially hard to forget emotion-laden memories or information).

240. Sklansky, *supra* note 237, at 408. An instruction to disregard "is used when the judge determines that a bit of testimony or an exhibit is inadmissible, but the jury has already heard or seen it." *Id.*

241. *Id.* "Limiting instructions are used when, as is often the case, the rules of evidence make particular testimony or a particular exhibit inadmissible, but only for a particular, forbidden purpose, or only against certain parties and not against others." *Id.*

242. *See, e.g.*, Peter J. Smith, *New Legal Fictions*, 95 GEO. L.J. 1435, 1491–92 (2007).

In the GDPR context, it is unlikely that human reviewers would be able to successfully ignore the automated decision-making systems' logic and decisions they are examining. The impact of such exposure would be similar to that of jurors that had been exposed to inadmissible evidence they were instructed not to "consider when arriving at a verdict in the case."[243] And while judges rarely grant mistrials, doing so is a possibility if the situation is sufficiently damaging to warrant such measure.[244] Therefore, given these two reasons, even if an algorithmic "right to explanation" exists under the GDPR, it is critical to understand that it is doubtful that such right would ensure that individuals get actual, effective, and successful genuine second opinions.

B. Hypernudging and Algorithmic Auditing

It is still possible, however, to enable people to benefit from many of the advantages that go along with outsourcing decision-making to algorithms, while minimizing the associated risks and challenges. The two main elements necessary to accomplish this are outlined below, and depend on society's ability to harness the power of big data algorithms to our benefit,[245] along with educating people about the importance of critical, innovative thinking.[246]

First, we should require algorithmic decision-makers to include user-friendly features or applications that enable users, to the extent possible, to check what data the algorithmic results they receive are

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243. Demaine, *supra* note 25, at 100 (citation omitted).

244. *Id.* As described by Professor Demaine,

> The standard generally used in making these determinations is that "there is an 'overwhelming probability' that the jury will be unable to follow the court's instructions . . . and a strong likelihood that the effect of the evidence would be 'devastating' to the defendant." Greer v. Miller, 483 U.S. 756, 766 n.8 (1987) (citations omitted). Although originally articulated in the criminal context, the standard has also been applied in civil litigation. *See, e.g.*, Ramirez v. Debs-Elias, 407 F.3d 444, 447–48 (1st Cir. 2005).

Id. n.3.

245. *See generally* Yeung, *supra* note 46.

246. Combining human and artificial intelligence analytical capabilities is a concept very common nowadays, originating, as some might argue, "in 1995 when Northwestern Engineering's J. Edward Colgate and Michael Peshkin undertook a research project on collaborative robots," an initiative they titled Cobots. Amanda Morris, *20 Years Later: Cobots Co-opt Assembly Lines*, Nw. U. (Aug. 4, 2016), http://www.mccormick.northwestern.edu/news/articles/2016/08/twenty-years-later-cobots-co-opt-assembly-lines.html; *see* J. Edward Colgate, Witaya Wannasuphoprasit & Michael A. Peshkin, *Cobots: Robots for Collaboration with Human Operators*, 58 PROCEEDINGS INT'L MECHANICAL ENGINEERING CONGRESS & EXHIBITION 433, 433 (1996), http://peshkin.mech.northwestern.edu/publications/1996_Colgate_CobotsRobotsCollaboration.pdf. Since then, this idea has become mainstream.

based on and examine the algorithms' underlying assumptions. Admittedly, this might not be easy to do. Sophisticated machine learning algorithms "can create paths of action independently of code written by programmers."[247] "The self-improving algorithms may make the right decisions more often, but when they make bad decisions influenced by biased training data, the programmers who developed them may not necessarily be able to explain why and how the program came to the conclusion it did."[248] Under the GDPR, which requires organizations using automated decision-making systems to be able to show how decisions were made, "that creates a problem for both organizations and regulators."[249] As a result, at least some EU regulators, using the help of AI experts, have started looking into ways in which this could be done.[250]

One way of potentially doing this is by using crowd-sourced algorithmic audits, offering, for example, bug bounties as incentives.[251] Crowd-sourced algorithmic audits—processes in which entities open up their technology for evaluation[252]—have recently become a beneficial and critical tool. And while there is "no standard protocol," generally an audit includes outside entities coming in to examine how businesses develop their undisclosed recipe—"without compromising that company's trade secrets."[253] Such reviews are mainly the result of the practical understanding that businesses may ultimately need to show regulators how their technology does not discriminate against

247. Liam Tung, *UK Watchdog Hires AI Expert to Figure Out How to Audit Algorithms that Violate EU Privacy Rules*, CSO (Nov. 21, 2018, 12:41 AM), https://www.csoonline.com/article/3504261/uk-watchdog-hires-ai-expert-to-figure-out-how-to-audit-algorithms-that-violate-eu-privacy-rules.html [https://perma.cc/G6W8-UPT5]; *see* Harry Surden, *Machine Learning and Law*, 89 WASH. L. REV. 87, 89 (2014) (defining machine learning as "a subfield of computer science concerned with computer programs that are able to learn from experience and thus improve their performance over time"; defining ability to learn as "capable of changing their behavior to enhance their performance on some task through experience"; and stating that "machine learning algorithms are designed to detect patterns in data in order to automate complex tasks or make predictions").

248. Tung, *supra* note 247.

249. *Id.*

250. *Id.*

251. Elazari, *supra* note 26.

252. *See* Hempel, *supra* note 44.

253. *Id.*; *see, e.g.*, CATHY O'NEIL, WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY 208 (2016). O'Neil describes harmful algorithmic modes as weapons of math destructions (WMDs), and recommends transparency-releasing data and auditing algorithms as an antidote to bad algorithms: "To disarm WMDs, we also need to measure their impact and conduct algorithmic audits. The first step, before digging into the software code, is to carry out research. We'd begin by treating the WMD as a black box that takes in data and spits out conclusions." *Id.*

protected classes of people, enabling them to avoid future litigation, and improve current marketing efforts.[254] There is no shortage of examples demonstrating the importance of conducting such examinations into algorithms, including the recent consumer finance case of UK airlines.[255] Moreover, it is clear that algorithms can also be extremely effective at reviewing and catching other algorithms' problematic code or biases,[256] as was the case in 2018 with Amazon's HR processes, and offer second opinions in cases where it might be difficult for people to successfully do so.[257]

Second, we must use behavioral economic tools to remind people and emphasize the importance of critical thinking. We can do so by nudging people to second-guess algorithmic results, especially when it is in their best interest to do so. And the best way to encourage individuals to take such action is by employing choice architecture using various behavioral incentivizing tools.[258] For example, if proven that people obey written signs without raising doubts more than they do when obeying human authority, having a human rather than a machine communicate a decision, in itself, might affect the recipients' urge to get a second opinion regarding the decision. In addition, it makes sense to provide algorithms' users with some type of a "second opin-

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254. *See* Hempel, *supra* note 44.

255. For example, airlines in the United Kingdom "used an algorithm to [not] assign families near each other when randomly picking seats[and] nudging families to pay for pre-assigned seats," until the Civil Aviation Authority investigated the issue and reported it to the government's Centre for Data Ethics and Innovation. Fenwick Mckelvey (@mckelveyf), TWITTER (Nov. 21, 2018, 7:33 PM), https://twitter.com/mckelveyf/status/1065402954918895619; *see* Helen Coffey, *Airlines Face Crack Down on Use of 'Exploitative' Algorithm that Splits Up Families on Flights*, INDEP. (Nov. 19, 2018, 12:22 PM), https://www.independent.co.uk/travel/news-and-advice/airline-flights-pay-extra-to-sit-together-split-up-family-algorithm-minister-a8640771.html.

256. *See, e.g.*, Kroll et al., *supra* note 188, at 682–92.

257. *See* Cathy O'Neil, *Amazon's Gender-Biased Algorithm Is Not Alone*, BLOOMBERG (Oct. 16, 2018, 9:00 AM), https://www.bloomberg.com/opinion/articles/2018-10-16/amazon-s-gender-biased-algorithm-is-not-alone (discussing how Amazon relied on an AI recruiting algorithm that discriminated against women, and only after Amazon tested it using other software and tools did it realize that it was not creating gender-neutral results).

258. As I describe in another article,

> Behavioral economic tools can help create better incentives, but also "debias" individuals through the structure of legal rules, and help change . . . culture. Under this debiasing approach, carefully designed legal guidelines can operate directly on actors' social and cognitive biases, as well as judgment errors, and attempt to help such actors either to reduce or to eliminate those biases and errors.

Nizan Geslevich Packin, *It's (Not) All About the Money: Using Behavioral Economics to Improve Regulation of Risk Management in Financial Institutions*, 15 U. PA. J. BUS. L. 419, 422–23 (2013).

ion warning," explaining that different algorithms process different data, or even the same datasets differently. Moreover, this nudge process could be done based on Karen Yeung's "hypernudge" concept, which itself is based on big data insights to nudge individuals regarding their use of algorithms.[259] After all, some people might be more skeptical about the results they receive, while others might passively follow algorithmic recommendations, and would therefore have greater need of hypernudges in order to know what other choices are available. Similarly, we might want to offer people tools to more successfully shop for second opinions, or research all available options, by harnessing the power of big data algorithms and making them do the work for the users, by exploring, screening, ordering, and even negotiating options in an automated, transparent way.[260]

In addition to the technical suggested changes of creating or including applications to offer more or different options, or double-check existing algorithmic recommendations, we must also teach and remind people the importance of developing their own innovative, critical thinking. Adopting algorithmic auditing cultural norms can help us push toward a reality in which it is accepted and expected of people to get second opinions and double-check recommendations. As part of this cultural change, we should also educate people to double check information, which is very similar to the notion of getting a second opinion. As discussed in this Article, institutions and individu-

259. *See* Yeung, *supra* note 46, at 119. Yeung "introduces the concept of a 'hypernudge' as a way to capture the way Big Data intensifies design-based 'nudges' as a form of regulation." Gordon Hull, *Hypernudges as Subjectification*, NEW APPS BLOG (May 23, 2018), https://www.newappsblog.com/2018/05/hypernudges-as-subjectification.html (citing Yeung, *supra* note 46). In contrast to ordinary nudging technologies, which are static, hypernudges

> provided by data analytics are dynamic, continuously and invisibly updating the choices a user sees. They work both to make decisions automatically based on what users have done or can be predicted to do, and by guiding decision-making by influencing what choices are available (and how they are presented). Because of both the dynamism and invisibility, [hypernudges] can be [an] incredibly powerful tool in comparison to their static cousins.

Id.; *see* Yeung, *supra* note 46, at 121–22.

260. *See* Michal S. Gal & Niva Elkin-Koren, *Algorithmic Consumers*, 30 HARV. J.L. & TECH. 309, 310 (2017) (predicting that "[h]uman decision-making could be completely bypassed" where "the next generation of e-commerce . . . will be conducted by digital agents based on algorithms that can handle entire transactions: using data to predict consumers' preferences, choosing the products or services to purchase, negotiating and executing the transaction, and even automatically forming coalitions of buyers to secure optimal terms and conditions."). Gal and Elkin-Koren also examine the challenges to human autonomous choice that arise from these developments and the extent to which the existing legal framework is adequate to address them. *See id.* at 322, 339.

als should be encouraged to consult various sources of information that they agree and disagree with, and then check third party sources that are neither necessarily for nor against, prior to taking action. While it requires more time, energy, and funds, doing so allows us to enjoy the automation gains, payoffs in terms of knowledge and truth, and maintaining a sense of freedom.[261]

CONCLUSION

In a world where automation is quickly replacing human judgment in all industries, the changes recommended in this Article are increasingly important. More and more people and institutions are passively outsourcing to and relying on algorithms to make decisions, in order to get more accurate and cost-effective results. This Article's empirical study compared whose recommendations people felt more comfortable following—reputable humans or algorithms—and showed a significant preference for algorithms as experts, whose guidance people preferred following. These results, in combination with the growing tendency to passively outsource decision-making processes to algorithms, are concerning. People are losing the desire to seek a second opinion, think creatively, compare among options, and actively benefit from their freedom to choose in our democracy. Instead, they rely on algorithms, which despite the halo effect and institutional aura attached to them, are not neutral or objectively accurate.

It is important to get second opinions. We should require algorithmic decision-making tools to include user-friendly features that enable users to show what the algorithmic results they received were based on, and possible second opinion alternatives. It is also important to nudge and hypernudge people to know that they should get a second opinion. Our sense of democracy and free choice, our ability to remain innovative, creative and critical, and even our belief in the American Dream, will all be jeopardized if we assume algorithms are experts that know better and we should just blindly rely on them. Moreover, there are negative biological implications to our human brain that result from the passive outsourcing of daily decisions to technology.

Advocating for individuals to be mindful of these risks and challenges, scholars have offered various methods to make sure people can still logically think for themselves in the information age.[262] One way of doing so is for people to triangulate information prior to taking

261. *See generally* HENDRICKS & HANSEN, *supra* note 47.

262. *Id.* at 138–39.

action, even though it requires more active work. Doing so pays off in terms of knowledge and truth, and helps us maintain a sense of freedom that is critical for our society and democracy.[263]

Since techno-social engineering—"designing and using technological and social tools to construct, influence, shape, manipulate, nudge, or otherwise design human beings"—is unavoidable, it is "easy to get used to the forms that develop and forget that alternatives are possible and worth fighting for."[264] But as Julie Cohen argues, individuals are "losing the 'breathing room' necessary to meaningfully pursue activities that cultivate self-[thinking]," and without that "freedom to experiment," we risk losing the power to govern ourselves[265]—the power that is unique to us as humans.

263. *Id.* at 139.

264. Evan Selinger & Brett Frischmann, *Will the Internet of Things Result in Predictable People?*, GUARDIAN (Aug. 10, 2015, 11:56 AM), https://www.theguardian.com/technology/2015/aug/10/internet-of-things-predictable-people.

265. *Id.* (citing Julie E. Cohen, *What Privacy Is For*, 126 HARV. L. REV. 1904, 1906 (2013)). As summarized by Jathan Sadowski, Cohen argues that "privacy is irreducible to a 'fixed condition or attribute (such as seclusion or control) whose boundaries can be crisply delineated by the application of deductive logic. Privacy is shorthand for breathing room to engage in the process of . . . self-development.'" Jathan Sadowski, *Why Does Privacy Matter? One Scholar's Answer*, ATLANTIC (Feb. 26, 2013), https://www.theatlantic.com/technology/archive/2013/02/why-does-privacy-matter-one-scholars-answer/273521/ (quoting Cohen, *supra*, at 1906).

Appendix

Table 1. T-test of the Difference in Post-Recommendation Comfort Levels Between Those with an Algorithmic and Human Expert

```
. ttest q15, by(hum_stock)

Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	404	3.65099	.0459519	.9236211	3.560655	3.741325
1	373	3.316354	.0451351	.8717031	3.227602	3.405106
combined	777	3.490347	.0327873	.9139368	3.425985	3.55471
diff		.3346362	.0645597		.2079037	.4613687

```
    diff = mean(0) - mean(1)                                      t =   5.1834
Ho: diff = 0                                     degrees of freedom =      775

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Table 2. T-test of the Difference in Willingness to Rely on the Algorithmic or Human Expert a Second Time

```
. ttest q16, by(hum_stock)

Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	204	4.593137	.047954	.6849199	4.498585	4.687689
1	185	4.340541	.0705747	.9599195	4.201301	4.47978
combined	389	4.473008	.0423709	.8356838	4.389703	4.556313
diff		.2525967	.0839765		.0874894	.4177041

```
    diff = mean(0) - mean(1)                                      t =   3.0079
Ho: diff = 0                                     degrees of freedom =      387

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9986         Pr(|T| > |t|) = 0.0028          Pr(T > t) = 0.0014
```

The clear significant difference is apparent by Pr(T>t)=0.0014, which essentially means that if the means were in fact the same, the likelihood of seeing the observed difference or a greater difference is 0.14%.