Worse Than Human?

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The rise of algorithm-driven decision making enabled by Big Data has generated widespread concern among legal scholars. However, few critics have considered data on people's existing preferences about the role of algorithms in decision systems. This Article uses empirical analysis of a novel, large dataset of consumer surveys to elucidate those preferences. The surveys explore whether people prefer to have an algorithm or a human determine an outcome affecting their welfare in a range of representative scenarios with varying stakes. The Article examines how preferences change when one type of decisionmaker produces results that are more accurate, faster, cheaper, or that incorporate private personal information. And it analyzes anchoring effects from the initial assignment of a decisionmaker, along with interactions among these variables, to test how malleable views about algorithms are.

The study's empirical results call the conventional wisdom sharply into question. People often preferred to have an algorithm decide, especially when the mathematical models offered benefits relative to humans. In particular, consumer preferences are highly sensitive to the relative costs or benefits of the two decisionmakers—even more so than to relative accuracy. The stickiness of default settings demonstrates that preferences are often path-dependent, emphasizing the importance of sound policy choices for algorithmic governance. The Article concludes by elaborating the policy implications of its empirical findings. It contends that consumer preferences deserve greater weight in regulatory choices; that transparency efforts should concentrate on the benefits or costs of algorithms to consumers; and

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that policy should treat high-stakes decisions differently from less weighty ones. And its data-driven findings can help shape reforms that are both effective for and acceptable to consumers.

INTRODUCTION

> The story so far:
> In the beginning the Universe was created.
> This has made a lot of people very angry and been widely regarded as a bad move.
> Douglas Adams, THE RESTAURANT AT THE END OF THE UNIVERSE[1]

Algorithms play an increasingly prominent role in a wide array of decisions affecting everyday life,[2] including who to date,[3] what appears in one's social media feed,[4] and how high one's interest rate is on a bank loan.[5] This has generated significant concern among scholars and is widely regarded as a bad move. However, few of the resulting critiques or proposals for reform have considered actual consumers' preferences about the role of algorithms

1. The joke, of course, is that in Adams's novel, the Earth is merely a giant algorithm created to find the question to Life, the Universe, and Everything. An earlier algorithm calculated the answer to the question, finding it to be "[f]orty-two," disappointing all concerned. *See* DOUGLAS ADAMS, THE HITCHHIKER'S GUIDE TO THE GALAXY 188 (Hanomag 2001).

2. *See generally Who Made That Decision: You or an Algorithm?*, KNOWLEDGE@WHARTON (Mar. 25, 2019), https://knowledge.wharton.upenn.edu/article/algorithms-decision-making/ [https://perma.cc/PM6J-VEWW] (statement of Wharton professor Kartik Hosanagar) ("On Amazon, for example, more than a third of the choices that we make are influenced by algorithmic recommendations . . . . On Netflix, they drive more than 80% of the viewing activity. Algorithmic recommendations also influence decisions such as whom we date and marry.").

3. *See* Annie Brown, *Am I Dating an Algorithm? Relationship Experts Weigh in on the Impacts of AI*, FORBES (Dec. 10, 2020, 3:09 PM), https://www.forbes.com/sites/anniebrown/2020/12/10/am-i-dating-an-algorithm-relationship-experts-weigh-in-on-the-impacts-of-ai/ [https://perma.cc/SV3Q-WFWJ]; Ujué Agudo & Helena Matute, *The Influence of Algorithms on Political and Dating Decisions*, PLOS ONE, Apr. 21, 2021, at 1, 16.

4. *See* Joanna Stern, *Facebook's Algorithm Powers What You See. Here Are New Tools To Give You Some Control*, WALL ST. J. (Apr. 2, 2021, 10:00 AM), https://www.wsj.com/articles/facebook-is-giving-us-some-control-of-our-feedsbut-not-enough-11617372000 [https://perma.cc/G9TW-ZRWC]; Kate Klonick, *The New Governors: The People, Rules, and Processes Governing Online Speech*, 131 HARV. L. REV. 1598, 1660 (2018).

5. *See* Sian Townson, *AI Can Make Bank Loans More Fair*, HARV. BUS. REV. (Nov. 6, 2020), https://hbr.org/2020/11/ai-can-make-bank-loans-more-fair [https://perma.cc/UC5Z-2655]; Tom C.W. Lin, *The New Financial Industry*, 65 ALA. L. REV. 567 (2014).

in decisions.[6] That failure is problematic, in part because the conventional wisdom is wrong[7]: consumers are surprisingly receptive to having algorithms make determinations that affect their lives, especially when mechanical decisionmakers offer some practical advantage over human ones.[8] For reasons of both democratic legitimacy and practical effect, social policy choices must take account of consumer views regardless of whether regulators ultimately heed or override them.[9]

This Article makes three claims. First, consumers prefer to have an algorithm rather than a human make decisions about them in a range of representative scenarios.[10] This preference stands in contrast to the algorithmic skepticism that dominates legal scholarship. Second, consumers' inclinations towards algorithms are strongly and significantly determined by utilitarian factors such as cost, speed, and accuracy. Finally, policy choices about the permissible role of algorithms in decision-making systems must

6. *See infra* Section I. This Article is part of a small but growing body of scholarship that employs empirical methods to evaluate algorithms. *See, e.g.*, Benjamin Minhao Chen et al., *Having Your Day in Robot Court* (May 10, 2021), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3841534 [https://perma.cc/295L-KTYV]; Ayelet Sela, *Can Computers Be Fair? How Automated and Human-Powered Online Dispute Resolution Affect Procedural Justice in Mediation and Arbitration*, 33 OHIO ST. J. DISP. RESOL. 91 (2018); Avital Mentovich et al., *Are Litigation Outcome Disparities Inevitable? Courts, Technology, and the Future of Impartiality*, 71 ALA. L. REV. 893 (2020).

7. *See, e.g.*, Aaron Smith, *Public Attitudes Toward Computer Algorithms*, PEW RSCH. CTR. (Nov. 16, 2018), https://www.pewresearch.org/internet/2018/11/16/public-attitudes-toward-computer-algorithms/ [https://perma.cc/43TX-PUWN] (finding "the public is frequently skeptical of these tools when used in various real-life situations"); Noah Castelo et al., *Let the Machine Decide: When Consumers Trust or Distrust Algorithms*, 11 NIM MKTG. INTELL. REV. 24, 24 (2019) ("While many algorithms can outperform even expert humans, many consumers remain skeptical: Should they rely more on humans or on algorithms? According to previous findings, the default option is to rely on humans, even when doing so results in objectively worse outcomes."); Mareike Möhlmann & Ola Henfridsson, *What People Hate About Being Managed by Algorithms, According to a Study of Uber Drivers*, HARV. BUS. REV. (Aug. 30, 2019), https://hbr.org/2019/08/what-people-hate-about-being-managed-by-algorithms-according-to-a-study-of-uber-drivers [https://perma.cc/FQ8Y-YVXR]; Charlie Warzel, *The Reason You Hate Online Ads*, N.Y. TIMES (May 28, 2019), https://www.nytimes.com/2019/05/28/opinion/online-ads.html/ [https://perma.cc/T85U-JDX8]; Amy Tori, *Dear Instagram, We Hate the Stupid Algorithm—Sincerely, Every User*, HUFFINGTON POST (May 24, 2017), https://www.huffpost.com/entry/dear-instagram-we-hate-you-the-stupid-algorithm_b_591a3b57e4b03e1c81b0083c [https://perma.cc/VL28-U5MP].

8. *See infra* Section III.

9. *See* Michal S. Gal, *Algorithmic Challenges to Autonomous Choice*, 25 MICH. TECH. L. REV. 59, 86 (2018).

10. There are a few other studies that come to similar conclusions. *See, e.g.*, Maurice Jakesch et al., *AI-Mediated Communication: How the Perception that Profile Text Was Written by AI Affects Trustworthiness*, PROC. OF THE 2019 CHI CONFERENCE ON HUMAN FACTORS IN COMPUTING SYSTEMS, May 2019, at 1, 1–13, https://doi.org/10.1145/3290605.3300469 [https://perma.cc/J76U-HFLJ].

grapple with these consumer preferences.[11] Failure to do so will undermine the legitimacy of legal reforms along with impeding their implementation.

This Article reveals extant consumer preferences using a novel dataset that offers unexpected insights into how people view algorithms. For example, consumers behave in ways that are highly rational in classic economic terms yet largely neglected by mainstream scholars.[12] Across a range of scenarios, from assessing creditworthiness to selecting participants for a clinical trial of a promising therapy, consumers significantly preferred algorithms when automated decision making offered benefits in speed, cost, or accuracy.[13] Moreover, these utilitarian considerations outweighed any deontological preferences that respondents may have had for putting a human in the loop.[14] Consumers demonstrated a mild increase for human decision making as the stakes at issue rose (for example, whether one would receive a gift card from a coffee shop versus whether one would receive a civil traffic fine).[15] This seems unsurprising, particularly since the scenarios tested in this study involved holistic decisions—judgment calls, in common parlance—rather than straightforward mathematical calculations. However, this stakes-based shift was outweighed both by more concrete considerations, such as speed or cost, and by the default setting, which was the random initial assignment of the decision to a person or a program. Surprisingly, and contrary to conventional wisdom, giving the decisionmaker access to private personal

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11. The definition of such a system is a contested topic. *See* Rashida Richardson, *Defining and Demystifying Automated Decision Systems*, 81 MD. L. REV. (forthcoming 2022)., https://ssrn.com/abstract=3811708 [https://perma.cc/29TN-PPAW].

12. *See, e.g.*, Dan L. Burk, *Algorithmic Legal Metrics*, 96 NOTRE DAME L. REV. 1147, 1147, 1166–71 (2021) (criticizing legal literature for failure to account for social effects of "algorithmic living"). *But see* Gal, *supra* note 9, at 75–77.

13. *Cf.* Chen et al., *supra* note 6, at 33 (showing how interventions can close perceptions of "fairness gap" between human and algorithmic judges).

14. *See* Kiel Brennan-Marquez & Stephen E. Henderson, *Artificial Intelligence and Role-Reversible Judgment*, 109 J. CRIM. L. & CRIMINOLOGY 137, 149 (2019) (arguing for human decision making on democratic equality grounds). There are, of course, utilitarian reasons to support human intervention. For example, two fatal crashes of Boeing 737 MAX planes occurred because flight control software (reacting to inaccurate sensor data) put the aircraft into steep dives. *See* Dominic Gates, *Q&A: What Led to Boeing's 737 MAX Crisis*, SEATTLE TIMES (Nov. 22, 2020, 5:52 PM), https://www.seattletimes.com/business/boeing-aerospace/what-led-to-boeings-737-max-crisis-a-qa/ [https://perma.cc/HCX7-V9J3]. Human pilots could easily have verified that the dives, designed to prevent a stall, were unnecessary and caused by sensor errors. *Id.* Even if the pilots in the two affected aircraft had reacted quickly enough to correct the dives, the software was programmed to override them ten seconds later. *Id.*

15. Other studies have found similar effects. *See, e.g.*, Shir Raviv, *When Do Citizens Resist AI-Usage in Public Policy? Evidence from the COVID-19 Crisis* (Sept. 29, 2021), https://ssrn.com/abstract=3932328 [https://perma.cc/ST44-W84D] (finding that people prefer humans over algorithms in making high-stakes decisions related to the COVID-19 pandemic).

information, as opposed to only publicly available data, had no significant effect on whether people preferred a human to an algorithm.

These findings strongly suggest that consumers currently behave in ways closer to standard models of the rational actor rather than employing bounded rationality.[16] When the error rates of both the human decisionmaker and algorithm were unknown, and all other factors (such as cost) were equal, survey respondents preferred to have a human make the choice 65% of the time. This might result from underlying assumptions about the base error rate for people versus code,[17] or it might demonstrate a deontological preference for having other humans determine outcomes.[18] Regardless of the rationale for that baseline choice, people rapidly became practical as soon as they learned that the algorithm option offered a concrete advantage such as faster decisions or greater benefits. The initial preference for having a human in the loop is thus a mild one, easily displaced by utilitarian considerations.

To assess existing consumer preferences about the role of algorithms, we asked over four thousand respondents in the United States a simple question: would they prefer to have a particular decision affecting them made by a human or by an algorithm? The survey software randomly assigned each respondent to one of four narrative vignettes involving decisions of varying importance: whether the participant would receive a coffee shop gift card as Customer of the Month; whether they would be found liable for a civil traffic offense and have to pay a fine; whether they would receive a bank loan; or whether they would be included in a clinical trial for a promising treatment for a disease from which they suffered.[19] Next, the survey randomly assigned the decision at issue to either a human or an algorithm. It told the respondent about that default assignment, and then provided additional information about the relative merits of each type of decisionmaker—for example, that a human would have a higher rate of accuracy under these circumstances. Finally, the survey gave the respondents the option to remain with their default decisionmaker or to switch.

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16. We thank Alan Trammell for elaborating this point. *See generally* Christine Jolls & Cass R. Sunstein, *Debiasing Through Law*, 35 J. LEGAL STUD. 199 (2006) (describing bounded rationality and policy interventions to address it); Stephanie Plamondon Bair, *Malleable Rationality*, 79 OHIO ST. L.J. 17 (2018) (noting that bounded rationality is altered by policy decisions).

17. *See* Brennan-Marquez & Henderson, *supra* note 14, at 148.

18. *See id.*; Chen et al., *supra* note 6. This article's survey results are similar when the error rate for each type of decisionmaker was low (respondents chose humans 60% of the time) and when the error rate for each was high (they picked humans 64% of the time). This implies a mix of deontological and utilitarian (error-rate / consequential) preferences.

19. The full details of the vignettes are described in Appendix A *infra*.

With a large sample size and a range of binary variables, our survey provided information about people's relative preferences through A/B testing.[20] For example, we could evaluate whether a statistically significant number of people switched from a human to an algorithm when they were told that the algorithm made faster decisions, with all other factors held constant. Analysis of this dataset shows that the conventional wisdom of people's preferences for having humans in the loop is simplistic and often flatly incorrect. Our analysis of the survey data against the backdrop of the growing consensus about how consumers should and do feel about having algorithms make choices that affect them forms the heart of this Article.

The scope of the survey, and thus of this Article's findings, is limited in one important respect. Respondents were asked about scenarios within the mainstream of daily life. The survey did not attempt to assess preferences about algorithms in less frequently encountered situations, such as criminal sentencing, where people face particularly grave or weighty consequences.[21] Both individual people and society as a whole may need to take account of deeper normative commitments in such circumstances, and tradeoffs of benefits such as lower cost may not be acceptable if they come at the price of greater rates of error.[22] The role of algorithms in areas such as criminal sentencing is of critical importance, with a growing body of legal scholarship devoted to it; it is outside this Article's analysis.[23] Our study design concentrates on the array of practical, meaningful, but more limited decisions that make up daily life. In this realm, people welcome algorithmic intervention based on a clear weighing of utilitarian costs and benefits.

This Article contends that whether one loves or loathes algorithms, consumer preferences about their role in decision making must be incorporated into policy analysis for at least four reasons. First, without evaluating consumers' views of algorithms and related issues such as privacy,

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20. *See* Amy Gallo, *A Refresher on A/B Testing*, HARV. BUS. REV. (June 28, 2017), https://hbr.org/2017/06/a-refresher-on-ab-testing [https://perma.cc/M664-M7PQ].

21. *See* Gall v. United States, 552 U.S. 38, 41, 46 (2007); Itay Ravid & Amit Haim, *Progressive Algorithms*, 12 U.C. IRVINE L. REV. (forthcoming), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3815744 [https://perma.cc/8ZM2-2AA2]; *see, e.g.*, United States v. Booker, 543 U.S. 220 (2005).

22. *See* Aziz Z. Huq, *Racial Equity in Algorithmic Criminal Justice*, 68 DUKE L.J. 1043, 1133 (2019).

23. *See, e.g.*, *id.*; Ravid & Haim, *supra* note 21; Andrea L. Roth, *Trial by Machine*, 104 GEO. L.J. 1245 (2016); Brennan-Marquez & Henderson, *supra* note 14; Mirko Bargaric et al., *The Solution to the Pervasive Bias and Discrimination in the Criminal Justice: Transparent Artificial Intelligence*, 59 AM. CRIM. L. REV. (forthcoming), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3795911 [https://perma.cc/4HNS-8K33].

one cannot establish a meaningful comparative baseline for policy analysis.[24] Consumers may, for example, be willing to accept some negative effects from using an algorithm if they receive greater offsetting benefits by so doing. Second, careful exegesis of consumer preferences provides data on both algorithmic inaccuracy *and* human inaccuracy, enabling policymakers to gauge how consumers compare the two.[25] Third, isolating preferences about the role of algorithms in decision mechanisms is vital to identifying the problem that requires a solution. People may dislike having machines make decisions in a particular context.[26] They might dislike the outcomes from the mechanism applicable to that context.[27] And of course they might dislike both.[28] Each of these concerns is likely to require a somewhat different remedial approach; conflating the different lines of criticism will limit corrective choices. Finally, algorithms are inevitably a component of modern decision-making ecosystems. Few if any judgments are made solely by a human without reference to any quantitative guideposts, or by an algorithm without human interaction.[29] Certain choices that have particularly important moral weight or significant consequences, such as sentencing after a criminal conviction, might be nominally committed to the discretion of a human policymaker.[30] But most choices involve some calculation. Netflix recommendations, newspaper restaurant reviews, and "top ten" lists all involve algorithms, no matter how crude. Each of these reasons supports this Article's task: first to explicate consumer preferences, and then to evaluate how they should factor into policy choices.

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24. *Cf.* Adam J. Kolber, *The Comparative Nature of Punishment*, 89 B.U. L. REV. 1565 (2009) (exploring problem of comparative nature of punishment, including effects of nominally equal sentences on offenders with different initial conditions).

25. *See, e.g.*, William M. Grove & Paul E. Meehl, *Comparative Efficiency of Informal (Subjective, Impressionistic) and Formal (Mechanical, Algorithmic) Prediction Procedures: The Clinical-Statistical Controversy*, 2 PSYCH. PUB. POL'Y & L. 293, 294 (1996).

26. *See* Gerhard Wagner & Horst Eidenmüller, *Down by Algorithms? Siphoning Rents, Exploiting Biases, and Shaping Preferences: Regulating the Dark Side of Personalized Transactions*, 86 U. CHI. L. REV. 581, 608 (2019).

27. *See* Sonia K. Katyal, *Private Accountability in the Age of Artificial Intelligence*, 66 UCLA L. REV. 54, 59 (2019).

28. *See id.*

29. *See* Derek E. Bambauer, *The Boundaries of Artificial Intelligence: Governance, Accountability, and Modes of Intervention*, *in* CAMBRIDGE RESEARCH HANDBOOK OF ARTIFICIAL INTELLIGENCE & THE LAW (Kristin Johnson & Carla Reyes, eds., forthcoming 2022) (on file with authors).

30. *See* Gall v. United States, 552 U.S. 38, 41, 46 (2007); United States v. Booker, 543 U.S. 220, 234 (2005). However, even this discretion is fettered, since judges must use the Sentencing Guidelines algorithm created by the United States Sentencing Commission as the "starting point and initial benchmark" for their choice of what sanction to impose. *Gall*, 552 U.S. at 39.

The Article first examines the extant scholarly literature on algorithms, finding that it has important qualitative shortcomings along with its neglect of empirical evidence of consumer preferences. Next, the Article describes the empirical methodology used to create the dataset of current consumer preferences regarding algorithmic versus human decisionmakers. Then, it analyzes the survey data obtained using that methodology. The final section concludes, and an appendix contains the text of the surveys and tables of relevant statistical data.

I. CRITIQUES OF ALGORITHMS

Algorithms have a long history in human society, including an appearance in the Bible.[31] Critiques of their role in decisions have been around for almost as much time.[32] It is only recently, though, that these decision-making tools have received sustained—and largely negative—attention from legal and computer science scholars.[33] The rise of "Big Data" has enabled organizations to repurpose the information they have collected for a wide range of social and economic decisions.[34] Distributed computing helps increasingly sophisticated mathematical models analyze this treasure trove of data.[35] Algorithms help decide whom one should date,[36] whether one should receive

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31. That appearance was unpleasant: "And all the firstborn in the land of Egypt shall die, from the firstborn of Pharaoh that sitteth upon his throne, even unto the firstborn of the maidservant that is behind the mill; and all the firstborn of beasts." *Exodus* 11:5 (King James). As far as algorithms go, the Biblical one was simple but inflexible. It was, however, easily gamed: "And the blood shall be to you for a token upon the houses where ye are: and when I see the blood, I will pass over you, and the plague shall not be upon you to destroy you, when I smite the land of Egypt." *Exodus* 12:13 (King James).

32. *See, e.g.*, Louis H. Feldman, *The Plague of the First-Born Egyptians in Rabbinic Tradition, Philo, Pseudo-Philo, and Josephus*, 109 REVUE BIBLIQUE 403 (2002) (reviewing criticism of the killing of the firstborn Egyptians described in Exodus 11:5).

33. *See generally* Christopher S. Yoo & Alicia Lai, *Regulation of Algorithmic Tools in the United States*, 13 J.L. & ECON. REG. 7 (2020) (examining the emergence and rapid growth of federal artificial intelligence regulation in the past five years). Note, however, that the first credit bureau began operations in the second half of the nineteenth century. Jonathan Weinberg, *"Know Everything That Can Be Known About Everybody": The Birth of the Credit Report*, 63 VILL. L. REV. 431, 431 (2018).

34. "Big Data" and algorithms are separate topics; one can use simple methods on large data sets, and one can employ sophisticated techniques on small ones. The confluence of the two trends, though, is principally responsible for the controversies over algorithms.

35. *See generally* AJAY D. KSHEMKALYANI & MUKESH SINGHAL, DISTRIBUTED COMPUTING: PRINCIPLES, ALGORITHMS, AND SYSTEMS (2008).

36. *See, e.g.*, Kevin Poulsen, *How a Math Genius Hacked OKCupid To Find True Love*, WIRED (Jan. 21, 2014, 6:30 AM), https://www.wired.com/2014/01/how-to-hack-okcupid/ [https://perma.cc/WB94-SN3W]. *But see* Eli J. Finkel et al., *Online Dating: A Critical Analysis from the Perspective of Psychological Science*, 13 PSYCH. SCI. IN THE PUB. INT. 3 (2012).

credit,[37] when one should undergo additional security screening at an airport,[38] which Web pages are considered in response[39] and ultimately judged most relevant to one's query,[40] what price one ought to be quoted for a purchase,[41] and which stocks one ought to buy as an investment.[42] These software-based models draw upon an ever-widening range of information, from one's history of paying bills,[43] to driving habits,[44] to social media behavior.[45] The advent of the much-hyped Internet of Things means that algorithms will have far more data to analyze.[46] Increasingly, humans will

37. *See, e.g.*, Tracy Alloway, *Big Data: Credit Where Credit's Due*, FIN. TIMES (Feb. 4, 2015), https://www.ft.com/content/7933792e-a2e6-11e4-9c06-00144feab7de [https://perma.cc/24K7-QHFN]; FED. TRADE COMM'N, BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION? (Jan. 2016), https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf [https://perma.cc/2ZYK-EGXE].

38. *See, e.g.*, Thom Patterson, *Is This the Future of TSA Passenger Screening?*, CNN (May 25, 2016), http://www.cnn.com/2016/05/25/aviation/tsa-atlanta-experimental-passenger-screening-lanes/ [https://perma.cc/RJ8S-99BG]; *Security Screening*, TRANSPORTATION SECURITY ADMINISTRATION, https://www.tsa.gov/travel/security-screening [https://perma.cc/YFJ4-8MHC].

39. *See* Andrea Fuller et al., *Google Hides News, Tricked by Fake Claims*, WALL ST. J. (May 15, 2020, 11:43 AM), https://www.wsj.com/articles/google-dmca-copyright-claims-takedown-online-reputation-11589557001 [https://perma.cc/98UU-T3FY].

40. *See, e.g.*, *How Search Algorithms Work*, GOOGLE, https://www.google.com/insidesearch/howsearchworks/algorithms.html [https://perma.cc/M8LY-CA64].

41. *See, e.g.*, Julia Angwin & Surya Mattu, *Amazon Says It Puts Customers First. But Its Pricing Algorithm Doesn't*, PROPUBLICA (Sept. 20, 2016, 8:00 AM), https://www.propublica.org/article/amazon-says-it-puts-customers-first-but-its-pricing-algorithm-doesnt [https://perma.cc/7X3N-37DA].

42. *See* Gregory Zuckerman & Bradley Hope, *The Quants Run Wall Street Now*, WALL ST. J. (May 21, 2017, 4:30 PM), https://www.wsj.com/articles/the-quants-run-wall-street-now-1495389108 [https://perma.cc/96WC-DSQK].

43. *See, e.g.*, Ken Sweet, *New Type of Credit Score Based on Whether Utility Bills Paid*, PORTLAND PRESS HERALD (Apr. 3, 2015), http://www.pressherald.com/2015/04/03/new-type-of-credit-score-based-on-whether-utility-bills-paid/ [https://perma.cc/N64M-A69C].

44. *See, e.g.*, Leslie Scism, *Car Insurers Find Tracking Devices Are a Tough Sell*, WALL ST. J. (Jan. 10, 2016, 8:45 PM), http://www.wsj.com/articles/car-insurers-find-tracking-devices-are-a-tough-sell-1452476714 [https://perma.cc/QF97-QQGP].

45. *See, e.g.*, Michael Koziol, *Software Is Being Developed To Allow Employers To Trawl Through Your Social Media*, SYDNEY MORNING HERALD (June 5, 2015, 4:12 PM), http://www.smh.com.au/technology/technology-news/software-is-being-developed-to-allow-employers-to-trawl-through-your-social-media-20150603-ghfs6m.html [https://perma.cc/9ECJ-QR97].

46. *See* Derek E. Bambauer, *Cybersecurity for Idiots*, 106 MINN. L. REV. HEADNOTES 172 (2021).

move from making decisions, supported by tools, to defining the criteria by which those tools make decisions, without a person in the loop.[47]

Legal scholarship has been quite skeptical of this rise in algorithmic decisions.[48] While a few scholars have lauded the potential for algorithmic decisions to enhance transparency and equality of treatment,[49] most have raised normative objections to the trend, seeing algorithms as fraught with risk for discrimination[50] and simple error.[51] Critics dislike the range of data collected, how algorithms weigh the information, and even the automation of decisions as an initial matter.[52] Their objections typically coalesce around one or more arguments. First, if algorithms offer similarly-situated people different opportunities, this might violate a dignity interest.[53] Or, algorithms

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47. *See* FRANK PASQUALE, NEW LAWS OF ROBOTICS: DEFENDING HUMAN EXPERTISE IN THE AGE OF AI (2020).

48. There is no shortage of examples. *See, e.g.*, FRANK PASQUALE, THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION (2015); TIM WU, THE ATTENTION MERCHANTS: THE EPIC SCRAMBLE TO GET INSIDE OUR HEADS (2016); Jack M. Balkin, *2016 Sidley Austin Distinguished Lecture on Big Data Law and Policy: The Three Laws of Robotics in the Age of Big Data*, 78 OHIO ST. L.J. 1217 (2017); Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CALIF. L. REV. 671 (2016); Ryan Calo, *Digital Market Manipulation*, 82 GEO. WASH. L. REV. 995 (2014); Salil K. Mehra, *Antitrust and the Robo-Seller: Competition in the Time of Algorithms*, 100 MINN. L. REV. 1323 (2016); Christopher P. Guzelian et al., *Credit Scores, Lending, and Psychosocial Disability*, 95 B.U. L. REV. 1807 (2015); Andrew Tutt, *An FDA for Algorithms*, 69 ADMIN. L. REV. 83 (2017).

49. *E.g.*, Aziz Z. Huq, *A Right to a Human Decision*, 106 VA. L. REV. 611, 686 (2020); Ravid & Haim, *supra* note 21; Ariel Porat & Lior Strahilevitz, *Personalizing Default Rules and Disclosure with Big Data*, 112 MICH. L. REV. 1417, 1477–78 (2014); Berkeley J. Dietvorst et al., *Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err*, 144 J. EXPERIMENTAL PSYCH.: GEN. 114, 123 (2015); Jon Kleinberg et al., *Discrimination in the Age of Algorithms*, 10 J. LEGAL ANALYSIS 1, 2 (2018).

50. *E.g.*, Gillian B. White, *When Algorithms Don't Account for Civil Rights*, ATLANTIC (Mar. 7, 2017), https://www.theatlantic.com/business/archive/2017/03/facebook-ad-discrimination/518718/ [https://perma.cc/DR3K-QVR3]. In some cases, algorithms are explicitly biased based upon factors such as race. *E.g.*, Rae Ellen Bichell & Cara Anthony, *For Black Kidney Patients, an Algorithm May Help Perpetuate Harmful Racial Disparities*, WASH. POST (June 6, 2021), https://www.washingtonpost.com/health/black-kidney-patients-racial-health-disparities/2021/06/04/7752b492-c3a7-11eb-9a8d-f95d7724967c_story.html [https://perma.cc/Z8HG-ABMK].

51. *E.g.*, Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 4 (2014); Barocas & Selbst, *supra* note 48, at 684; Elizabeth E. Joh, *The New Surveillance Discretion: Automated Suspicion, Big Data, and Policing*, 10 HARV. L. & POL'Y REV. 15, 31 (2016); CATHY O'NEIL, WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY 154–55 (2016).

52. *See, e.g.*, BRETT FRISCHMANN & EVAN SELINGER, RE-ENGINEERING HUMANITY (2018).

53. Alina Köchling & Marius Claus Wehner, *Discriminated by an Algorithm: A Systematic Review of Discrimination and Fairness by Algorithmic Decision-Making in the Context of HR Recruitment and HR Development*, 13 BUS. RSCH. 795, 836–37 (2020); *see also* SAFIYA UMOJA NOBLE, ALGORITHMS OF OPPRESSION: HOW SEARCH ENGINES REINFORCE RACISM (2018).

may treat people alike even if they face vastly different social and economic circumstances that cannot be so easily measured.[54] Second, if algorithms reduce one's scope of choice, that might violate an autonomy interest.[55] Third, collection of previously obscure or unconnected data about a person may contravene a deontological interest in human flourishing[56] or, if it introduces error into the system, may run afoul of a consequentialist interest in maximizing human welfare.[57] Critics have proposed a wide range of reforms to mitigate these problems, from enhancing transparency[58] to imposing fiduciary responsibilities[59] to regulating algorithms[60] to banning certain processing altogether.[61]

Yet legal scholarship on algorithms only infrequently starts with, or even addresses in any detail, how people actually respond to decision systems that give these formulas a prominent role.[62] There are a few articles—too few—that have examined consumer preferences with empirical rigor. Some assess

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54. Olivia Solon, *Facebook Ignored Racial Bias Research, Employees Say*, NBC NEWS (July 23, 2020, 12:29 PM), https://www.nbcnews.com/tech/tech-news/facebook-management-ignored-internal-research-showing-racial-bias-current-former-n1234746 [https://perma.cc/A4ET-CKKS].

55. Michal S. Gal, *Algorithms Challenge Human Autonomous Choice: Should We Care?*, OXFORD BUS. L. BLOG (Aug. 24, 2017), https://www.law.ox.ac.uk/business-law-blog/blog/2017/08/algorithms-challenge-human-autonomous-choice-should-we-care [https://perma.cc/G4CS-N4HD].

56. *See* Elena Esposito, *Algorithmic Memory and the Right To Be Forgotten on the Web*, 4 BIG DATA & SOC'Y 1, 5–8 (2017); Eduard Fosch Villaronga et al., *Humans Forget, Machines Remember: Artificial Intelligence and the Right To Be Forgotten*, 34 COMPUT. L. & SEC. REV. 304, 307–08 (2018).

57. *See* Michele Gilman, *How Algorithms Intended To Root Out Welfare Fraud Often Punish the Poor*, PBS NEWS HOUR (Feb. 17, 2020, 7:15 AM), https://www.pbs.org/newshour/economy/column-how-algorithms-to-root-out-welfare-fraud-often-punish-the-poor [https://perma.cc/E58U-MJC6].

58. Robert Brauneis & Ellen P. Goodman, *Algorithmic Transparency for the Smart City*, 20 YALE J.L. & TECH. 103, 176 (2018). *Contra* Lilian Edwards & Michael Veale, *Slave to the Algorithm? Why a "Right to an Explanation" Is Probably Not the Remedy You Are Looking for*, 16 DUKE L. & TECH. REV. 18, 22–23 (2017); Joshua Kroll et al., *Accountable Algorithms*, 165 U. PA. L. REV. 633, 657–60 (2017).

59. Ifeoma Ajunwa, *The Paradox of Automation as Anti-Bias Intervention*, 41 CARDOZO L. REV. 1671, 1722 (2020).

60. Tutt, *supra* note 48.

61. *See* Lynn M. Lopucki, *Algorithmic Entities*, 95 WASH. U. L. REV. 887, 951 (2018); Michael Livermore & Dan Rockmore, *France Kicks Data Scientists Out of Its Courts*, SLATE (June 21, 2019, 7:30 AM), https://slate.com/technology/2019/06/france-has-banned-judicial-analytics-to-analyze-the-courts.html [https://perma.cc/DMN9-Q9RP].

62 Other disciplines also offer examples of rigorous empirical work, but it is still uncommon. *See, e.g.*, Ethan LaMothe & Donna Bobek, *Are Individuals More Willing to Lie to a Computer or a Human? Evidence from a Tax Compliance Setting*, 167 J. BUS. ETHICS 157 (2020) (finding taxpayers more willing to lie to software than humans).

specific contexts, such as e-commerce,[63] online dispute resolution,[64] and consumer finance.[65] Others use empirical tools to address systemic questions, including the perceived "fairness gap" between human and robot judges,[66] and whether a shift from in-person to online civil infraction hearings can reduce race, gender, and age bias.[67] This Article contributes to both context-specific and system-level studies of consumer preferences. It evaluates how people view algorithmic involvement in decisions across a range of scenarios. And, because of the design of its dataset, the Article can advance generalizable claims about the common factors that shift consumer preferences across different contexts.

This Article does not take a normative position on the proper role of algorithms in decision-making ecosystems, nor on the desirability of the various reforms proposed in the scholarly debate. We are neutral about what preferences society ought to have regarding the relative importance of human and algorithms in deciding outcomes. Our normative claim is a more cautious one: consumer preferences are strongly relevant to these questions, and normative proposals must grapple with existing societal views about algorithms. One of the Article's most surprising findings, for example, is that when all other factors were held equal, a statistically significant majority of respondents (52.2%) chose an algorithm to decide their fate (across all four scenarios). Consumer preferences for algorithms increased as soon as a code-based decisionmaker offered an advantage in cost, speed, accuracy, or error rate. People are not only willing to have algorithms make decisions that affect them—they affirmatively prefer formulas over humans in a range of representative cases.

Based upon its empirical findings, this Article also contends that much of the normative legal scholarship could use more skepticism about algorithmic skepticism.[68] One finds four common but important errors in the literature: lack of proper baselines for measurement; inconsistent attitudes about accuracy; a simplistic reliance on sports analogies; and failure to distinguish between disagreement with outcomes versus disagreement with algorithms

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63. *See* Szabolcs Nagy & Noémi Hajdú, *Consumer Acceptance of the Use of Artificial Intelligence in Online Shopping: Evidence from Hungary*, 23 AMFITEATRU ECON. 155 (2021) (assessing consumer acceptance of AI in e-commerce using technology acceptance model and survey data).

64. *See* Sela, *supra* note 6, at 120–38.

65. *See* Nizan Geslevich Packin, *Consumer Finance and AI: The Death of Second Opinions?*, 22 N.Y.U. J. LEGIS. & PUB. POL'Y 319 (2020).

66. Chen et al., *supra* note 6, at 30–31.

67. Mentovich et al., *supra* note 6.

68. *See* Kevin Kelly, *The Myth of a Superhuman AI*, WIRED (Apr. 25, 2017, 12:00 AM), https://www.wired.com/2017/04/the-myth-of-a-superhuman-ai/ [https://perma.cc/6RJG-4DFC].

in arriving at them. Robust data on consumer preferences can help ameliorate each of these shortcomings.

The first problem is establishing a relevant and useful baseline for criteria such as accuracy. Critics tend to point out the failings of algorithms: denying credit to the genuinely creditworthy[69] or bail to those unlikely to violate its terms,[70] for example. All too often, however, this approach makes a typical mistake of temporal framing: it evaluates the success or failure of an algorithm's ex ante determinations against the (perfect) knowledge of outcomes ex post.[71] On that metric, every evaluator would be a failure, since errors are impossible to avoid, particularly in large-scale undertakings. The perfect becomes the judge of the good. Many critics ignore comparative rankings—for example, how do the outcomes from using a risk assessment algorithm in criminal sentencing compare with the outcomes from relying on human judges?[72] The proper comparison is with the next-best alternative in a given context, not with an infallible judge or program.[73] And, while accuracy is an important criterion and social value, it is not the only one relevant to determining when to employ algorithms. For example, survey respondents for this Article preferred cheaper but less accurate algorithms in some cases.[74] When presented with an algorithm that had a high error rate and a human with an unknown error rate, and all other factors equal, people chose the algorithm only 24% of the time.[75] However, when asked to choose under the same error rate conditions, but with an algorithm that offered greater

69. *See* Kaveh Waddell, *How Algorithms Can Bring Down Minorities' Credit Scores*, ATLANTIC (Dec. 2, 2016), https://www.theatlantic.com/technology/archive/2016/12/how-algorithms-can-bring-down-minorities-credit-scores/509333/ [https://perma.cc/GLX3-24WJ].

70. *See* Julia Dressel & Hany Farid, *The Accuracy, Fairness, and Limits of Predicting Recidivism*, 4 SCI. ADVANCES 1 (2018); Tom Simonite, *Algorithms Were Supposed to Fix the Bail System. They Haven't*, WIRED (Feb. 19, 2020, 8:00 AM), https://www.wired.com/story/algorithms-supposed-fix-bail-system-they-havent/ [https://perma.cc/KD2Z-XMSQ].

71. *Cf.* Barbara H. Fried, *Ex Ante/Ex Post*, 13 J. CONTEMP. LEGAL ISSUES 123 (2003) (discussing the differences between an ex ante perspective and an ex post compensation theory in the context of welfarism).

72. *See, e.g.*, Ethan Chiel, *Secret Algorithms That Predict Future Criminals Get a Thumbs up from Wisconsin Supreme Court*, SPLINTER (July 27, 2016, 4:00 PM), https://splinternews.com/secret-algorithms-that-predict-future-criminals-get-a-t-1793860613 [https://perma.cc/7FWC-25JW].

73. *See* Thomas S. Ulen, *Courts, Legislatures, and the General Theory of Second Best in Law and Economics*, 73 CHI.-KENT L. REV. 189, 195–96 (1998). This is a well-understood psychological problem known as the "nirvana fallacy," which occurs when "scholars erroneously compare real-world institutions with some abstract or ideal institution, even if the ideal institution has never existed or . . . has been proven impossible to devise." Maxwell L. Stearns, *The Misguided Renaissance of Social Choice*, 103 YALE L.J. 1219, 1229–30 (1994).

74. *See infra* Section III.B.3.

75. *See infra* Section III.B.3.

pecuniary benefits, respondents picked the algorithm 42% of the time, a statistically significant difference.[76] Thus, incorporating empirical data on consumer preferences offers at least two benefits for the problem of baselines: it inherently requires comparative analysis, and it can push scholars to broaden the scope of their inquiries to assess the tradeoffs policymakers will have to confront in regulating decision making systems.

A second, related problem occurs when critics nominally focus on the perceived inaccuracy of algorithmic choices. Accuracy, however, is a contested normative value, not a neutral artifact of data and calculation.[77] And, algorithms offer at least some opportunity to reduce invidious bias in areas such as employment discrimination[78] and law enforcement.[79] The scholarly literature is inconsistent: critics press for both more and less accuracy in decision-making, especially where algorithms are involved. For example, Cathy O'Neil argues that accuracy ought to be sacrificed in some cases for fairness.[80] For example, when law enforcement uses predictive software that includes low-level, nuisance crimes along with more serious crimes in its analysis, it tends to concentrate policing efforts in minority communities, exacerbating existing problems with police bias towards members of those communities.[81] Someone drinking on their stoop in Bloomfield Hills, Michigan, is far less likely to receive police attention than someone who does so on their porch in downtown Detroit.[82] Thus, ignoring accurate, but perhaps less relevant, information about low-level crimes may

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76. *See infra* Section III.B.3.

77. *See* Derek E. Bambauer, *Schrödinger's Cybersecurity*, 48 U.C. DAVIS L. REV. 791, 801 (2015).

78. *See, e.g.*, Jon Kleinberg et al., *Algorithms as Discrimination Detectors*, 117 PROC. NAT'L ACAD. SCIS. U.S. AM. 30096 (2020); Thomas Macaulay, *New AI Tool Detects Hiring Discrimination Against Ethnic Minorities and Women*, THE NEXT WEB (Jan. 21, 2021, 1:05 PM), https://thenextweb.com/neural/2021/01/21/new-ai-tool-detects-hiring-discrimination-against-ethnic-minorities-and-women/ [https://perma.cc/WC7G-KJHH].

79. *See* P. Jeffrey Brantingham et al., *Does Predictive Policing Lead to Biased Arrests? Results from a Randomized Controlled Trial*, 5 STAT. & PUB. POL'Y 1 (2018).

80. *See* O'NEIL, *supra* note 51, at 84–104.

81. *See* ANDREW GUTHRIE FERGUSON, THE RISE OF BIG DATA POLICING 75 (2017); Sandra G. Mayson, *Bias In, Bias Out*, 128 YALE L.J. 2218, 2224 (2018); BERNARD HARCOURT, AGAINST PREDICTION 3 (2007).

82. Bloomfield Hills has an average household income over $270,000. Charles Crumm, *Bloomfield Hills Is Oakland County's Wealthiest Community but Others Are Catching Up*, OAKLAND PRESS (June 17, 2021, 5:36 AM), https://www.theoaklandpress.com/2019/02/15/bloomfield-hills-is-oakland-countys-wealthiest-community-but-others-are-catching-up/ [https://perma.cc/4WE4-GKS8]. The town is 82% white. *QuickFacts: Bloomfield Charter Township*, U.S. CENSUS BUREAU (July 1, 2019), https://www.census.gov/quickfacts/fact/table/bloomfieldchartertownshipoaklandcountymichigan,birminghamcitymichigan,auburnhillscitymichigan,annarborcitymichigan/PST045219 [https://perma.cc/63NZ-6U3R].

reduce the disparate impacts of law enforcement.[83] By contrast, giving police routine access to more data—such as tax returns or investment portfolio statistics—might enable detection of less visible but arguably more serious crimes, such as insider trading and tax fraud.[84] This would increase the accuracy of prosecution for those crimes, but at the cost of greater governmental surveillance.[85]

Empirical data on consumer preferences can help reveal how people's views about accuracy vary, or not, across different contexts. This enables policymakers to determine where, and to what degree, algorithmic decision making should be employed. It also uncovers the issues that actually underlie some debates that are purportedly about the accuracy of algorithms. O'Neil's example above is only tangentially about accuracy.[86] At base, her objection is to how society distributes law enforcement resources and the set of offenses that it chooses to pursue with greater efforts.[87] It is also about the tradeoffs of system design: the algorithm-driven law enforcement software may be quite accurate in predicting crime in some places, but at the cost of inaccuracy elsewhere, since it fails to correctly predict offenses that occur in more affluent, less diverse areas.[88] Here, too, rigorous empirical data can surface the true costs and benefits of different decision mechanisms, including but not limited to accuracy.[89]

A third problem with legal scholarship on algorithms—including analysis that favors algorithms—is, candidly, sports envy. Scholars point to the explosion of empirically-driven decision making in sports—particularly baseball—as an exemplar of a rational algorithmic system that correlates variables tightly with outcomes and that has a built-in feedback loop.[90]

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83. *See* Aaron Shapiro, *Reform Predictive Policing*, 541 NATURE 458 (2017).

84. *See* Jane Bambauer, *Hassle*, 113 MICH. L. REV. 461, 503 n.209 (2015).

85. Similarly, some argue that more algorithmic processes in hiring will reduce discrimination. ThriveMap, *6 Tips To Reduce Discrimination When Hiring*, MEDIUM (Feb. 28, 2017), https://medium.com/@ThriveMap/6-tips-to-reduce-discrimination-when-hiring-d6dce068b35e [https://perma.cc/WA35-KRPU].

86. *See* O'NEIL, *supra* note 51.

87. *See* Laura M. Moy, *A Taxonomy of Policy Technology's Racial Inequity Problems*, 2021 U. ILL. L. REV. 139, 154–58; Crystal S. Yang & Will Dobbie, *Equal Protection Under Algorithms: A New Statistical and Legal Framework*, 119 MICH. L. REV. 291, 315 (2020); Andrew Guthrie Ferguson, *Policing Predictive Policing*, 94 WASH. U. L. REV. 1109 (2017).

88. *See* Moy, *supra* note 87.

89. *See* Emily Berman, *A Government of Laws and Not of Machines*, 98 B.U. L. REV. 1277, 1302–09 (2018).

90. *See, e.g.*, Dawinder S. Sidhu, *Moneyball Sentencing*, 56 B.C. L. REV. 671 (2015); Jason Kreag, *Prosecutorial Analytics*, 94 WASH. U. L. REV. 771 (2017); Matthew T. Bodie et al., *The Law and Policy of People Analytics*, 88 U. COLO. L. REV. 961 (2017). *See generally* MICHAEL LEWIS, MONEYBALL: THE ART OF WINNING AN UNFAIR GAME (2003) (offering popular account of this trend in baseball).

Coaches, managers, and executives who use empirical methods poorly—or, worse, ignore them—are rapidly replaced by more competent or open-minded peers.[91] The competitive pressures of professional sports lead teams to innovate in how they select players and in the tactics they use in games.[92] And sports have readily-measured outcomes, such as wins, losses, and scoring differentials. Teams that come up with insights, such as the importance of on-base percentage in baseball, are rapidly rewarded with success.[93] Those that stick with tried but unproven methods, such as sacrifice bunts, suffer losses more often.[94]

The problem with this newfound scholarly admiration for sports is that sports are tailor-made for relatively simple algorithmic analysis.[95] Cause and effect are tightly linked: a basketball player misses free throws, and his team loses.[96] Sports—even complex ones such as baseball—are replete with data and can be readily modeled even by casual empiricists.[97] Indeed, a profitable

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91. The Arizona Diamondbacks, for example, rejected the "Moneyball" empirical approach in the last few years. *See, e.g.*, Seth Pollack, *Arizona Diamondbacks Spring Training 2011: Moneyball Out, Dirtball In*, SBNATION (Feb. 13, 2011, 1:46 PM), http://arizona.sbnation.com/2011/2/13/2329726/arizona-diamondbacks-spring-training-2011-moneyball-out-dirtball-in [https://perma.cc/UT2X-DVQG]. This experiment did not end well. *Arizona Diamondbacks Fire General Manager Dave Stewart, Manager Chip Hale*, ARIZ. SPORTS (Oct. 3, 2016, 5:56 PM), http://arizonasports.com/story/744855/diamondbacks-fire-manager-chip-hale/ [https://perma.cc/58UY-8GQY]. The team has returned to an empirically-driven approach. *See, e.g.*, Nick Piecoro, *Arizona Diamondbacks Name Mike Hazen General Manager*, AZCENTRAL (Oct. 17, 2016, 1:16 PM), http://www.azcentral.com/story/sports/mlb/diamondbacks/2016/10/16/arizona-diamondbacks-name-mike-hazen-general-manager/92204978/ [https://perma.cc/6Y97-LPP3].

92. *See, e.g.*, Benjamin Morris, *When To Go for 2, for Real*, FIVETHIRTYEIGHT (Feb. 3, 2017, 10:39 AM), https://fivethirtyeight.com/features/when-to-go-for-2-for-real/ [https://perma.cc/6KZN-WUUN] (describing statistical approach to deciding when to attempt two-point conversion after a touchdown in football); Jay Rigdon, *Celtics Execute Intentionally Missed Free Throw to Perfection, Drill Buzzer Beating Three To Force Overtime*, THE COMEBACK (Feb. 29, 2020), https://thecomeback.com/nba/celtics-execute-intentionally-missed-free-throw-to-perfection-drill-buzzer-beating-three-to-force-overtime.html [https://perma.cc/FF6C-52NH].

93. *See* LEWIS, *supra* note 90.

94. *See id.*

95. *See* Margot E. Kaminski, *Binary Governance: Lessons from the GDPR's Approach to Algorithmic Accountability*, 92 S. CAL. L. REV. 1529, 1539–40 (2019).

96. *But see* Rigdon, *supra* note 92. Shaquille O'Neal is the obvious exception.

97. Baseball's statistical revolution was launched by Bill James, who wrote his initial articles while working night shifts as a security guard. *See The Man Behind the 'Moneyball' Sabermetrics*, NPR (Sept. 26, 2011, 2:27 PM), https://www.npr.org/2011/09/26/140813409/the-man-behind-the-moneyball-sabermetrics [https://perma.cc/DWX8-5TKY]; Ben McGrath, *The Professor of Baseball*, NEW YORKER (July 14, 2003), https://www.newyorker.com/magazine/2003/07/14/the-professor-of-baseball [https://perma.cc/P8JH-GRJQ].

industry—fantasy sports—has arisen on precisely this basis.[98] Furthermore, professional sports tend to be relatively closed ecosystems: there are a small number of players and teams, and many players compete for more than one season.[99]

This simplicity contrasts unfavorably with the complexity of real-world problems, such as determining which potential borrowers present manageable credit risk[100] and which potential probation recipients present manageable recidivism risk.[101] The number of potential variables is vast if not infinite.[102] Algorithm developers cannot always defend their choices, if they make such choices public at all.[103] Sometimes, seemingly random indicators turn out to serve as surprisingly useful proxies. Customers who put felt pads on the bottom of chair legs (to keep the chairs from damaging floors) are better credit risks than those who don't mind scratches on their wood or tile.[104] Moreover, the subjects of analysis may exit the system, impeding the feedback loop that would improve algorithms. A bank may sell a homeowner's mortgage to another lender, eliminating the risk of default and removing that homeowner from its data pool.[105] Or a person convicted of a crime in one state may re-offend in another or commit a federal crime.[106] Thus, when scholars hold the use of algorithms in sports up as a model, what they really admire is a simpler world, not better calculations.

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98. *See* Marc Edelman, *A Short Treatise on Fantasy Sports and the Law: How America Regulates Its New National Pastime*, 3 HARV. J. SPORTS & ENT. L. 1 (2012).

99. *See generally* Marc Edelman & Brian Doyle, *Antitrust and Free Movement Risks of Expanding U.S. Professional Sports Leagues into Europe*, 29 NW. J. INT'L L. & BUS. 403, 405–07 (2009). It helps in this regard that in most major American professional sports, such as baseball, American football, and basketball, the U.S. leagues are the world's best. Nearly all players in those sports seek to play for a team in an American league, meaning that few exit the system voluntarily.

100. *See generally* L.C. Thomas et al., *A Survey of the Issues in Consumer Credit Modelling Research*, 56 J. OPERATIONAL RES. SOC'Y 1006 (2005).

101. *See* sources cited *supra* note 70.

102. There may be important second-order effects from automating decision making in the judicial system, for example. *See* Joseph Blass, *Observing the Effects of Automating the Judicial System with Behavioral Equivalence*, 72 S. CAROLINA L. REV. (forthcoming 2022), https://ssrn.com/abstract=3852966 [https://perma.cc/9Z6K-AKRH].

103. Algorithms are often maintained as trade secrets. *See* Meghan J. Ryan, *Secret Algorithms, IP Rights, and the Public Interest*, 21 NEV. L.J. 61 (2020).

104. *See* Alden M. Hayashi, *Thriving in a Big Data World*, MIT SLOAN MGMT. REV. (Dec. 9, 2013), http://sloanreview.mit.edu/article/thriving-in-a-big-data-world/ [https://perma.cc/8EQV-WJKD].

105. *See generally* Karl E. Case & Robert J. Schiller, *Mortgage Default Risk and Real Estate Prices: The Use of Index-Based Futures and Options in Real Estate*, 7 J. HOUS. RES. 243 (1996).

106. *See* MATTHEW R. DUROSE ET AL., U.S. DEP'T OF JUST., BUREAU OF JUST. STATS., MULTISTATE CRIMINAL HISTORY PATTERNS OF PRISONERS RELEASED IN 30 STATES 4 (Sept. 2015), https://www.bjs.gov/content/pub/pdf/mschpprts05.pdf [https://perma.cc/ZKC2-DJUK].

Data on consumer preferences probably will not directly affect the prevalence of sports comparisons in legal scholarship, but the possibility does indirectly point up a useful insight. Empirical analysis makes teams, and players, better at sports. It is not clear, however, whether fans prefer the better version.[107] For example, National Basketball Association (NBA) teams will at times deliberately foul their opponent's worst free throw shooter.[108] This tactic, known colloquially as the "Hack-A-Shaq," is mathematically rational under some circumstances: a poor shooter may miss the resulting free throws, giving the offending team another chance to score, or at least to prevent their opponents from scoring.[109] However, fans and commentators generally dislike the tactic because it slows and disrupts the flow of the game.[110] The NBA changed its rules to reduce (but not eliminate) the strategy.[111] Similarly, the advent of improved statistical analysis has led to an increase in the number of relief pitchers used by Major League Baseball (MLB) teams, as managers try to optimize match-ups against batters to prevent runs from scoring.[112] This shift in strategy increased strikeouts and reduced scoring, making it a success for teams that practice it.[113] However, it also increased the duration of games.[114] This, along with decreased scoring, made baseball fans unhappy.[115]

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107. Many college football fans were pleased when an algorithm-based method for selecting playoff teams was replaced by a committee of 13 people, even though the committee is actually less transparent, more at risk of bias, and more vulnerable to a mistake by a single member. *See* Rodger Sherman, *OK Computers: A Formal Apology to College Football's Biggest Scapegoat*, RINGER (Dec. 3, 2021), https://www.theringer.com/2021/12/3/22815192/college-football-playoff-bcs-computer-formulas-ranking-system [https://perma.cc/877L-PPNG].

108. *See* Andrew Keh, *The Birth of Hack-a-Shaq*, N.Y. TIMES (Apr. 30, 2016), https://www.nytimes.com/2016/05/01/sports/basketball/the-birth-of-hack-a-shaq.html [https://perma.cc/Y65B-HUEB]; Sam Apple, *Hack-A-League*, NEW YORKER (May 28, 2015), https://www.newyorker.com/sports/sporting-scene/hack-a-league [https://perma.cc/8YTX-AVAU].

109. *See* sources cited *supra* note 108. To be precise, the Hack-A-Shaq involves fouling a player not in possession of the ball.

110. *See* sources cited *supra* note 108.

111. *See* Jahmal Corner, *Rule Changed To Curb 'Hack-a-Shaq' Incidents*, REUTERS (July 12, 2016 9:40 PM), https://www.reuters.com/article/us-nba-rules/rule-changed-to-curb-hack-a-shaq-incidents-idUSKCN0ZT0B9 [https://perma.cc/8TJ5-AS2Y].

112. *See* Nate Silver, *Relievers Have Broken Baseball. We Have a Plan to Fix It.*, FIVETHIRTYEIGHT (Feb. 25, 2019, 10:54 AM), https://fivethirtyeight.com/features/relievers-have-broken-baseball-we-have-a-plan-to-fix-it/ [https://perma.cc/DEU8-ABBD].

113. *See id.*

114. *See id.*; *see also* Dave Sheinin, *Three-Batter Minimum for Relief Pitchers Highlights MLB Rule Changes for 2020*, WASH. POST (Feb. 12, 2020), https://www.washingtonpost.com/sports/2020/02/12/three-batter-minimum-relief-pitchers-highlights-mlb-rule-changes-2020/ [https://perma.cc/4F2P-9WJU].

115. *See* Silver, *supra* note 112.

MLB responded by changing its rules to increase the minimum number of batters that a relief pitcher must face.[116]

The larger question for both the NBA and MLB was whether to respond to extant consumer preferences (principally for faster, more continuous play and for more scoring). Some commentators opposed the relevant changes, even knowing they would increase viewer satisfaction in the short term, on the grounds that they were too great a shift from the historical rules of play and thus normatively undesirable.[117] (The wider statistical revolution in baseball has been hotly debated.[118]) Since the preferences of baseball fans are malleable, how much weight should they be accorded in MLB policy decisions? For example, people might, after an adjustment period, enjoy seeing more strikeouts.[119] It is not just that preferences are heterogenous, but preferences about responding to preferences are mixed as well. While baseball is entertainment and law is social policy, the same question about preferences arises in each area.[120]

Finally, legal scholarship too often blames algorithms for undesirable outcomes.[121] This simplistic approach does not distinguish among causes that are superficially similar but that require different solutions. The algorithm, as a formula, may function correctly, but the data it processes are problematic. For example, Microsoft used machine learning and natural language processing techniques to create a Twitter chat bot, called Tay, in 2016.[122] The

116. *See* Sheinin, *supra* note 114.

117. *See* Apple, *supra* note 108; Jayson Stark, *Managers Plan for the New Three-Batter Rule—'I'm Having a Hard Time'*, ATHLETIC (Mar. 6, 2020), https://theathletic.com/1656469/2020/03/06/stark-managers-react-to-the-new-three-batter-rule-thats-not-fair/ [https://perma.cc/EP78-QMPW].

118. *See* LEWIS, *supra* note 90.

119. *See generally* Tim Kurkjian, *How the 'K' Became the Most Destructive Letter in Major League Baseball*, ESPN (May 19, 2021), https://www.espn.com/mlb/story/_/id/31454952/how-k-became-most-destructive-letter-major-league-baseball [https://perma.cc/G6WL-P2EX] (reviewing the controversy).

120. *See generally* Louis Kaplow & Steven Shavell, *Fairness Versus Welfare*, 114 HARV. L. REV. 961, 1334–38 (2001); *cf.* Mike Decourcy, *MLB's Analytics Revolution Led to More Home Runs—But It's Striking Out with Many Who Love the Game*, SPORTING NEWS (Oct. 22, 2020), https://www.sportingnews.com/us/mlb/news/mlbs-analytics-revolution-led-to-more-home-runs-but-its-striking-out-with-many-who-love-the-game/ovknk78xd8if117eh6l9szegj [https://perma.cc/YAE7-B7GG] (quoting Crash Davis from "Bull Durham" that ground balls are "more democratic").

121. There are noteworthy exceptions. *See* Ngozi Okidegbe, *Discredited Data*, 107 CORNELL L. REV. (forthcoming 2022), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3835414.

122. Oscar Schwartz, *In 2016, Microsoft's Racist Chatbot Revealed the Dangers of Online Conversation*, IEEE SPECTRUM (Nov. 25, 2019), https://spectrum.ieee.org/tech-talk/artificial-intelligence/machine-learning/in-2016-microsofts-racist-chatbot-revealed-the-dangers-of-online-conversation [https://perma.cc/93F7-JLWJ].

underlying techniques and training data Microsoft employed were sound.[123] However, someone posted a link to Tay's Twitter account and instructions to abuse the bot's learning capabilities on the infamous 4chan site.[124] In less than a day, Tay began spouting offensive tweets, and Microsoft closed the account.[125] The problem was not that Tay learned from her interlocutors; the problem was that many of her (human) correspondents fed the bot data that contained racist, sexist, and otherwise objectionable content.

Or the algorithm may explicitly include biased variables. The dominant methodology for calculating who will receive a donor kidney for transplantation expressly includes race in its formula.[126] Unsurprisingly, black patients wait longer for a kidney transplant.[127] A similar variable used to determine treatment for kidney disease causes black patients to receive therapy later and leads to underdiagnosis of the disease in black patients.[128] The chief point of disagreement in the medical community is whether removing the variable will improve or worsen outcomes for black patients, particularly given systemic inequities in medical care.[129]

And last, the algorithm might function in a way that is formally neutral and technically accurate, but nonetheless produces outcomes that we deem normatively unacceptable. Credit applicants from lower socioeconomic status (SES) circumstances are, on average, likely to be worse credit risks than those from more privileged ones.[130] This generally results not from any difference in moral character, but from marginal economic conditions that make lower-SES applicants vulnerable to small disruptions.[131] Middle class borrowers can endure a sudden hospital bill or car repair without missing a

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123. *Id.* Daniel Victor, *Microsoft Created a Twitter Bot To Learn from Users. It Quickly Became a Racist Jerk*, N.Y. TIMES (Mar. 24, 2016), https://www.nytimes.com/2016/03/25/technology/microsoft-created-a-twitter-bot-to-learn-from-users-it-quickly-became-a-racist-jerk.html [https://perma.cc/6VCS-F4ZY].

124. Schwartz, *supra* note 122.

125. James Vincent, *Twitter Taught Microsoft's AI Chatbot To Be a Racist Asshole in Less than a Day*, THE VERGE (Mar. 24, 2016, 6:43 AM), https://www.theverge.com/2016/3/24/11297050/tay-microsoft-chatbot-racist [https://perma.cc/2T8V-29B3].

126. Bichell & Anthony, *supra* note 50.

127. Darshali A. Vyas et al., *Hidden in Plain Sight—Reconsidering the Use of Race Correction in Clinical Algorithms*, 383 NEW ENG. J. MED. 874, 875 (2020).

128. *See* Jyoti Madhusoodanan, *Is a Racially-Biased Algorithm Delaying Health Care for One Million Black People?*, 588 NATURE 546, 546–47 (2020).

129. *Id.* at 547.

130. *See* Luke Herrine, *Credit Reporting's Vicious Cycles*, 40 N.Y.U. REV. L. & SOC. CHANGE 305, 322–23 (2016); Sarah Miller & Cindy K. Soo, *Do Neighborhoods Affect the Credit Market Decisions of Low-Income Borrowers? Evidence from the Moving to Opportunity Experiment*, 34 REV. FIN. STUD. 827, 828 (2020).

131. Herrine, *supra* note 130, at 331.

payment.[132] Less well-off borrowers cannot. An accurate algorithm will correctly calculate that the middle-class applicant is less risky than the working-class one. Since even sophisticated algorithms are stochastic in nature, processing data that can be laden with errors or unseen information, some reliable low-SES applicants will be denied credit even though they would not default.[133] That does not mean either that the algorithm is unacceptably flawed, or that poorer people should be blocked from credit. It does not mean that a human would make more desirable credit decisions. Humans are biased,[134] and even well-intentioned bank officers might not overlook factors such as a lack of credit history resulting from past discrimination.[135]

An accurate decision from an algorithmic decision-making system does not, and likely should not, be the final word in the process. It may be preferable to turn to structural remedies instead of algorithmic tweaks.[136] For example, even in the face of an unfavorable calculation about credit risk, the government might require financial institutions to extend credit (similar to the mandate that health insurers offer coverage regardless of an insured's actuarial risk due to pre-existing conditions)[137] or might provision it directly (as is the case with federal home mortgage programs administered through

132. *See, e.g.*, Aimee Picchi, *A $500 Surprise Expense Would Put Most Americans into Debt*, CBS NEWS (Jan. 12, 2017, 11:39 AM), https://www.cbsnews.com/news/most-americans-cant-afford-a-500-emergency-expense/ [https://perma.cc/U7A5-NS7N].

133. *See* Matthew Adam Bruckner, *The Promise and Perils of Algorithmic Lenders' Use of Big Data*, 93 CHI.-KENT L. REV. 3, 25–27 (2018); MAUREEN MAHONEY, CONSUMERS UNION OF U.S., INC., ERRORS AND GOTCHAS: HOW CREDIT REPORT ERRORS AND UNRELIABLE CREDIT SCORES HURT CONSUMERS 5 (2014), https://advocacy.consumerreports.org/wp-content/uploads/2014/04/Errors-and-Gotchas-report.pdf [https://perma.cc/LGG5-T2BR].

134. *See* Christine Jolls et al., *A Behavioral Approach to Law and Economics*, 50 STAN. L. REV. 1471, 1501 (1998).

135. *See* Laura Blatter & Scott Nelson, How Costly Is Noise? Data and Disparities in Consumer Credit 2–3 (May 17, 2021) (unpublished manuscript), https://arxiv.org/pdf/2105.07554.pdf [https://perma.cc/X24Y-E8A9] (finding that lower-income and minority applicants typically have less information in their credit files); Natalie Campisi, *From Inherent Racial Bias to Incorrect Data—The Problems with Current Credit Scoring Models*, FORBES (Feb. 26, 2021, 9:00 AM), https://www.forbes.com/advisor/credit-cards/from-inherent-racial-bias-to-incorrect-data-the-problems-with-current-credit-scoring-models/ [https://perma.cc/P6DN-2GKU].

136. *See* Omer Tene & Jules Polonetsky, *Taming the Golem: Challenges of Ethical Algorithmic Decision-Making*, 19 N.C. J.L. & TECH. 125, 155–56 (2017).

137. *See Coverage for Pre-Existing Conditions*, HEALTHCARE.GOV https://www.healthcare.gov/coverage/pre-existing-conditions/ [https://perma.cc/3A96-K29M]; *At Risk: Pre-Existing Conditions Could Affect 1 in 2 Americans*, CMS.GOV, https://www.cms.gov/CCIIO/Resources/Forms-Reports-and-Other-Resources/preexisting [https://perma.cc/YZ79-8ABQ].

intermediaries such as Freddie Mac and Fannie Mae).[138] Scholars such as Elizabeth Warren have convincingly demonstrated the social ills that flow from lack of access to credit for low-SES borrowers,[139] and it might well be wise to subsidize that access directly (through payments or governmental provision) or indirectly (by forcing lenders to cross-subsidize). Attacking algorithms for the credit squeeze that these borrowers face is to blame the flies for the garbage: it distracts from the real causes of the problems.

Each of these critiques would be enhanced by incorporating preference analysis. Thus, perhaps the most profound issue with the corpus of legal scholarship treating algorithms is that—with but few exceptions[140]—it fails to account for what people actually prefer, or dislike, about these mathematical models. This Article seeks to learn the conditions under which, faced with a straightforward tradeoff of known costs and benefits, consumers will prefer algorithms to humans? The next Section describes how the authors created a novel dataset to assess these extant consumer preferences about algorithms.

II. EMPIRICAL METHODOLOGY

A. Humans Versus (?) Algorithms

This Section describes the Article's survey of preferences for human versus algorithmic decision making in four scenarios: eligibility for consumer credit via a bank loan; health care coverage through access to a clinical trial for a relevant therapy; law enforcement through a disputed civil traffic fine; and consumer retail via the chance to win a small prize from a store. Each of these areas is a source of concern for algorithmic skeptics, and each presents a range of examples for automated decisions, some of which are promising, and some of which appear to be failures.[141] By presenting respondents with

138. *See About Fannie Mae and Freddie Mac*, FED. HOUS. FIN. AGENCY, https://www.fhfa.gov/SupervisionRegulation/FannieMaeandFreddieMac/Pages/About-Fannie-Mae---Freddie-Mac.aspx [https://perma.cc/97NS-KS8C]; s*ee also* Kimberly Amadeo, *Fannie Mae vs. Freddie Mac*, BALANCE (Dec. 15, 2020), https://www.thebalance.com/fannie-mae-vs-freddie-mac-3305695 [https://perma.cc/29BG-S95G].

139. *See, e.g.*, Elizabeth Warren, *The Economics of Race: When Making It to the Middle Is Not Enough*, 61 WASH. & LEE L. REV. 1777, 1797 (2004).

140. *See, e.g.*, FRISCHMANN & SELINGER, *supra* note 52, at 69–71 (discussing the role of consumer choice and pricing in electronic contracting).

141. On credit, see Marcus Wohlsen, *Tech's Hot New Market: The Poor*, WIRED (Jan. 1, 2013, 6:30 AM), https://www.wired.com/2013/01/techs-hot-new-market-the-poor/ [https://perma.cc/A962-KJLC]; EXEC. OFF. OF THE PRESIDENT, BIG DATA: A REPORT ON

surveys that vary attributes such as the accuracy, speed, and cost of both human and algorithmic decisionmakers, we gain insight into how people currently perceive the relative merits and demerits of mathematical models. This Section also discusses the limitations inherent to this methodology.

B. Description of Methodology

We used a survey instrument developed with the Qualtrics software application[142] to measure current consumer preferences regarding the use of algorithms to make decisions. To obtain survey respondents, we used Amazon's Mechanical Turk platform.[143] Mechanical Turk ("MTurk") matches requesters with workers: the requesters specify a task that requires human respondents at scale, and MTurk workers perform that task in exchange for compensation.[144] MTurk has a number of virtues: it is cheap (we offered respondents fifty cents per survey, estimating that it could be completed quickly, which it was); it makes demographic data readily available; it allows requesters to reject responses if they are completed inaccurately; and its setup is easy.[145] While the demographics of MTurk respondents can vary from those of the larger U.S. population, a sample size

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ALGORITHMIC SYSTEMS, OPPORTUNITY, AND CIVIL RIGHTS 12–13 (2016), https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/2016_0504_data_discrimination.pdf [https://perma.cc/5S5J-3LEA]. On health care, see Ravi B. Parikh et al., *Making Predicting Analytics a Routine Part of Patient Care*, HARV. BUS. REV. (Apr. 21, 2016), https://hbr.org/2016/04/making-predictive-analytics-a-routine-part-of-patient-care [https://perma.cc/QCD5-3KLL]; Wullianallur Raghupathi & Viju Raghupathi, *Big Data Analytics in Healthcare: Promise and Potential*, 2 HEALTH INFO. SCI. SYS., Feb. 7, 2014, at 2, https://link.springer.com/content/pdf/10.1186%2F2047-2501-2-3.pdf [https://perma.cc/E5CH-KXJH]. On law enforcement, see Mark van Rijmenam, *The Los Angeles Police Department Is Predicting and Fighting Crime with Big Data*, DATAFLOQ (Apr. 14, 2014, 5:00 PM), https://datafloq.com/read/los-angeles-police-department-predicts-fights-crim/279 [https://perma.cc/GV3Y-SBTY]; Andrew D. Selbst, *Disparate Impact in Big Data Policing*, 52 GA. L. REV. 109, 119 (2017). On retail, see Kyle Wiggers, *Cashierless Tech Could Detect Shoplifting, but Bias Concerns Abound*, VENTUREBEAT (Jan. 23, 2021, 8:45 AM), https://venturebeat.com/2021/01/23/cashierless-tech-could-detect-shoplifting-but-bias-concerns-abound/ [https://perma.cc/R7DY-UWWJ].

142. *See Survey Software: The Best Tool & Platform*, QUALTRICS XM, https://www.qualtrics.com/core-xm/survey-software/ [https://perma.cc/X46W-S77D].

143. *See* AMAZON MECHANICAL TURK, https://www.mturk.com/ [https://perma.cc/R6KL-ER35].

144. *What Is Amazon Mechanical Turk?*, AMAZON WEB SERVS., (Feb. 8, 2021), https://aws.amazon.com/premiumsupport/knowledge-center/mechanical-turk-use-cases/ [https://perma.cc/MXS6-BMA7].

145. *See* Alexandra Samuel, *Amazon's Mechanical Turk Has Reinvented Research*, JSTOR DAILY (May 15, 2018), https://daily.jstor.org/amazons-mechanical-turk-has-reinvented-research/ [https://perma.cc/7DSR-PJEC].

with sufficient power can overcome that shortcoming,[146] and MTurk workers are more representative demographically than most survey respondents.[147] And since this study uses observational treatment data, for which well-designed surveys are appropriate, concerns regarding physical or psychological experimental interventions and validity are less relevant.[148] Furthermore, because we did not expect treatment results to differ by group (and they do not), generalizability is less of a concern.[149]

Each MTurk survey respondent read a vignette describing one of four upcoming (hypothetical) decisions: receiving credit in response to a loan application; being evaluated for inclusion in a clinical trial for a relevant therapy; determining liability for a civil traffic offense; and deciding who would win a $15 gift card as "Consumer of the Month" at a coffee shop.[150] For example, the civil traffic offense vignette read:

> Recently, you were stopped by a police officer on your way home from work. The officer issued you a ticket, claiming that you failed to stop completely at a stop sign. The ticket imposes a civil fine, but no criminal liability. While it was close, you feel you came to a stop in the same way that most drivers do (commonly known as a "rolling stop," where the car does not completely cease motion, but nearly does so, allowing the driver to evaluate traffic before proceeding). Thus, you decide to contest the ticket.
>
> The traffic court in your area uses two different methods for deciding cases that involve alleged traffic violations. (There are no trials for traffic violations, only reviews of information submitted by the motorist and by the police officer involved.) One method involves a traffic court judge – a human – who reviews the ticket and associated information, and then makes a decision based on his/her experience. The other method involves a specialized computer software program – an algorithm – that reviews the ticket and associated information, and then makes a decision based on a set of variables built into the program. The traffic court will randomly assign your application either to a human employee or to

146. This Article's survey had sufficient power to allow the authors to analyze results based upon demographic variables.

147. *See* Samuel, *supra* note 145; Erin C. Cassese et al., *Socially Mediated Internet Surveys: Recruiting Participants for Online Experiments*, 46 PS: POL. SCI. & POL. 775 (2013); Connor Huff & Dustin Tingley, *"Who Are These People?" Evaluating the Demographic Characteristics and Political Preferences of MTurk Survey Respondents*, RSCH. & POL., July–Sept. 2015, at 1.

148. The authors obtained IRB approval for this study (documentation on file with authors).

149. *See* Kevin E. Levay et al., *The Demographic and Political Composition of Mechanical Turk Samples*, SAGE OPEN, Jan.–Mar. 2016, at 1, 9.

150. Respondents were assigned randomly to one of the four vignettes. The vignette descriptions provided to survey participants are reproduced in Appendix A *infra*.

> the algorithm, but you will have the opportunity to switch (from a human to an algorithm, or vice versa) if you want to do so.

For each vignette, Mechanical Turk randomly selected one of two choices for a set of five binary (or, in one case, trinary) variables.

Table 1 - Vignette Variables

Variable	**Options**
Initial/default assignment of decisionmaker[151]	Human Algorithm
Expected error rate for *each* type of decisionmaker[152]	High Low Unknown
Information to which decisionmaker has access	Public information Privately-held information[153]
Relative cost/benefit	Human and algorithm have same cost/benefit Algorithm has greater benefit/less cost
Relative time to render a decision	Human and algorithm have same speed/time Algorithm is faster

The descriptions of the variables remained constant across vignettes, with one exception: the cost/benefit (price) choice varied in amount by vignette. For example, the coffee shop gift card was worth $10 for each decisionmaker in one option (same cost/benefit), but $15 for the algorithm and $5 for the human in the other option (algorithm has greater benefit/lesser cost). By contrast, for the civil traffic fine vignette, the fine was $250 for each decisionmaker in one option (same cost/benefit), but $200 for the algorithm and $300 for the human in the other option (algorithm has greater benefit/lesser cost). This mirrors real world circumstances, where gift cards

151. The surveys could have used a forced choice mechanism (such as requiring, at the end of the survey, the respondent to select between decisionmakers, with the ordering of presentation of the two decisionmaker options randomized). We kept the default allocation variable to test for anchoring effects.

152. We offered slightly different choices in a pilot/beta survey but enhanced them here. For example, initially, the survey only offered a choice between high and low error rates for the default option, leaving the error rate for the other option unknown. This led to uncertainty in interpreting answers to the pilot survey. And, in the pilot survey, we included an additional piece of information: the choice of decisionmaker that other people favored. This information had no effect on survey responses, so we eliminated it in the final survey to produce more robust results.

153. This could include, for example, credit or health data.

typically cost less than traffic tickets. The variation also enabled the study to detect whether consumer preferences shifted as the stakes at issue for the decision changed. For each cost option, the vignette stated that the added benefit (for example, a lower price in the form of a better loan interest rate) would only apply if the decision favored the survey respondent.[154] Thus, survey takers could decide whether the risk of refusal was worth the potential added benefit.

Except for the price variable, only the scenario (such as the decision to be made) varied; the survey described the factual circumstances in the initial paragraphs of the prompt. After setting out the scenario and variables, the survey prompt asked the respondents whether to stay with the decisionmaker to whom they were initially and randomly assigned, or whether to switch adjudicators (for example, from human to algorithm).

We used Cloud Research (formerly TurkPrime) to gather data from the MTurk survey responses. The Cloud Research platform offers many advantages to increase data quality.[155] These include exclusion of low-quality respondents,[156] blocking based upon Internet Protocol (IP) address and GeoCode[157] location, and worker qualification settings.[158] We also included an attention-check question to detect bots or survey takers who responded arbitrarily or too quickly to gain the MTurk payment.[159] The attention check was substantive: it asked which default decisionmaker had been assigned to the respondent just before asking whether the survey taker wanted to keep that decisionmaker or switch. With this check, we could confirm that the respondent had read the various short bits of information provided in the survey. We also designed the check to avoid common pitfalls of attention checks.[160]

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154. Thus, for example, if the respondent's credit application were to be rejected, they would not receive the benefit of the better interest rate if they picked the algorithm (or, similarly, the cost of the worse interest rate if they picked the human).

155. Leib Litman et al., *TurkPrime.com: A Versatile Crowdsourcing Data Acquisition Platform for the Behavioral Sciences*, 49 BEHAV. RSCH. METHODS 433 (2017).

156. These were respondents with high rejection rates on MTurk or bad reviews on Cloud Research.

157. *See* U.S. Census Bureau, *Geocoding Definition*, GEOCODING SERVS. WEB APPLICATION PROGRAMMING INTERFACE (API), https://geocoding.geo.census.gov/geocoder/Geocoding_Services_API.html [https://perma.cc/X58R-V3ZL].

158. For example, we required respondents to connect from a U.S. IP address, since this project seeks to measure American attitudes about algorithmic decisions.

159. *See* R. Michael Alvarez et al., *Paying Attention to Inattentive Survey Respondents*, 27 POL. ANALYSIS 145, 146 (2019).

160. *See* Franki Y.H. Kung et al., *Are Attention Check Questions a Threat to Scale Validity?*, 67 APPLIED PSYCH. 264, 278 (2018) (finding no general harm from instructional manipulation);

More than 93% of survey respondents correctly answered the attention-check question. Those who answered incorrectly were rejected, and we did not include their results in the dataset.[161] Several more respondents were rejected for additional reasons, including submission of duplicate surveys and bot-like behavior.

Table 2 - Number of Included and Excluded Observations Based upon Attention-Check Question Response

	Excluded	**Included**
Failed Attention Check	296	0
Passed Attention Check	65	3971

We obtained 3971 usable survey responses out of over 4300 gathered.

In addition, we employed several techniques to ensure response quality. First, over time, we imposed a set of decreasingly stringent requirements for survey respondents. (MTurk keeps track of how many assignments a worker completes and how often their results are rejected in those tasks. Cloud Research rates workers with more completed tasks and lower rejection rates as more qualified.) This allowed us to compare results from more qualified respondents (who were fewer in number) and less qualified ones (who were more plentiful).[162] We found no difference in rejection rates between the two groups. Second, we checked IP addresses against known Virtual Private Networks (VPNs) in accordance with best practices.[163] Since the study's goal was to survey American attitudes about algorithms, we had to be cautious

David J. Hauser & Norbert Schwarz, *It's a Trap! Instructional Manipulation Checks Prompt Systematic Thinking on "Tricky" Tasks*, 5 SAGE OPEN, Apr.–June 2015, at 4 (finding that instructional manipulation not only measures focus, it induces it). Hauser and Schwarz report a 92% pass rate for attention check questions, *id.* at 3, which is similar to this study's 93% rate. For a discussion of concerns about attention-check questions, see Dave Vannette, *Using Attention Checks in Your Surveys May Harm Data Quality*, QUALTRICS (June 28, 2017), https://www.qualtrics.com/blog/using-attention-checks-in-your-surveys-may-harm-data-quality/ [https://perma.cc/2Q4L-86QZ] (comparing demographics for those that pass attention checks and those that fail).

161. For a robust discussion of the ethics of rejecting failed attention users (versus simply exiting the survey so that the user does not suffer a drop in approval rate), see *R/Mturk: As a First-Time Requester, What Is the Best Way To Deal with Failed Attention Checks?*, REDDIT, https://www.reddit.com/r/mturk/comments/bq6wsj/as_a_firsttime_requester_what_is_the_best_way_to/ [https://perma.cc/GS7P-HQTQ].

162. The less qualified respondents had an average acceptance rate of 96% for completed tasks. Obviously, MTurkers prefer a greater acceptance rate, and hence more compensation, leading to the debates referenced *supra* note 161.

163. Ryan Kennedy et al., *The Shape of and Solutions to the MTurk Quality Crisis*, 8 POL. SCI. RSCH. & METHODS 614, 623 (2020).

about users employing VPNs as it is more difficult to determine their true geographic location. And VPNs can enable a single user to complete multiple survey responses, either manually or using a bot, which reduces the quality of the study data. While we did not discard all results from VPN users, we did discard any responses coming from the same Geocodes and from VPNs if other surveys from those same VPNs failed our attention-check question or otherwise exhibited bot-like behavior. Third, we checked for duplicate IP addresses or Geocodes in the initial few results (which did not use TurkPrime), discarding duplicates.

Though we did not have control over the Qualtrics randomization (nor how many results would be excluded), randomization among all choices was successful.[164] Two-way frequency analysis among all randomization combinations (vignettes and A/B options) yielded a range of chi-squared probabilities between 17% and 95%. This means that even the most common combination of variable options would be expected at least 17% of the time if one flipped a coin to determine the option presented by each question of the survey, and that some combinations would be expected to occur 95% of the time. Furthermore, the distribution generated sufficient power to make statistical conclusions. Each vignette had about 1000 participants, and each variable option had about 300 (for error rate, which had three choices) or 500 (for other variables) respondents.[165]

C. Study Limitations

A few words about the limitations of this study design are in order. First, the pricing and time variables (along with the others, of course) in the survey are hypothetical. Respondents faced no tangible tradeoffs in their choices. In real life, a dollar invested in changing the identity of the decisionmaker cannot be spent on other goods or services. In the survey, though, foregone

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164. It turns out that it is difficult to create software that generates truly random numbers. *See, e.g.*, Jason M. Rubin, *Can a Computer Generate a Truly Random Number?*, MIT SCH. OF ENG'G: ASK AN ENG'R (Nov. 1, 2011), https://engineering.mit.edu/engage/ask-an-engineer/can-a-computer-generate-a-truly-random-number/ [https://perma.cc/X5JH-2RYR].

165. Power tests for a study of this type are difficult to find. *See* Esther W. de Bekker-Grob et al., *Sample Size Requirements for Discrete-Choice Experiments in Healthcare: A Practical Guide*, 8 PATIENT 373 (2015) (discussing paucity of options and proposing one). Because we are interested in how many people were assigned to different combinations of variables, we used a chi-squared sample size test with 28 degrees of freedom. For a sample size required to be 90% confident that our p-value of .01 did not find false positives for any differences of .1 or more, we needed at least 3718 valid responses. *See Chi-Squared Sample Size Calculator*, STAT. KINGDOM, https://www.statskingdom.com/sample_size_chi2.html [https://perma.cc/4ZGG-ZAGW] (website implementing R's chi-squared power test). We obtained 3971 valid responses. Accordingly, our dataset's power is closer to 93%.

opportunities are imaginary. While it might be possible to require respondents to surrender part of their MTurk compensation to switch, this carries the same problem: the participant receives no actual benefit from the change, and thus is likely to elect the option with the higher payment. Moreover, since MTurk payments are small ($.50 in our survey), a foregone portion risks being either negligible (a few cents) or relatively overwhelming (perhaps 25-50% of compensation). While real, this limitation is inherent in all survey data that employs hypothetical scenarios.

Second, we used the Qualtrics software package to design the survey. Qualtrics has standardized modules that capture demographic data, including gender, age, ethnic background, and education level. This study did not collect some useful data that is available from MTurk and Qualtrics (such as geographic location or 5-digit ZIP code) because it posed a non-trivial risk of identifying the data subject.[166] The study limited MTurk respondents to participants from the United States (as self-reported, and as verified by IP address and Geocode) since it sought to measure American preferences regarding algorithms.

This is a between-subjects experiment, as most A/B testing is. The results are an aggregation of preferences from which one can infer similar behavior when people face similar choices and circumstances. An ideal study might be within-subjects: asking each person how their decisions change under different treatments. However, such a study design is problematic when there are anchoring effects (as is the case here).[167] Once a study subject has been offered one type of decisionmaker, they might never change, even when faced with new variable options, due to anchoring.

The demographics of MTurk participants do not perfectly mirror those of the country as a whole, although study respondents displayed a wide array of age, income, race, and political preferences.[168] In addition, respondents actively choose to participate in the surveys, rather than being randomly selected for inclusion. Increasing the size of the sample reduces this problem but does not eliminate it. If underrepresented groups have substantially different preferences regarding humans versus algorithms as decisionmakers,

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166. *See* Standards for Privacy of Individually Identifiable Health Information, 67 FED. REG. 53,182, 53,233–34 (Aug. 14, 2002) (to be codified at 45 C.F.R. pts. 160–164) (discussing when inclusion of ZIP code information is permissible in de-identified data for purposes of the Privacy Rule of the Health Insurance Portability and Accountability Act). Approximately thirty respondents identified themselves to us after taking the survey, mostly to complain about their answers being rejected. For unknown reasons, Mechanical Turk does not anonymize the email addresses of either the MTurk worker or the requester. In any event, we did not store any contact information in the dataset.

167. *See infra* Section III.B.5.

168. *See supra* notes 145–149 and accompanying text.

or if consumers' future preferences diverge from their preferences today, this study may not fully detect those preferences. This is an important limitation. However, with limited exceptions (such as participants in specialized tribunals like children's,[169] veterans',[170] and Native American tribal courts[171]), choices about decisionmakers are likely to be made at broad societal levels covering large numbers of people, such as state governments and major financial institutions. Those design choices are likely to impose a sort of rough justice, reflecting an aggregate consensus while concededly failing to tailor decision making systems to each individual's preferences.[172] Thus, in somewhat cynical fashion, this study's limitation in this regard is likely to be mirrored in larger societal processes due to public choice factors.[173] That does not reduce the importance of the limitation overall, but it makes it more acceptable within the parameters of this project. In any case, demographic issues require limiting the descriptive force of this Article's conclusions appropriately.

D. Analytical Methods

To determine the conditions under which people prefer an algorithm to a human, we analyzed the study dataset using a logistic choice model. This model is ideal for the Article's study design because it enables considering each variable in isolation (for example, the effect of error rate on the choice of human or algorithm in each of the four vignettes) and also together (for example, the effect of error rate across all four vignettes).

The tables in Section III show the results of the primary regression. The analysis also included demographic variables such as age, political views, and sex. However, for brevity they are not reported in the tables, since none of the demographic variables even approached statistical significance, except that men were about 18% more likely to choose an algorithm across the four vignettes, all other variables held equal (p=.02).

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169. *See* Jeffrey Fagan et al., Be Careful What You Wish for: Legal Sanctions and Public Safety Among Adolescent Offenders in Juvenile and Criminal Court (Dec. 21, 2007) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=491202 [https://perma.cc/C43R-H5Y9].

170. *See* Kristine A. Huskey, *Justice for Veterans: Does Theory Matter?*, 59 ARIZ. L. REV. 697 (2017).

171. *See* Elizabeth Reese, *The Other American Law*, 73 STAN. L. REV. (forthcoming 2021) (discussing tribal law).

172. *See generally* MAXWELL L. STEARNS, PUBLIC CHOICE AND PUBLIC LAW: READINGS AND COMMENTARY (1997).

173. *See* Robert D. Tollison, *Public Choice and Legislation*, 74 VA. L. REV. 339 (1988).

The primary regression reports relative risk ratios (odds ratios). This means a number greater than one indicates that an algorithm is more likely to be selected than a human as compared to the default option for that particular variable; conversely, a number less than one means that an algorithm is less likely to be selected than a human as compared to the default option for that variable. Furthermore, the odds are essentially the fraction above or below one. So, a result (coefficient) of .75 means that the odds of selecting an algorithm are 25% less, and a result (coefficient) of 2 means that the odds of picking the algorithm doubled.[174]

The next Section reports the results of the analysis of this Article's dataset.

III. RESULTS

This Section describes the study's key findings. The results demonstrate the complex relationship people have with algorithms that offer varied costs, benefits, accuracy, usage of private personal data, and speed, relative to humans and relative to other models. With that caveat, several clear patterns emerged. As the stakes at issue for a decision increased, respondents' preference for a human to make that judgment increased. The strongest factor in participants' choices was the cost or benefit offered by the decisionmaker; this price variable's effects outweighed those of error rate and decision speed, although each of these latter variables also had strong effects. Surprisingly, the study found no difference in respondent preferences when decisionmakers had access to private personal information, as opposed to only publicly available data. And default settings were powerful: people had a strong tendency to remain with the decisionmaker randomly assigned to them initially, although the introduction of other variables diminished the anchoring effect. Overall, one important contribution of this study is that it not only shows that people's preferences for algorithms versus humans are malleable, but also reveals the factors that shift preferences and their relative power to do so.

Perhaps the most surprising result was that, in the aggregate, respondents selected an algorithm to decide their outcome more than half the time. A total of 52.2% of participants chose the algorithm, while 47.8% chose a human. One must apply some caution in interpreting this finding. MTurk workers earn compensation performing tasks online, and thus may be more amenable to allowing algorithms to decide. However, responses from workers who were rejected for failing the attention-check question suggest discontent with

174. Odds ratios are not precisely a percentage increase, though. For example, an odds ratio of 2 means an increase of 33% (66%/33% = 2).

a computer algorithm determining whether they would get paid. Each of those more than twenty workers entreated a human (one of us) to override the decision made by the survey software.

This aggregate result presents a fascinating contrast with another finding: overall, when asked to choose between an algorithm and a human, each with an unknown error rate and with all other variables held constant, respondents picked humans almost twice as often (65% versus 35%). The study data do not reveal why people had this preference when confronted with a lack of information about the relative accuracy of the two types of decisionmakers. It might derive from a baseline deontological preference for having humans determine outcomes; from utilitarian factors based on initial assumptions about the true error rates for each option (in the absence of concrete information); from a combination of these; or from some other unidentified influence.

As discussed below, that strong preference for humans, under conditions of unknown accuracy and no other differences, was easily shifted once the survey began to modify the relevant variables (price, speed, and error rate).

A. Aggregate Results

This subsection presents the aggregate results from analysis of the survey dataset. Table 3 below shows the regression results. Each of these ratios (results) is the *relative* likelihood of choosing an algorithm compared to the *other options*, not compared to choosing a human. For example, respondents were 10% more likely to pick the algorithm in the health care vignette than in the gift card vignette. But that result reveals nothing about whether they were more likely to pick an algorithm or a human in the health care vignette.[175] Thus, the odds ratios are most useful to compare results within each variable, rather than to compare results between variables. While one can calculate the difference between variable outcomes from this table, other methods perform this task with greater ease. Section III.B *infra* discusses how the choice between humans and algorithms is affected based upon each variable option, as well as how the different variable options interact with one another.

175. To put it concretely, 50% of respondents could pick the algorithm in the gift card scenario, and 55% could pick the algorithm in the health care one (55/50=1.1=10%). The same odds ratio obtains if 77% of participants pick the gift card algorithm and 70% pick the health care algorithm (77/70=1.1=10%). In both cases, the odds ratio shows a 10% greater preference for the algorithm in the health care scenario, but the absolute values of the preferences generate different policy implications depending on which case applies.

Table 3 - Choice Model Mixed Logit of All Observations

Choice	**RRR**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**	
Algorithm						
Vignette						
Bank Loan	1.109	.113	1.02	0.308	.908	1.355
Civil Traffic	.539	.054	-6.11	0.000	.443	.658
Gift Card	1	(base)				
Health Care	.739	.076	-2.94	0.003	.605	.905
Default						
Human	1	(base)				
Algorithm	2.771	.201	14.02	0.000	2.404	3.196
Error Rate- Human						
High	2.451	.219	10.05	0.000	2.058	2.920
Low	.684	.059	-4.39	0.000	.577	.810
Unknown	1	(base)				
Error Rate- Algorithm						
High	.442	.039	-9.37	0.000	.372	.525
Low	1.826	.156	6.88	0.000	1.538	2.168
Unknown	1	(base)				
Algorithm Cost						
Lower	2.562	.186	12.92	0.000	2.222	2.956
Same	1	(base)				
Algorithm Speed						
Faster	1.561	.112	6.20	0.000	1.356	1.798
Same	1	(base)				
Information Used						
Public and private	1.0818	.077	1.10	0.272	.940	1.245
Public only	1	(base)				
[omitted demographics]	…	…	…	…	…	…
Constant	.318	.064	-5.69	0.000	.214	.472
Human		(base alt.)				

These results show that (with two exceptions) each of the relevant variable choices is statistically significant (most at p<.001). Thus, changing the scenario (which presented different levels of stakes for the decision), error rate, timing, or benefits all affected which decisionmaker respondents preferred. The two exceptions are the lack of a statistically significant difference between the bank vignette and the gift card scenario, and between making public-only or public plus private personal information available to the decisionmaker. In other words, people were no more likely—as a statistical matter—to choose the algorithm for a bank loan than they were to choose the algorithm for a gift card.[176] This is mildly surprising since the stakes involved in the two vignettes are considerably different. The other exception is decisionmaker access to public-only versus public and private personal information. Respondents showed no statistical preference for the algorithm when private information was involved, even when comparing the results vignette by vignette. This was surprising, and we explore it further below.

In certain ways, respondents' preferences for an algorithm differ as one would expect based on the conventional economic and scholarly wisdom. As the stakes increased, people were less likely to select the algorithm. As error rate goes up for humans, people are more likely to select the algorithm. As algorithms became cheaper, more beneficial, or faster, people are more likely to choose them. But since the odds ratios are not a fixed proportion of who selected each decisionmaker and the regression analysis separates each variable into its constituent parts, what does that say about the effect of each option for each variable? Marginal effects analysis enabled us to answer this question.

B. Marginal Effects of Survey Variables

Marginal effects analysis breaks the regression into components and reports the probability of a respondent's selection given a combination of one or more A/B variables. This marginal-effects analysis revealed that respondents preferred humans to algorithms as the stakes at issue increased.[177] When one decisionmaker's error rate differed from the other's rate, many (but not all) shifted their preferences to the more accurate option. Survey takers were on average indifferent between the two options when told that the error rate was unknown, though this apparent indifference disappears as other variables are included in the analysis. The relative cost or benefits of

176. Again, note that neither of these results speaks to the likelihood of choosing an algorithm versus a human under these conditions—that requires calculations involving the constant term and the base cases. See the analysis of marginal effects *infra* Section III.B.

177. Each result reported is statistically significant unless otherwise noted. Most are significant at $p<.001$.

the two decisionmakers had a major effect on respondents, who also preferred more rapid determinations (albeit to a lesser degree than better pricing). Surprisingly, access to private personal information, such as credit reports, made no appreciable difference in whether survey takers preferred a human or an algorithm to assess that more sensitive data. Lastly, default assignments had real anchoring power, particularly for algorithms, although that inertia can be deracinated by offering people an alternative that is faster, more accurate, or provides a better payoff.

Table 4 below lists "margins," or marginal probabilities, that a respondent will select one type of decisionmaker based upon a particular configuration of variable options. (We provide a complete table here, but further discussion of marginal analysis refers to summary tables presented in Appendix B.) Table 4, for example, shows the likelihood that the respondent would pick an algorithm for each vignette. It is not the final probability, obviously, as there are other variables that are not analyzed here. Instead, Table 4 displays the chance of selecting the algorithm in light of the total of all the other variables' options, the effects of which may well cancel each other out. Since this study's model has equal randomization for each variable, one can think of Table 4 as presenting the aggregate probability that users will select a human or algorithm for each vignette given each possible alternative for the other variables. So, to determine the probability of a respondent choosing the algorithm under the bank vignette, the model combines all the people who chose the algorithm when it decided faster than the human decisionmaker and all the people who chose it when it offered the same decision speed. Because there were equal numbers of respondents for each variable option (here, speed), the overall result is the average of the results for the two options.[178] One could, of course, generate a margins table that includes more and more variables until each and every variable option is considered. This would eliminate averaging but would yield a large number of combinations. The resulting table would essentially list the percentage of people who picked the algorithm when presented with each variable combination.

The probabilities listed in Table 4 are complements of each other. For example, if there is a 56% chance that respondents selected an algorithm for the gift card, then there is a 44% chance they selected a human for the gift card. The table presents both components for ease of comprehension.

178. For the study's variables, such as error rate, this is relatively simple as the study design allocated the variable options equally among respondents. Thus, the results average out to the midpoint of the options. But since demographics were not divided equally, the probabilities represent the average respondent. However, because the demographic variables did not affect the regression results, we conclude any differences based upon age, income, or political views would be negligibly small.

Table 4 - Probability That Respondents Select Decisionmaker By Vignette

(Decisionmaker#) Vignette	Prob.	Std. Err.	Z	P>|z|	[95% Conf.	Interval]
algorithm#Bank	58.4%	.014	41.65	0.000	.557	.612
algorithm#Civil Traffic	44.0%	.014	31.89	0.000	.413	.467
algorithm#Gift Card	56.4%	.014	39.22	0.000	.535	.592
algorithm#Health Care	50.3%	.015	34.57	0.000	.475	.532
human#Bank	41.6%	.014	29.66	0.000	.388	.443
human#Civil Traffic	56.0%	.013	40.54	0.000	.532	.587
human#Gift Card	43.6%	.014	30.37	0.000	.408	.465
human#Health Care	49.7%	.015	34.11	0.000	.468	.525

1. Effects From Different Stakes (Vignettes)

Table 4 shows that the probability that a respondent would choose the algorithm decreased as the stakes of the decision increased. The single exception was the bank loan scenario, which surprisingly garnered roughly the same level of support for an algorithmic decisionmaker as the gift card; although Table 4 shows a difference, that difference was not statistically significant. These results seem to make intuitive sense—as people worry more about the result, they want the human touch when that decision is made. Even so, the highest probability of picking a human was only 56.0%, for the civil traffic fine. This is somewhat surprising, especially given that the greatest probability for the algorithm was even higher, at 58.4% for the bank loan.[179] When compared by vignette, the probability of selecting one type of decisionmaker in a given scenario (other than between the gift card and bank loan) is statistically significantly different from each of the other scenarios ($p<.001$).[180] Therefore, we conclude that survey takers perceived each of the scenarios' stakes as meaningfully different from the others, aside from the gift card and bank loan. And respondents preferred humans more as the consequences of the decision became weightier.

Given the differences between the other vignettes, it is unclear why the dissimilar stakes did not lead to a difference in respondents choosing an

179. The pilot study for this Article included an even higher stakes vignette: deciding guilt in prosecution for a criminal offense. Surprisingly, there were no statistically significant differences in preferences for a human in the criminal scenario compared to the civil traffic offense. We removed the criminal vignette for simplicity and increased statistical power of the other vignettes.

180. For example, the probability of selecting an algorithm differs in statistically significant fashion for the civil traffic fine and gift card scenarios.

algorithm for the bank loan. One explanation might be that participants viewed the bank loan decision as less subjective, and thus were not as interested in human intervention.

2. Effects From Decisionmakers' Error Rates

Error rates were a significant factor in participants' choice of human versus algorithm. Moreover, the results suggest a marked but highly malleable default preference for humans in the absence of information about error rates. Survey respondents could learn that either type of decisionmaker had a high, low, or unknown rate of making mistakes. Table 5, listed in Appendix B, presents the marginal probabilities of selecting each decisionmaker based on information only about human error rate; information only about algorithmic error rate; and information about both error rates together. These results reveal, for example, whether a high human error rate always makes a significant difference in decisionmaker choice, or only when combined with a low algorithmic error rate.

When respondents learned that one type of decisionmaker had a high error rate, two-thirds selected the other option. This result holds across all three options. Even more people selected the other decisionmaker if that option had a low error rate, for example, but that was offset by the lower number who chose the other option when it also had a high error rate.

The effects of low error rates were not as consistent between humans and algorithms. When the human error rate was low, 59% selected humans, but when the algorithmic error rate was low, 66% picked an algorithmic decisionmaker. (Here, too, this is an average across all three variable options for the other decisionmaker.) Considering the error rates of both decisionmakers, if humans and algorithms had opposite risks of making mistakes, then even more respondents chose the decisionmaker with the lower error rate.[181] When one decisionmaker had a high error rate and the other a low rate, the more accurate decisionmaker had a 74% or greater chance of being selected.[182]

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181. The opposite is obviously true: fewer respondents selected the decisionmaker with the higher error rate. The first two columns of Table 5 report the average of the lower and higher (and unknown) variable option selections.

182. Some respondents' preferences (as much as 25%!) remained firm even with a significant gap between error rates—for example, choosing a low accuracy algorithm over a highly accurate human. This may reflect an endogenous and relatively sticky bias towards one type of decisionmaker for some subsets of the population, or it may reflect preferences driven by one of the other variables: price, speed, or even anchoring.

Parity in known error rates for the two decisionmakers led respondents to split their choices roughly evenly. When both error rates were revealed to be high, the algorithm had a 52% chance of selection, and when both decisionmakers had a low error rate, algorithms were 55% likely to be selected. Neither of these percentages was statistically significantly different from the others.

An interesting result derived from the situation when respondents were informed that both decisionmakers had unknown error rates, with equal price and speed. With the other variables set as equal (for example, humans and algorithms made decisions at the same speed), respondents selected humans 65% of the time. (Table 6, listed in Appendix B, presents this in a partial margins table.) This initially suggests a strong inherent preference for humans when people and formulas offer the same perceived costs and benefits, but their accuracies are a mystery. As explained further *infra*, this seemingly stark preference was easily manipulated, though. For example, when both decisionmakers had unknown error rates, but the algorithm was either faster or cheaper, now 65% of respondents selected the algorithm—a complete turnabout.[183] One interpretation of this result is that the conventional wisdom about consumers possessing a preference for human decisionmakers may be based on inherent assumptions, or biases, about the likely error rates of algorithms and people.[184] Empirically, even when faced with uncertainty or high risk, respondents were more than willing—about half the time (and even more if there were some benefits)—to accept an algorithm. It was not until they received information that the algorithm made copious errors *and* humans did not, or that algorithms did not offer any pricing or speed benefits, that participants significantly preferred humans. Accuracy is clearly important in attitudes about algorithms, but people are more accepting of mathematical models than much of the literature suggests.

3. Effects From Price (Cost/Benefit) and Speed

As suggested in the prior subsection, the speed at which a decisionmaker came to a decision, and the relative level of benefits it offered, strongly affected respondents' choices. The study included two variables. The first

183. And, as previously noted, these opposite results average out to about 50% in the aggregate because equal numbers of respondents saw each of the price/speed options. This is an example of the "Flaw of Averages." *See generally* SAM L. SAVAGE, THE FLAW OF AVERAGES: WHY WE UNDERESTIMATE RISK IN THE FACE OF UNCERTAINTY (2012) (suggesting dryly "Consider a drunk staggering down the middle of a busy highway . . . his average position is the centerline. Then the state of the drunk at his *average* position is alive, but on *average* he's dead.").

184. *See* Chen, *supra* note 6, at 11.

was price: did the algorithm offer greater benefits or lower costs? The second was speed: did the algorithm decide more quickly? In both cases, the survey made clear that the chance of a positive outcome would not change. For speed, the decisionmaker would render judgment more quickly, but the content of the decision would not be altered. For price, the cost or benefit advantage would accrue *only if the decisionmaker ruled in favor of the respondent*. Table 7, listed in Appendix B, shows probabilities of selecting each decisionmaker based on pricing, speed, and a combination of both by vignette.

Price and speed generated predictable but powerful effects. Algorithms had more than a 61% chance of being selected when their cost was lower or their benefit was higher, but only a 43% chance of being chosen when their value was the same as for a human. Similarly, when the algorithm rendered a faster decision, it had a 57% chance of being selected, but only a 48% chance when it decided at the same speed as humans.

Speed matters more to respondents' preferences as the stakes at issue increase, but in unexpected ways. When the algorithm was faster, respondents chose it more than 60% of the time in the context of bank loans and gift cards. We expected the respondents to especially prefer a faster decision on the loan. In the health care scenario, participants picked the faster algorithm only 55% of the time. With the civil traffic fine, people preferred slower humans to faster algorithms—fewer than half (48.5%) chose the algorithm when it was more rapid than a person. Perhaps consumers are not in a hurry to pay fines.

For each vignette, when the speed of the two decisionmakers was equal, respondents became less likely to choose the algorithm. The bank loan and gift card percentages dropped to 54% and 52%, respectively (from over 60% when the algorithm was faster). Survey takers still preferred algorithms to humans, all other things equal, but not by nearly as much. However, when humans and algorithms took the same amount of time, respondents chose the formula in the health care scenario less than half the time (45%, versus 55% when the code was faster). Participants' preferences for the algorithm with the civil traffic fine declined even further below 50% under conditions of equal speed, to 40% (against 48.5% with a quicker calculation). This result seems to disprove the supposition that respondents wanted a slower decision in traffic court to avoid paying fines. They preferred a faster decision for fines as well, but generally preferred algorithms less in that context.

Price was so important to respondents that it even outweighed error rate risk.[185] For example, when the cost/benefit was the same for both varieties of decisionmaker, respondents chose the algorithm 24% of the time when its error rate was high and the human error rate was unknown. But if the algorithm offered the possibility of more benefits, then the chance of selection increased to 42% under the same error rate conditions. Even when respondents learned humans had a low error rate and algorithms had a high one, differences based upon price persisted: 17% chose algorithms when prices were equal, versus 34% when algorithms had better prices. In effect, respondents seemed willing to gamble with accuracy for a larger potential payout.

When speed and price interacted, price won. When the algorithm offered the same benefit as humans, at the same speed as humans, respondents were 38% likely to pick the algorithm. But when it offered the same benefits faster, that percentage rose to 47%. Conversely, if the algorithm conferred better benefits at the same speed as a human, respondents picked the formula in 57% of instances. Overall, survey takers preferred better benefits to faster decisions. Finally, when the algorithm was both cheaper *and* faster, it was 66% likely to be selected.

These results demonstrate that respondents were strongly influenced by both price and speed in their preferences for a decisionmaker, and that the magnitude of the effect varied with the type of decision at issue.

4. Effects From Decisionmaker Access to Private Personal Information

One highly surprising result was that respondents were indifferent between humans and algorithms when informed that the decisionmaker would have access to private personal information about them. Survey takers were told either that the decisionmaker would have access only to publicly available information about them, such as that available in response to a Google query, or that the decider could also access private personal information, such as credit report data or employment records. Table 8, in Appendix B, shows the probability that users selected an algorithm for each variable option (access only to public information, or to public and private personal information). Intuitively, we expected respondents to have a clear preference, either for a human who might offer empathy or for an algorithm that would not draw moral conclusions. One survey taker contacted us to

185. We do not present tables for this data, as the combination of pricing with six error rates generates a very large listing of combinations.

explain that they chose the algorithm in the coffee shop vignette because they did not want a person knowing all the details of their purchasing habits. Although this was only one anecdote, it might indicate a more generalized sentiment.

And yet, analysis of the dataset generated a surprising and likely counterintuitive result. When the decisionmaker had access to private personal information as well as public data, the odds of the recipient choosing an algorithm were not appreciably (or statistically) different from even odds or random choice. Furthermore, the chances of the recipient picking the algorithm under these circumstances were not appreciably (or statistically) different from those of choosing a human. Although this finding is unexpected, with 4,000 survey respondents the result is robust.

This seeming indifference between human and algorithm when the decisionmaker can access private personal information likely derives from mixed preferences in the larger population. Studies on medical interviews find that some patients prefer revealing sensitive information to humans,[186] who may be more emotionally engaged and empathetic, and some prefer algorithms, which are incapable of moral judgment.[187] Some respondents may have preferred humans because algorithms access and process private personal information more rapidly and with less context, fulfilling the stereotype of cold machine logic.[188] Some participants may have preferred algorithms because, while humans process information more slowly, they also carry implicit social biases and judgments[189] that could affect how they perceive the respondent even if these attitudes do not alter the outcome at issue.[190] Or, perhaps survey takers would like it best if *no* decisionmaker could access their private personal information, and hence regarded the choice between humans and algorithms as equally unattractive alternatives.

186. *See* Christopher K. Fairley et al., *Computer-Assisted Self Interviewing in Sexual Health Clinics*, 37 SEXUALLY TRANSMITTED DISEASES 665, 667 (2010); Chiara Longoni & Carey K. Morewedge, *AI Can Outperform Doctors. So Why Don't Patients Trust It?*, HARV. BUS. REV. (Oct. 30, 2019), https://hbr.org/2019/10/ai-can-outperform-doctors-so-why-dont-patients-trust-it. [https://perma.cc/4R63-QND9].

187. *See* Christina Oxholm et al., *Attitudes of Patients and Health Professionals Regarding Screening Algorithms: Qualitative Study*, J. MED. INTERNET RSCH. FORMATIVE RSCH. (Aug. 9, 2021), https://pubmed.ncbi.nlm.nih.gov/34383666/ [https://perma.cc/JS4F-Z6PA]. *But see* Longoni & Morewedge, *supra* note 179.

188. *See* James E. Bailey, *Does Health Information Technology Dehumanize Health Care?*, 13 AM. MED. ASS'N J. ETHICS 181 (2011).

189. *See* Anthony K Waruru et al., *Audio Computer-Assisted Self-Interviewing (ACASI) May Avert Socially Desirable Responses About Infant Feeding in the Context of HIV*, 5 BMC MED. INFORMATICS & DECISION MAKING 24 (2005).

190. *See* Bryan Borzykowski, *Truth Be Told, We're More Honest with Robots*, BBC (Apr. 18, 2016), https://www.bbc.com/worklife/article/20160412-truth-be-told-were-more-honest-with-robots [https://perma.cc/94NQ-BF6A].

This study's data do not enable us to draw conclusions about the underlying reasons for respondents' unexpected disinterest in whether a human or machine evaluates their personal information, but the result offers a promising path for future research.

5. Effects From Default Assignments and Anchoring

Defaults matter.[191] This study evaluated the ultimate effect of an initial assignment of one type of decisionmaker to a respondent. The survey software explicitly assigned a decisionmaker and, at the end of the process, asked if the user wanted to switch for two reasons. First, it allowed for a useful attention check when the survey later asked respondents what they had been assigned.[192] Second, it enabled testing of anchoring effects: does the initial decisionmaker choice cause people to stay with that same choice, all else equal? The initial choice model estimate presented in Table 3 shows some stickiness: participants assigned an algorithm initially were more than twice as likely to choose an algorithm as their final decisionmaker. And Table 9, listed in Appendix B, provides more granularity, showing the probabilities for retaining (or changing) the default decisionmaker based upon initial type of assignment.

The results show a clear anchoring effect.[193] More than 62% of those surveyed stayed with an algorithm when given the algorithm initially, and more than 58% of those assigned to a human stayed with the human. These differences are statistically significant, as is the difference between humans and algorithms. Respondents were more attached to algorithms than humans based on initial assignment. If there were no anchoring, one would expect to see results closer to the overall preferences of respondents. For example, without anchoring, if 52% of people in the aggregate preferred the algorithm, all else equal, then 52% should prefer the algorithm regardless of their initial

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191. *See* RICHARD H. THALER & CASS R. SUNSTEIN, NUDGE: IMPROVING DECISIONS ABOUT HEALTH, WEALTH, AND HAPPINESS 83–87 (2008); Michal Lavi, *Evil Nudges*, 21 VAND. J. ENT. & TECH. L. 1, 8–9 (2018).

192. Respondents who answered this question incorrectly had their results removed from the data set and were not compensated.

193. Ideally, we would repeat this survey with no default, enabling a clearer conclusion as to whether the initial choice was a true anchor. We must be satisfied here simply comparing the choices to what one would expect in a random distribution. *See* Andrea Isoni et al., *Do Markets Reveal Preferences or Shape Them?*, 122 J. ECON. BEHAV. & ORG. 1, 6 (2016) (performing test for anchoring requires comparing actual to expected results).

decisionmaker assignment.[194] Instead, respondents preferred to stay with both humans and algorithms more than half the time if that type of decisionmaker was assigned first, something one would not expect unless survey takers were anchored (or residents of Lake Wobegon).[195] It is perhaps unsurprising that people are more anchored to algorithms, given that they allow algorithms to determine many aspects of their lives already. Indeed, the four percent difference in anchoring (62% versus 58%) may account for the four percent overall average preference for algorithms across all choices (52% versus 48%).

These results do not imply that anchoring outweighs all other variables. This study's marginal effects analysis takes each of the other variable options into account and determines their effect on average, aggregating preferences for each of the other variables. Thus, some of the other variables will overcome the anchoring effect, and some will be weighed down by it; the 62% of respondents reported here who remained with an algorithm is the combination of those.

Similarly, anchoring interacts with each variable option. Table 10, in Appendix B, presents marginal effects of price, speed, and error rate on whether and how much the chances of picking a given type of decisionmaker differed based on the initial decisionmaker assignment. This reveals the relative influence of anchoring compared to these other variables. Thus, the study evaluates anchoring effect in part by comparing the percentage who chose a type of decisionmaker based on both of the defaults. For example, it compares the likelihood of a respondent choosing a human when initially assigned to one when an algorithm decides faster with the likelihood of a participant choosing a human when *instead initially assigned to an algorithm* and the algorithm remains faster.

The results show that default decisionmaker assignment had widely varying interactive effects on the different variable options. Take price (expressed as cost of or benefit from a decisionmaker). With participants assigned initially to an algorithm, 71% ultimately chose the algorithm if it was cheaper or offered a greater benefit. But if respondents were assigned to a human at first, only 51% picked the algorithm when it had a price advantage

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194. It is possible, of course, to distribute the other choices, such as error rate, such that those initially assigned humans were also assigned more favorable options, such as a low error rate. However, this study's data is not distributed in that fashion; instead, it is roughly equally divided and any random differences are insufficient to skew the results this much.

195. *Lake Wobegon Effect*, OXFORD REFERENCE, https://www.oxfordreference.com/view/10.1093/oi/authority.20110810105237549 [https://perma.cc/GKE3-S89K]. *See generally* Derek E. Bambauer, *Shopping Badly: Cognitive Biases, Communications, and the Fallacy of the Marketplace of Ideas*, 77 U. COLO. L. REV. 649, 674–76 (2006) (discussing optimism bias, including the Lake Wobegon Effect).

(cheaper cost or greater benefit). This is slightly better than even or random odds but represents a much lower percentage than when participants were presented with identical options except for the algorithmic default. While algorithms were more effective anchors, respondents also held tight to initial human assignments. If assigned to a human, survey takers were 68% likely to keep that choice if the human's cost/benefit (price) was the same as the algorithm. If assigned to an algorithm, however, anchoring was weaker when there was no price advantage, with only 53% of respondents retaining the algorithm at the same cost/benefit as a person.

Results were similar for processing speed, but with important, nuanced differences. The anchoring effect was weaker than with price for variable options that conferred some advantage to the respondent. For speed, those assigned to an algorithm first were 67% likely to remain with it if the formula was faster. Participants initially assigned to a human were 62% likely to retain it if the human's speed was the same as an algorithm. Similarly, anchoring demonstrated greater effects than price for the less desirable variable options. More than 58% of respondents stayed with their original algorithm assignment when decisionmaker speeds were equal; 54% stayed with an initial human assignment even if the algorithm was faster. The study also evaluated these results in light of the interaction between price and speed. As described above, when humans delivered the same price at the same speed, respondents chose the algorithm only 38% of the time.[196] When breaking that 38% group down by their initial assignments, however, the impact of anchoring is clear. At the same price and speed levels, 48% of survey takers kept the algorithm if initially assigned to it, but only 28% elected to switch to the algorithm if assigned to the human first.[197] In other words, the group of people who chose an algorithm when price and speed were equal included many more people who were initially assigned an algorithm than were initially assigned a human.

The anchoring effect was weakest—although it did not disappear—when considered in combination with decisionmaker error rates. If human error rate was high and the algorithm rate was low, only 28% of respondents chose the human, even though they were initially assigned to one. In other words, there was a 72% switch rate under those circumstances, wiping out most anchoring effects. But anchoring did not vanish completely. For those assigned to humans, 83% remained with that decisionmaker when human error rate was low and algorithms' rate was high. Even the previous even or random splits for unknown/unknown, low/low, and high/high error rate pairings

196. *See supra* Section III.B.3.

197. The 38% overall choice is obviously the average of these two points.

disappeared, with probabilities in the high 50 and 60 percentages that people would retain their initial decisionmaker assignment when humans and algorithms displayed equal error rates. The even splits from the earlier analysis resulted from the equal distribution of default decisionmakers to respondents, which averaged out the differences. These results for error rate are telling. Error rate effects can overwhelm anchoring effects where there is a clear separation between error rates for humans and algorithms. But when error rates are the same for the two decisionmakers, anchoring effects are actually magnified.

In general, anchoring effects play an important role in consumer decision-making about algorithms, and regulators should account for this when determining policy. Next, the final Part concludes by exploring the implications of the complex, often subtle consumer preferences elucidated above for policy choices about algorithmic governance.

CONCLUSION

The preceding Parts reviewed the results of this Article's study, how the authors obtained them, and the shortcomings in the conventional scholarly wisdom about algorithms in decision making ecosystems. The Article concludes with a few suggestions for future research and policymaking.

First, the received wisdom from legal scholars is that people do not want algorithms making decisions affecting them—we always want a human in the loop, even if that preference is irrational in utilitarian terms.[198] People are, in other words, boundedly rational.[199] There is a point at which we no longer want to weigh the costs and benefits of different regulatory schemes, but instead simply want to trust other humans to arrive at the correct judgment in a given situation. This Article's empirical findings show that conclusion to be ill-founded. People are highly rational, in the classical sense, when evaluating their options as to who decides their fate, at least in relatively ordinary situations.[200] The conventional wisdom is that we object to algorithms on principle.[201] The reality is that people want to know concrete

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198. *See* Brennan-Marquez & Henderson, *supra* note 14; PASQUALE, *supra* note 47; Ric Simmons, *Big Data, Machine Judges, and the Legitimacy of the Criminal Justice System*, 52 U.C. DAVIS L. REV. 1067, 1070–71 (2018) (claiming "[o]rdinary people have shown reluctance to embrace predictive algorithms that make significant decisions in other contexts").

199. *See, e.g.*, Russell Korobkin, *Bounded Rationality, Standard Form Contracts, and Unconscionability*, 70 U. CHI. L. REV. 1203, 1243 (2003).

200. *See generally* Gregory Mitchell, *Why Law and Economics' Perfect Rationality Should Not Be Traded for Behavioral Law and Economics' Equal Incompetence*, 91 GEO. L.J. 67 (2002).

201. *See* Simmons, *supra* note 198.

details: how accurate is a given judgment methodology; how much does it cost; and how quickly will it render a decision?

Second, people's views on how and whether algorithms ought to be part of decision-making systems should factor into relevant regulatory decisions. Consumer preferences might be right, wrong, or path-dependent, but they deserve more weight in policy decisions than they currently receive.[202] The scholarly legal literature tends to skip past what actual people want and to move directly to what the author prefers. That is a mistake for at least three reasons. The first is scholarly humility: legal researchers do not always know best what will improve people's lives.[203] The second is public choice: proposed reforms that contravene popular attitudes face an uphill climb.[204] Even if merely for instrumental reasons, legal scholars ought to consider extant preferences for including algorithms in decision structures. The only way to implement this, of course, is to assess these attitudes empirically. And the third is that, even if consumer preferences are utterly misguided, they at least help map the distance to travel to reach a preferred state of the world.[205] It is important to know the state of play—either to assess how far policy must travel to achieve a given goal, or to decide what regulatory choices to make in the first instance.

Third, regulatory decisions about algorithms potentially have broad sweep. This Article's findings implicate consumer law, privacy law, contract doctrine, torts, and administrative rulemaking among other areas. The Article's results are cross-cutting because the role of formulas run by software in the age of Big Data affects an array of regulatory regimes.[206] Consumer preferences about algorithms do not fit neatly into any single

202. One response from philosophers is to emphasize adaptive preferences: the tendency for humans to alter their perceptions and desires to adapt to current conditions, especially ones of deprivation. *See* Martha C. Nussbaum, S*ymposium on Amartya Sen's Philosophy: 5 Adaptive Preferences and Women's Options*, 17 ECON. & PHIL. 67, 80 (2001); Amartya Sen, *Gender Inequality and Theories of Justice*, *in* WOMEN, CULTURE, & DEVELOPMENT: A STUDY OF HUMAN CAPABILITIES 259, 270 (Martha C. Nussbaum & Jonathan Glover eds., 1995). Even if this theory is correct, its implications for this study are unclear: current decision-making systems vary tremendously in the degree to which they incorporate algorithms, so it is not obvious to what people would be adapting. We believe that consumer preferences remain important guideposts, especially in a rapidly changing technological environment.

203. *See* Nicolas Cornell, *A Third Theory of Paternalism*, 113 MICH. L. REV. 1295, 1314–18 (2015); Mario J. Rizzo & Douglas Glen Whitman, *The Knowledge Problem of New Paternalism*, 2009 BYU L. REV. 905, 910 (2009).

204. *See, e.g.*, David Adam Friedman, *Public Health Regulation and the Limits of Paternalism*, 46 CONN. L. REV. 1687, 1745 (2014).

205. We thank Brett Frischmann for elucidating this point.

206. *See* Ignacio N. Cofone, *Algorithmic Discrimination Is an Information Problem*, 70 HASTINGS L.J. 1389, 1391 (2019); Katyal, *supra* note 27, at 60.

category of legal doctrine.[207] But ignoring them is malpractice in a range of areas.

Fourth, if reform of the decision-making roles of algorithms is necessary, this Article's findings can help point the way forward. One important threshold question is whether and when concerns arise about automated decisions. Early in the information age, many people were skeptical about allowing computers to have input into important decisions like selecting a mate. But from 2005 to 2013, the fraction of adults who agreed that online dating is a good way to meet people increased from 44% to 59%, and 30% of all adults have used an online dating site or application.[208] People have grown accustomed to having algorithms recommend Web sites,[209] suggest products to purchase,[210] select who will have their taxes audited by the Internal Revenue Service,[211] give them driving directions,[212] and offer to make social

207. *See* sources cited *supra* note 206; Philip Sales, *Algorithms, Artificial Intelligence, and the Law*, 105 JUDICATURE 23, 30–33 (2021).

208. Emily A. Vogels, *10 Facts About Americans and Online Dating*, PEW RSCH. CTR. (Feb. 6, 2020), https://www.pewresearch.org/fact-tank/2020/02/06/10-facts-about-americans-and-online-dating/ [https://perma.cc/BP88-UVLZ]; Aaron Smith & Maeve Duggan, *Online Dating & Relationships*, PEW RSCH. CTR. (Oct. 21, 2013), https://www.pewresearch.org/internet/2013/10/21/online-dating-relationships/ [https://perma.cc/RZ7S-WHX6].

209. *See* Kimberly Collins, *Google's PageRank Algorithm, Explained*, SEARCH ENGINE WATCH (Oct. 25, 2018), https://www.searchenginewatch.com/2018/10/25/googles-pagerank-algorithm-explained/ [https://perma.cc/Z8Q2-LL6N]; Eric Goldman, *What Would Happen If Search Engines Had to Give Higher Visibility to Less Relevant Results?*, TECH. & MKTG. L. BLOG (May 19, 2021), https://blog.ericgoldman.org/archives/2021/05/what-would-happen-if-search-engines-had-to-give-higher-visibility-to-less-relevant-results.htm [https://perma.cc/9SJ9-UZXH]; Bin Han, Chirag Shah, & Daniel Saelid, *Users' Perception of Search Engine Biases and Satisfaction* (May 6, 2021), https://arxiv.org/pdf/2105.02898.pdf [https://perma.cc/YYT5-9TNU].

210. *See* Brent Smith & Greg Linden, *Two Decades of Recommender Systems at Amazon.com*, 21 IEEE INTERNET COMPUTING 12 (2017); Dokyun Lee, Kartik Hosanagar, & Harikesh Nair, *Advertising Content and Consumer Engagement on Social Media: Evidence from Facebook*, 64 MGMT. SCI. 5105, 5129 (2018).

211. *See* Jeff Butler, *Analytical Challenges in Modern Tax Administration: A Brief History of Analytics at the IRS*, 16 OHIO ST. TECH. L.J. 258, 259 (2020); Kimberly A. Houser & Debra Sanders, *The Use of Big Data Analytics by the IRS: Efficient Solutions or the End of Privacy as We Know It?*, 19 VAND. J. ENT. & TECH. L. 817, 820 (2017).

212. *See* Riley Panko, *The Popularity of Google Maps: Trends in Navigation Apps in 2018*, THE MANIFEST (July 10, 2018), https://themanifest.com/mobile-apps/popularity-google-maps-trends-navigation-apps-2018 [https://perma.cc/V3C2-NUEC]; Michael Byrne, *The Simple, Elegant Algorithm That Makes Google Maps Possible*, VICE (Mar. 22, 2015), https://www.vice.com/en/article/4x3pp9/the-simple-elegant-algorithm-that-makes-google-maps-possible [https://perma.cc/C6V3-S4HL].

connections for them.[213] Our results demonstrate that people are more accepting of algorithms than mainstream legal scholarship would suggest (or admit).

In addition, the Article can help suggest the form that policy interventions should take. Its data offer guidance on when people—at least given current preferences—favor algorithms, and when they want a human in the loop. The results also focus attention on the algorithms' competitors. The error rate of the alternative—humans—matters.[214] When pressing for transparency in algorithmic decision making, critics should be cognizant that consumers also value transparency in human decision making and may well prefer an accurate algorithm to an inaccurate human.[215] And transparency may take a different form than typically considered: it could involve entities that use algorithms explaining how the formulas benefit the subjects of decisions, rather than going into detail about the mechanics of the algorithm itself.[216] As this study's findings show, people care a great deal when informed that an algorithm gets them faster, more accurate, or more lucrative outcomes.

Fifth, much of the current debate in legal scholarship over algorithms may result from participants talking past one another. This Article's results show that consumers prefer algorithms when they offer concrete advantages—when algorithms are faster, less expensive, and more accurate. Designers and programmers are undoubtedly aiming for these goals as well.[217] We contend they should be evaluated on how well they achieve these objectives. But both this Article's empirical work and the mine run of algorithmic decision-making take place in situations that matter to people, yet do not involve singular consequences. For some decisions, the outcome is so weighty or meaningful that ordinary cost-benefit analysis ought to be inapplicable.[218] This position seems uncontroversial. Yet this distinction between the

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213. *See* Courtney Johnson, *The Linkedin Algorithm Explained + How To Make It Work for You*, LINKEDIN (Nov. 18, 2019), https://www.linkedin.com/pulse/linkedin-algorithm-explained-how-make-work-you-courtney-johnson [https://perma.cc/D2KQ-RLBA]; Elle Hunt, *How Does Facebook Suggest Potential Friends? Not Location Data–Not Now*, GUARDIAN (June 28, 2016), https://www.theguardian.com/technology/2016/jun/29/how-does-facebook-suggest-potential-friends-not-location-data-not-now [https://perma.cc/8FKC-XXQ3].

214. *See* Huq, *supra* note 49, at 640.

215. *See id.* at 643–46.

216. *Cf.* Cary Coglianese & David Lehr, *Transparency and Algorithmic Governance*, 71 ADMIN. L. REV. 1, 21–22, 47–50 (2019) (describing reasoned transparency, which "emphasizes the usefulness of [given] information").

217. *See generally* Nicolas Terry, *Of Regulating Healthcare AI and Robots*, 18 YALE J. HEALTH POL'Y L. & ETHICS 133, 168 (2019) (noting that "[r]ecently there has been progress in programming AI to improve ethical and other hard choices").

218. *See, e.g.*, Andrea Roth, *Machine Testimony*, 126 YALE L.J. 1972 (2017); Huq, *supra* note 22; Berman, *supra* note 89, at 1290–92.

mundane and the sacred may elude both sides of the debate. Those who create algorithms overestimate the desire for speed and technical accuracy in high stakes situations.[219] Their critics underestimate the value of speed and accuracy in lower states situations. Much would be gained by distinguishing carefully between how society determines a fifteen dollar gift card drawing versus a sentence to life in prison.

Sixth, the default choice matters. Concerns about blind acceptance of algorithmic choices are warranted because the anchoring effect is real.[220] This is one of the less flattering results from this study, at least for those who prefer to regard humans as generally careful, rational decisionmakers. People are often ruled by default settings.[221] They prefer initial allocations, even when these assignments are random: post hoc, ergo propter hoc. This finding illuminates one of this Article's key cautions. Suboptimal selections may be sticky.[222] Getting policy decisions right in the first instance is important. There are no shortcuts: sometimes people prefer algorithms; sometimes they prefer humans; and sometimes preferences are irrelevant because policymakers ought to override people's views.[223] Systems with a dominant anchoring effect may provide a good example of the last set of circumstances. Alternatively, if a human-centric system and an algorithmic-centric one work equally well, then anchoring is irrelevant and random allocation may be an efficient mechanism. Path dependency may shape collective expectations about algorithms. And while people may not prefer algorithms as the default, they may ultimately opt for them depending on the formulas' quality relative to the quality of the alternative.

But this Article also provides a blueprint for breaking through the inertia of default choices: providing consumers with relevant, accurate information

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219. In criminal trials, for example, the Fourth Amendment prevents the prosecution from introducing improperly obtained evidence, even if that evidence is highly probative and reliable. Accuracy thus yields to concerns about deterrence of misconduct and procedural fairness. *See* U.S. CONST. amend. IV; Michael L. Rich, *Machine Learning, Automated Suspicion Algorithms, and the Fourth Amendment*, 164 U. PA. L. REV. 871, 879, 925–926 (2016).

220. *See generally* Jennifer M. Logg et al., *Do People Trust Algorithms More Than Companies Realize?*, HARV. BUS. REV. (Oct. 26, 2018), https://hbr.org/2018/10/do-people-trust-algorithms-more-than-companies-realize [https://perma.cc/U925-26Y3] (finding that "people are often comfortable accepting guidance from algorithms, and sometimes even trust them more than other people.").

221. *See* Yuval Feldman et al., *Anchoring Legal Standards*, 13 J. EMPIRICAL LEGAL STUD. 298, 299 (2016).

222. *See* Cass R. Sunstein, *Choosing Not To Choose*, 64 DUKE L.J. 1, 4 (2014).

223. For a proposal supporting overrides of consumer preferences because of cognitive bias concerns, see Adam S. Zimmerman, *Funding Irrationality*, 59 DUKE L.J. 1105 (2010).

(along with meaningful choice, of course).[224] When confronted with information about the alternatives, people are capable of choosing the better option.[225] However, regulators must remain wary about whether the alternative is actually superior (and whether it is perceived that way even if it is not[226]).

Finally, the Article can help set realistic expectations for any reform that is undertaken. Canonizing humans as decisionmakers is foolish: people are biased, opaque, and remarkably capable of justifying their actions after the fact.[227] De-automating decisions will have real costs, not only for efficiency, but potentially for other important values like transparency, accountability, self-governance, equality, and consistency.[228] The baseline is not the better angels of our nature; it is more likely to be Josef K.'s bureaucrats.[229] Legitimate reform efforts must acknowledge the tradeoffs involved in different decision-making systems and give a rigorous accounting for why we ought to prefer one regime to another. This Article offers a starting point for that effort.

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224. *See generally* Daniel D. Barnhizer, *Inequality of Bargaining Power*, 76 U. COLO. L. REV. 139 (2005) (outlining the reality of inequality of bargaining power and how courts should adapt to ensure fairness in contracting and contract disputes).

225. *See* Karen Bradshaw Schulz, *Information Flooding*, 48 IND. L. REV. 755, 762–64 (2015).

226. *See* Rizzo & Whitman, *supra* note 203, at 922.

227. *See* Jolls et al., *supra* note 134, at 1541–42; Jeffrey J. Rachlinski, *A Positive Psychological Theory of Judging in Hindsight*, 65 U. CHI. L. REV. 571, 571–72 (1998).

228. *See* Cary Coglianese & Erik Lampmann, *Contracting for Algorithmic Accountability*, 6 ADMIN. L. REV. ACCORD 175 (2021).

229. *See* FRANZ KAFKA, THE TRIAL (1925).

APPENDIX A: SURVEY VIGNETTES

This Appendix provides the text of the vignettes used in the study's survey as presented to respondents. Conceptually, it is structured like a menu: the Qualtrics survey software randomly selected one of the four scenario variable options (vignettes) and an initial decisionmaker (human or algorithm), then randomly chose and presented variable options for the price, speed, error rates (for both types of decisionmaker), and information accessible (public only, or public plus private personal data) for that decisionmaker. Next, the software administered an attention check question. Finally, it asked the respondent whether they wanted to stay with the initially assigned decisionmaker or switch to the other alternative. The variables in each selection are contained below in brackets. So, if a given variable has several options in brackets, the Qualtrics software would randomly select one of those options to present to the user. In some cases, variable options are embedded in text, where they are separated by a slash. Thus, for example, the description "You will receive [A / B]" means that the participant saw either "You will receive A" or "You will receive B," with the survey software randomly selecting between the two (A or B). This Appendix appends an example of a complete vignette at the end to make the overall structure clear. Note that the initial assignment was given right before the error rate, rather than right after the vignette as portrayed below for readability.

A. Scenario Variable / Vignette Descriptions (4 Options)

1. Credit

You have applied for a $20,000 loan from your bank to finance the purchase of a new car. While your credit history is not perfect, you believe that you should qualify for the loan, and you need the car. The bank discloses that it uses two different methods for evaluating whether to extend credit to an applicant. One method involves a bank employee—a human—who reviews the application and associated information, and then makes a decision based on his/her experience. The other method involves a specialized computer software program—an algorithm—that reviews the application and associated information, and then makes a decision based on a set of variables built into the program. The bank will randomly assign your application either to a human employee or to the algorithm, but you will have the opportunity to switch (from a human to an algorithm, or vice versa) if you want to do so.

You learn that the bank has randomly assigned your application to [a human / an algorithm].

2. Health care

After a routine visit to your doctor, you learn that you have a rare blood disorder. The consequences of the disorder vary—for some people, they are mild, and for some, they can be serious and even life-threatening. The standard drug treatment for the disorder reduces symptoms to a small extent, but does not eliminate them. Your doctor tells you that a drug company is running a clinical trial for a new drug to treat your disorder. Early results are very promising: most patients who take the new drug become symptom-free. You would like to be symptom-free, and so you apply to take part in the clinical trial.

The drug company discloses that it uses two different methods for evaluating whether to allow a patient to join the clinical trial. One method involves a company employee—a human—who reviews the application and associated information, and then makes a decision based on his/her experience. The other method involves a specialized computer software program—an algorithm—that reviews the application and associated information, and then makes a decision based on a set of variables built into the program. The drug company will randomly assign your application either to a human employee or to the algorithm, but you will have the opportunity to switch (from a human to an algorithm, or vice versa) if you want to do so.

You learn that the drug company has randomly assigned your application for the clinical trial to [a human / an algorithm].

3. Traffic offense (civil)

Recently, you were stopped by a police officer on your way home from work. The officer issued you a ticket, claiming that you failed to stop completely at a stop sign. The ticket imposes a civil fine, but no criminal liability. While it was close, you feel you came to a stop in the same way that most drivers do (commonly known as a "rolling stop," where the car does not completely cease motion, but nearly does so, allowing the driver to evaluate traffic before proceeding). Thus, you decide to contest the ticket.

The traffic court in your area uses two different methods for deciding cases that involve alleged traffic violations. (There are no trials for traffic violations, only reviews of information submitted by the motorist and by the police officer involved.) One method involves a traffic court judge—a human—who reviews the ticket and associated information, and then makes a decision based on his/her experience. The other method involves a specialized computer software program—an algorithm—that reviews the ticket and associated information, and then makes a decision based on a set of variables built into the program. The traffic court will randomly assign your application either to a human employee or to the algorithm, but you will have the opportunity to switch (from a human to an algorithm, or vice versa) if you want to do so.

You learn that the traffic court has randomly assigned your challenge to the ticket to [a human/an algorithm].

4. Gift card

Every morning before work, you have coffee at your favorite neighborhood coffee shop. You are one of their most frequent customers. This month, the coffee shop is offering a gift card to the winner of its "Best Customer" contest. Because you think you are the shop's best customer, you enter your name in the contest.

The coffee shop discloses that it uses two different methods for evaluating who is its "best customer." One method involves an employee—a human—who reviews the entries and associated information, and then makes a decision based on his/her experience. The other method involves a specialized computer software program—an algorithm—that reviews the entries and associated information, and then makes a decision based on a set of variables built into the program. The coffee shop will randomly assign your application either to a human employee or to the algorithm, but you will have the opportunity to switch (from a human to an algorithm, or vice versa) if you want to do so.

You learn that the coffee shop has randomly assigned your application to [a human/an algorithm].

B. Pricing Variable (Two Options)

1. Credit

[The loan interest rate is 4%, if you are able to obtain the loan.]

[Because the algorithm is cheaper, if you obtain the loan using the algorithm, the interest rate will be 3%. If you obtain the loan using a human processor, the interest rate will be 5%. Of course, you may not obtain the loan at all.]

2. Health care

[Because this is a new drug, the cost will be $150, if you are selected into the trial.]

[Because the algorithm is cheaper, if you are selected into the trial using that method, the cost will be $100. If you are selected into the trial when a human decides, it cost $200. Of course, if you are not selected into the trial, you will not have to pay any money.]

3. Traffic Offense (civil)

[The fine is $250, if you lose the challenge.]

[Because the algorithm is cheaper, if you lose and the algorithm decides, the fine will be $200. If you lose and a human decides, the fine will be $300. Of course, if you win, you won't have any fine at all.]

4. Gift Card

[The gift card is $15, if you win it.]

[Because the algorithm is cheaper, if you get the gift card using that method, it will be $20. If you get the gift card when a human decides, it will be $10. Of course, if you do not win the gift card, you won't get any amount at all.]

C. Speed Variable (Two Options)

[Each method will take the same amount of time to process.]

[The algorithm allows for much faster processing. If you use an algorithm, you will receive a decision (one way or the other) in two hours. If you choose a human, you will receive your decision in five days.]

D. Error Rate Variable (Three Options for Each Decisionmaker)[230]

[You learn that algorithms are fairly inaccurate based on past performance.]

[You learn that algorithms are fairly accurate based on past performance.]

[You don't know anything about the accuracy of algorithms based on past performance.]

[You learn that humans are fairly inaccurate based on past performance.]

230. Each respondent received one algorithm error rate and one human error rate.

[You learn that humans are fairly accurate based on past performance.]
[You don't know anything about the accuracy of humans based on past performance.]

E. Information Used by Decisionmaker Variable (Two Options)

[To make this choice, the decisionmaker can access and use only publicly-available information about you, such as what a search on Google would uncover.]
[To make this choice, the decisionmaker can access and use publicly-available information about you, such as what a search on Google would uncover, as well as private information, such as whether you pay your bills on time and whether you have ever been fired from a job.]

F. Attention Check Question

What were you initially assigned?
(The participant chooses via a radio button with two options: "a human" or "the algorithm".)

G. Survey Prompt to Respondent[231]

Do you want to:
(The participant chooses via a radio button with two options: "Keep it?" or "Switch?" These options refer to the initially assigned decisionmaker the respondent just selected.)

H. Complete Sample Vignette

You have applied for a $20,000 loan from your bank to finance the purchase of a new car. While your credit history is not perfect, you believe that you should qualify for the loan, and you need the car. The bank discloses that it uses two different methods for evaluating whether to extend credit to an applicant. One method involves a bank employee—a human—who reviews the application and associated information, and then makes a decision based on his/her experience. The other method involves a specialized computer software program—an algorithm—that reviews the

231. This question appeared on the same screen as the attention check question. If the respondent answered the attention check question incorrectly, their answer to this question lost validity. Any survey with that error was excluded from the dataset.

application and associated information, and then makes a decision based on a set of variables built into the program. The bank will randomly assign your application either to a human employee or to the algorithm, but you will have the opportunity to switch (from a human to an algorithm, or vice versa) if you want to do so.

The loan interest rate is 4%, if you are able to obtain the loan.

The algorithm allows for much faster processing. If you use an algorithm, you will receive a decision (one way or the other) in two hours. If you choose a human, you will receive your decision in five days.

You learn that the bank has randomly assigned your application to an algorithm.

You learn that algorithms are fairly accurate based on past performance.

You don't know anything about the accuracy of humans based on past performance.

To make this choice, the decisionmaker can access and use only publicly available information about you, such as what a search on Google would uncover.

APPENDIX B: PROBABILITY MARGINS

This Appendix shows all the varying probability margins presented in the text. For ease of comprehension, we do not present standard errors and p-values. In virtually every case, the result was p<.0.000.

Table 5 - Probability That Respondents Select Decisionmaker By Error Rate

Decisionmaker Choice#Error Rate	**Human Error**	**Algorithmic Error**	**Both**
algorithm#Human High	66.8%		
algorithm#Human Low	41.1%		
algorithm#Human Unknown	48.9%		
human#Human High	33.2%		
human#Human Low	58.9%		
human#Human Unknown	51.2%		
algorithm#Algorithm High		37.0%	
algorithm#Algorithm Low		65.8%	
algorithm#Algorithm Unknown		53.7%	
human#Algorithm High		63.0%	
human#Algorithm Low		34.2%	
human#Algorithm Unknown		46.3%	
algorithm#Human High#Algo High			52.0%
algorithm#Human High#Algo Low			79.2%
algorithm#Human High#Algo Unk			68.9%
algorithm#Human Low#Algo High			26.0%
algorithm#Human Low#Algo Low			55.1%
algorithm#Human Low#Algo Unk			42.0%
algorithm#Human Unk#Algo High			33.0%
algorithm#Human Unk#Algo Low			63.1%
algorithm#Human Unk#Algo Unk			50.2%
human#Human High#Algo High			48.0%
human#Human High#Algo Low			20.8%
human#Human High#Algo Unk			31.1%
human#Human Low#Algo High			74.0%
human#Human Low#Algo Low			44.9%
human#Human Low#Algo Unk			58.0%
human#Human Unk#Algo High			67.0%
human#Human Unk#Algo Low			36.9%
human#Human Unk#Algo Unk			49.8%

Table 6 - Probability That Respondents Select Decisionmaker When Both Human and Algorithm Error Rates Unknown

(Decisionmaker#) Human Error#Algo Error#Price#Time	Prob.	Std. Err.	Z	P>|z|	[95% Conf.	Interval]
algorithm#Human Unk#Algo Unk#Same#Same	34.8%	.019	18.00	0.000	.310	.386
human#Human Unk#Algo Unk#Same#Same	65.2%	.019	33.72	0.000	.614	.690

Table 7 - Probability That Respondents Select Decisionmaker By Pricing, Speed, and Vignette

Decisionmaker Choice #Option	**Price**	**Speed**	**Speed by Vignette**
algorithm#cheaper	61.6%		
algorithm#same	42.7%		
human#cheaper	38.4%		
human#same	57.3%		
algorithm#faster		56.7%	
algorithm#same		47.8%	
human#faster		43.4%	
human#same		52.2%	
algorithm#faster#Bank Loan			62.8%
algorithm#faster#Civil Traffic			48.5%
algorithm#faster#Gift Card			60.8%
algorithm#faster#Health Care			54.9%
algorithm#same#Bank Loan			54.1%
algorithm#same#Civil Traffic			39.6%
algorithm#same#Gift Card			52.0%
algorithm#same#Health Care			45.9%
human#faster#Bank Loan			37.2%
human#faster#Civil Traffic			51.5%
human#faster#Gift Card			39.2%
human#faster#Health Care			45.1%
human#same#Bank Loan			45.9%
human#same#Civil Traffic			60.4%
human#same#Gift Card			48.0%
human#same#Health Care			54.1%

Table 8 - Probability That Respondents Select Decisionmaker By Type of Information Used

Decisionmaker Choice#Info Type	**Probability**
algorithm#Private+Public	52.9%
algorithm#Public Only	51.4%
human#Private+Public	47.1%
human#Public Only	48.6%

Table 9 - Probability That Respondents Select Decisionmaker By Initial Assignment

Decisionmaker Choice#Initial Assignment	**Probability**
algorithm#human	41.7%
algorithm#algorithm	62.4%
human#human	58.3%
human#algorithm	37.6%

Table 10 - Probability That Respondents Select Algorithm
By Initial Assignment and Other Variables

Final Decisionmaker#Initial Assignment#Option	**Price**	**Speed**	**Error Rate**
algorithm#human#lower	51.4%		
algorithm#human#same	32.1%		
algorithm#algorithm#lower	71.7%		
algorithm#algorithm#same	53.0%		
human#human#lower	48.6%		
human#human#same	67.9%		
human#algorithm#lower	28.3%		
human#algorithm#same	47.0%		
algorithm#human#faster		46.3%	
algorithm#human#same		37.3%	
algorithm#algorithm#faster		66.8%	
algorithm#algorithm#same		58.1%	
human#human#faster		53.7%	
human#human#same		62.7%	
human#alogrithm#faster		33.2%	
human#algorithm#same		41.9%	
algorithm#human#Human High#Algo High			40.4%
algorithm#human#Human High#Algo Low			71.5%
algorithm#human#Human High#Algo Unk			58.9%
algorithm#human#Human Low#Algo High			17.0%
algorithm#human#Human Low#Algo Low			43.5%
algorithm#human#Human Low#Algo Unk			30.7%
algorithm#human#Human Unk#Algo High			22.7%
algorithm#human#Human Unk#Algo Low			52.2%
algorithm#human#Human Unk#Algo Unk			38.6%
algorithm#algorithm#Human High#Algo High			63.4%
algorithm#algorithm#Human High#Algo Low			86.8%
algorithm#algorithm#Human High#Algo Unk			78.8%
algorithm#algorithm#Human Low#Algo High			34.8%
algorithm#algorithm#Human Low#Algo Low			66.4%
algorithm#algorithm#Human Low#Algo Unk			53.1%
algorithm#algorithm#Human Unk#Algo High			43.1%
algorithm#algorithm#Human Unk#Algo Low			73.8%
algorithm#algorithm#Human Unk#Algo Unk			61.6%
human#human#Human High#Algo High			59.6%
human#human#Human High#Algo Low			28.5%
human#human#Human High#Algo Unk			41.1%

human#human#Human Low#Algo High	83.0%
human#human#Human Low#Algo Low	56.5%
human#human#Human Low#Algo Unk	69.4%
human#human#Human Unk#Algo High	77.3%
human#human#Human Unk#Algo Low	47.8%
human#human#Human Unk#Algo Unk	61.4%
human#algorithm#Human High#Algo High	36.6%
human#algorithm#Human High#Algo Low	13.2%
human#algorithm#Human High#Algo Unk	21.3%
human#algorithm#Human Low#Algo High	65.2%
human#algorithm#Human Low#Algo Low	33.6%
human#algorithm#Human Low#Algo Unk	46.9%
human#algorithm#Human Unk#Algo High	56.9%
human#algorithm#Human Unk#Algo Low	26.2%
human#algorithm#Human Unk#Algo Unk	38.4%