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The Algorithmic Divide and Equality in the Age of Artificial Intelligence

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Abstract

In the age of artificial intelligence, highly sophisticated algorithms have been deployed to provide analysis, detect patterns, optimize solutions, accelerate operations, facilitate self-learning, minimize human errors and biases, and foster improvements in technological products and services. Notwithstanding these tremendous benefits, algorithms and intelligent machines do not provide equal benefits to all. Just as the "digital divide" has separated those with access to the Internet, information technology, and digital content from those without, an emerging and ever-widening "algorithmic divide" now threatens to take away the many political, social, economic, cultural, educational, and career opportunities provided by machine learning and artificial intelligence. Although policy makers, commentators, and the mass media have paid growing attention to algorithmic bias and the shortcomings of machine learning and artificial intelligence, the algorithmic divide has yet to attract much policy and scholarly attention. To fill the lacuna, this Article draws on the digital divide literature to systematically analyze this new inequitable gap between the technology haves and have-nots. Utilizing an analytical framework that the Author developed in the early 2000s, the Article discusses the five attributes of the algorithmic divide: awareness, access, affordability, availability, and adaptability. This Article then turns to three major problems precipitated by an emerging and fast-expanding algorithmic divide: algorithmic deprivation, algorithmic discrimination, and algorithmic distortion. This Article concludes by proposing seven non-exhaustive clusters of remedial actions to help bridge this emerging and ever-widening divide. Combining law, communications policy, ethical principles, institutional mechanisms, and business practices, the Article fashions a holistic response to foster equality in the age of artificial intelligence.

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INTRODUCTION

In the age of artificial intelligence (AI), highly sophisticated algorithms[1] have been deployed to provide analysis, detect patterns, optimize solutions, accelerate operations, facilitate self-learning, minimize human errors and biases, and foster improvements in

1. As the U.S. Public Policy Council of the Association for Computing Machinery explained:

> An algorithm is a self-contained step-by-step set of operations that computers and other "smart" devices carry out to perform calculation, data processing, and automated reasoning tasks. Increasingly, algorithms implement institutional decision-making based on analytics, which involves the discovery, interpretation, and communication of meaningful patterns in data. Especially valuable in areas rich with recorded information, analytics relies on the simultaneous application of statistics, computer programming, and operations research to quantify performance.

ASS'N FOR COMPUTING MACH. U.S. PUB. POLICY COUNCIL, STATEMENT ON ALGORITHMIC TRANSPARENCY AND ACCOUNTABILITY 1 (2017) [hereinafter ACM STATEMENT], https://www.acm.org/binaries/content/assets/public-policy/2017_usacm_statement_algorithms.pdf [https://perma.cc/8DK3-ZHMY].

technological products and services.[2] As Pedro Domingos observed in the opening of his best-selling book, *The Master Algorithm*:

> You may not know it, but machine learning is all around you. When you type a query into a search engine, it's how the engine figures out which results to show you (and which ads, as well). When you read your e-mail, you don't see most of the spam, because machine learning filtered it out. Go to Amazon.com to buy a book or Netflix to watch a video, and a machine-learning system helpfully recommends some you might like. Facebook uses machine learning to decide which updates to show you, and Twitter does the same for tweets. Whenever you use a computer, chances are machine learning is involved somewhere.[3]

Indeed, without the enhancements that algorithms provide, machines will not be able to acquire the "intelligence" needed to effectively function in today's fast-evolving technological environment.[4]

Despite the tremendous promise of machine learning and artificial intelligence, algorithms and intelligent machines do not provide equal

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2. *See id.* ("Computer algorithms are [now] widely employed throughout our economy and society to make decisions that have far-reaching impacts, including their applications for education, access to credit, healthcare, and employment."); VIRGINIA EUBANKS, AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR 9 (2017) ("Digital tracking and decision-making systems have become routine in policing, political forecasting, marketing, credit reporting, criminal sentencing, business management, finance, and the administration of public programs."); NAT'L SCI. & TECH. COUNCIL, THE NATIONAL ARTIFICIAL INTELLIGENCE RESEARCH AND DEVELOPMENT STRATEGIC PLAN 3 (2016), https://www.nitrd.gov/pubs/national_ai_rd_strategic_plan.pdf [https://perma.cc/5N4S-VHW4] ("Artificial intelligence . . . is a transformative technology that holds promise for tremendous societal and economic benefit. AI has the potential to revolutionize how we live, work, learn, discover, and communicate."); Sonia K. Katyal, *Private Accountability in the Age of Artificial Intelligence*, 66 UCLA L. REV. 54, 56 (2019) ("Today, algorithms determine the optimal way to produce and ship goods, the prices we pay for those goods, the money we can borrow, the people who teach our children, and the books and articles we read—reducing each activity to an actuarial risk or score."). *See generally* Tarleton Gillespie, *The Relevance of Algorithms*, *in* MEDIA TECHNOLOGIES: ESSAYS ON COMMUNICATION, MATERIALITY, AND SOCIETY 167 (Tarleton Gillespie et al. eds., 2014) (providing an excellent discussion of the role of algorithms in producing and certifying publicly relevant information). For discussions of the transformation provided by the deployment of algorithms, see generally PEDRO DOMINGOS, THE MASTER ALGORITHM: HOW THE QUEST FOR THE ULTIMATE LEARNING MACHINE WILL REMAKE OUR WORLD (2015); CHRISTOPHER STEINER, AUTOMATE THIS: HOW ALGORITHMS CAME TO RULE OUR WORLD (2012).

3. DOMINGOS, *supra* note 2, at xi.

4. *See* Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 GEO. L.J. 1147, 1149 (2017) ("Many products and services, including email spam filters, medical diagnoses, product marketing, and self-driving cars, . . . depend on machine-learning algorithms and their ability to deliver astonishing forecasting power and speed." (footnotes omitted)).

benefits to all[5]—or, for that matter, all countries across the world.[6] Just as the "digital divide" has separated those with access to the Internet, information technology, and digital content from those without,[7] an emerging and ever-widening "algorithmic divide" now prevents a large segment of the population—in both developed and developing countries—from enjoying access to machine learning and artificial intelligence. Without such access, those who are on the unfortunate side of the divide will miss out on the many political, social, economic, cultural, educational, and career opportunities provided by machine learning and artificial intelligence. Even worse, the lack of access to these technologies will trigger a vicious cycle in which the technology rich will get richer and the gap between the have and have-nots will widen even further.[8]

Although policy makers, commentators, and the mass media have paid growing attention to algorithmic bias[9] and the shortcomings of machine learning and artificial intelligence, the algorithmic divide has yet

5. *See* discussion *infra* Section II.A (discussing algorithmic deprivation).

6. As the International Telecommunication Union noted in an issue paper:

> According to the simulation, economies with higher readiness to benefit from AI may achieve absorption levels about 11 percentage points higher than those of slow adopters by 2023, and this gap looks set to widen to about 23 percentage points by 2030. This indicates that like the digital divide, an AI divide may emerge between advanced and developing economies.

INT'L TELECOMM. UNION, ASSESSING THE ECONOMIC IMPACT OF ARTIFICIAL INTELLIGENCE 32 (2018); *see also* GREGG ALLEN & TANIEL CHAN, ARTIFICIAL INTELLIGENCE AND NATIONAL SECURITY 40–41 (2017) (discussing how "[a] country with a significant advantage in AI-based intelligence analysis achieves decisive strategic advantage decision-making and shaping"); JACQUES BUGHIN ET AL., MCKINSEY GLOB. INST., NOTES FROM THE AI FRONTIER MODELING THE IMPACT OF AI ON THE WORLD ECONOMY 1 (2018) ("Those that establish themselves as AI leaders (mostly developed economies) could capture an additional 20 to 25 percent in economic benefits compared with today, while emerging economies may capture only half their upside."); LEE KAI-FU, AI SUPERPOWERS: CHINA, SILICON VALLEY, AND THE NEW WORLD ORDER 169 (2018) (expressing concern about the fast-growing "divide between the AI haves and have-nots"); William J. Magnuson, *Artificial Financial Intelligence*, 9 HARV. BUS. L. REV. (forthcoming 2020) (manuscript at 24), https://ssrn.com/abstract=3403712 [https://perma.cc/26R9-NVE4] (noting the worry about the benefits that artificial intelligence has provided to "actors that have the scientific know-how, research budgets, and access to information that are necessary to develop artificial intelligence systems").

7. *See generally* Peter K. Yu, *Bridging the Digital Divide: Equality in the Information Age*, 20 CARDOZO ARTS & ENT. L.J. 1 (2002) (discussing the digital divide).

8. *See* Ralph Hamann, *Developing Countries Need to Wake Up to the Risks of New Technologies*, CONVERSATION (Jan. 4, 2018, 2:06 AM), https://theconversation.com/developing-countries-need-to-wake-up-to-the-risks-of-new-technologies-87213 [https://perma.cc/YE9H-DPFD] ("Elites within these countries will be more likely to make use of AI and other new technologies. This will further increase returns to capital widening the gap between elites' productive capacity and that of everyone else.").

9. *See* discussion *infra* Section II.B (discussing algorithmic biases).

to attract much policy and scholarly attention.[10] To fill this lacuna, Part I draws on the digital divide literature to systematically analyze this new inequitable gap between the technology haves and have-nots. Utilizing an analytical framework that the Author developed in the early 2000s,[11] this Part discusses the five attributes of the algorithmic divide: (1) awareness; (2) access; (3) affordability; (4) availability; and (5) adaptability.

Part II turns to three major problems precipitated by an emerging and fast-expanding algorithmic divide: (1) algorithmic deprivation; (2) algorithmic discrimination; and (3) algorithmic distortion. While the first two problems affect primarily those on the unfortunate side of the divide, the last problem impacts individuals on both sides. Taken together, all of these problems show that the algorithmic divide has posed challenges not only to the poor, the disadvantaged, and the vulnerable, but to virtually everybody in what Jack Balkin has called an "Algorithmic Society."[12]

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10. Most of the discussions in this area are found in popular media. *See, e.g.*, Jacques Bughin & James Manyika, *Technology Convergence and AI Divides: A Simulation Appraisal*, VOX (Sept. 7, 2018), https://voxeu.org/article/technology-convergence-and-ai-divides [https://perma.cc/5RN6-42WC] (discussing three levels of the artificial intelligence divide: "individuals (workers), companies, and countries" (emphasis omitted)); Cosette Jarrett, *AI Could Be Driving a New Digital Divide*, VENTUREBEAT (Oct. 5, 2017, 2:10 PM), https://venturebeat.com/2017/10/05/ai-could-be-driving-a-new-digital-divide/ [https://perma.cc/TLR2-RVCV] (discussing the corporate artificial intelligence divide); Vyacheslav Polonski, *AI Trust and AI Fears: A Media Debate That Could Divide Society*, MEDIUM (Jan. 9, 2018), https://medium.com/@drpolonski/ai-trust-and-ai-fears-a-media-debate-that-could-divide-society-52e16a74c979 [https://perma.cc/L3Y9-R3CE] (discussing the divide between those who trust artificial intelligence and those who do not); Anjana Susarla, *The New Digital Divide Is Between People Who Opt Out of Algorithms and People Who Don't*, CONVERSATION (Apr. 17, 2019, 6:54 AM), https://theconversation.com/the-new-digital-divide-is-between-people-who-opt-out-of-algorithms-and-people-who-dont-114719 [https://perma.cc/PH84-V2BP] (discussing the digital divide between those who opt out of algorithms and those who do not). A rare exception is a white paper released by the International Development Research Centre:

> This AI divide transcends geographic, socio-economic, gender, and race boundaries. The infrastructure required for the development of AI applications restricts this activity, for the most part, to locales with sufficient computing power, access to (or resources to collect) relevant data, and the requisite AI skills. The geography of the participation gap is perhaps best illustrated by the relative dominance of a few countries (and a few large tech companies) in the development of AI.

MATTHEW L. SMITH & SUJAYA NEUPANE, INT'L DEV. RESEARCH CTR., ARTIFICIAL INTELLIGENCE AND HUMAN DEVELOPMENT: TOWARD A RESEARCH AGENDA 58 (2018), https://www.idrc.ca/sites/default/files/ai_en.pdf [https://perma.cc/MB96-R6V5].

11. *See* Yu, *supra* note 7, at 8–16 (providing the framework).

12. 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, 1219 (2017) (defining "Algorithmic Society" as "a society organized around social and economic decision-making by

Part III proposes seven non-exhaustive clusters of remedial actions to help bridge this emerging and ever-widening divide. To fashion a holistic response to address the three problems identified earlier and taking note of the "multidimensional phenomenon" generated by the algorithmic divide,[13] this Part outlines solutions that combine law, communications policy, ethical principles, institutional mechanisms, and business practices.[14] While it will not be easy to bridge this divide, these solutions strive to ensure greater access to machine learning and artificial intelligence and, in turn, equality in the age of artificial intelligence.

I. ATTRIBUTES

Although the algorithmic divide has not yet garnered much policy and scholarly attention, those commentators who have studied this divide have remarked on the strong resemblance between this new inequitable gap and the earlier digital divide.[15] The latter began attracting considerable interest and attention two and a half decades ago.[16] From the mid-1990s to the early 2000s, the Clinton Administration released four

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algorithms, robots, and AI agents, who not only make the decisions but also, in some cases, carry them out"). Aneesh Aneesh would go further to describe an algorithm-pervasive society as an "algocracy." A. ANEESH, VIRTUAL MIGRATION: THE PROGRAMMING OF GLOBALIZATION 5 (2006) (defining "algocracy" as the "rule of the algorithm[] or [the] rule of the code" and noting that such governance structure is "the key difference between the current and previous rounds of global integration"). *See generally* Coglianese & Lehr, *supra* note 4 (discussing whether the use of machine-learning algorithms, robotic decision tools, and artificial intelligence by government agencies can pass muster under core administrative and constitutional law doctrines).

13. *Cf.* PIPPA NORRIS, DIGITAL DIVIDE: CIVIC ENGAGEMENT, INFORMATION POVERTY, AND THE INTERNET WORLDWIDE 4 (2001) (calling for "the concept of the digital divide [to be] understood as a multidimensional phenomenon encompassing three distinct aspects"—namely the "global divide," the "social divide," and the "democratic divide"); JAN A.G.M. VAN DIJK, THE DEEPENING DIVIDE: INEQUALITY IN THE INFORMATION SOCIETY 3 (2005) (conceiving of the digital divide "as a social and political problem, not a technological one").

14. *See* INST. ELEC. & ELEC. ENG'RS, ETHICALLY ALIGNED DESIGN: A VISION FOR PRIORITIZING HUMAN WELL-BEING WITH AUTONOMOUS AND INTELLIGENT SYSTEMS 58 (2017), https://standards.ieee.org/content/dam/ieee-standards/standards/web/documents/other/ead_v2.pdf [https://perma.cc/389L-CKSW] (noting the need for "meaningful interdisciplinary collaboration" between engineers and designers of autonomous and intelligent systems, on the one hand, and "ethicists, legal scholars, and social scientists, both in academia and industry," on the other).

15. *See* sources cited *supra* note 10 (collecting sources that refer to the algorithmic or artificial intelligence divide as the "new digital divide").

16. *See* VAN DIJK, *supra* note 13, at 1 ("At the end of the 1990s, the issue of the so-called digital divide was suddenly put on the agenda of public, political, and scholarly debate, starting in the United States and spreading to Europe and the rest of the world."); JAN VAN DIJK, THE DIGITAL DIVIDE 1 (2020) ("In the year 2020 both the concept of and the research into the digital divide will be twenty-five years old. In 1995 the term 'digital divide' was first used in a number of newspapers in the United States.").

detailed surveys in a series entitled *Falling Through the Net*.[17] Since then, book-length treatments of the digital divide have been published.[18] Two U.S. law reviews have also organized symposia to explore the topic.[19] While issues relating to the digital divide no longer attract as much attention as they used to, they remain relevant in the public policy debate and come back from time to time, especially around presidential elections.[20]

In the past few years, commentators have begun to pay greater attention to the algorithmic or artificial intelligence divide.[21] Some commentators have recently referred to this divide as the "new digital divide," noting the parallels between this inequitable gap and the earlier

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17. In chronological order, these four surveys were as follows: NAT'L TELECOMMS. & INFO. ADMIN., U.S. DEP'T OF COMMERCE, FALLING THROUGH THE NET: A SURVEY OF THE "HAVE NOTS" IN RURAL AND URBAN AMERICA (1995), https://files.eric.ed.gov/fulltext/ED399126.pdf [https://perma.cc/2HXV-KE2S]; NAT'L TELECOMMS. & INFO. ADMIN., U.S. DEP'T OF COMMERCE, FALLING THROUGH THE NET II: NEW DATA ON THE DIGITAL DIVIDE (1998), https://www.ntia.doc.gov/files/ntia/publications/falling-through-net-ii.pdf [https://perma.cc/M3MK-X8LQ]; NAT'L TELECOMMS. & INFO. ADMIN., U.S. DEP'T OF COMMERCE, FALLING THROUGH THE NET: DEFINING THE DIGITAL DIVIDE (1999), https://www.ntia.doc.gov/legacy/ntiahome/fttn99/FTTN.pdf [https://perma.cc/9ZGE-YMEE]; NAT'L TELECOMMS. & INFO. ADMIN., U.S. DEP'T OF COMMERCE, FALLING THROUGH THE NET: TOWARD DIGITAL INCLUSION (2000) [hereinafter FALLING THROUGH THE NET IV], https://www.ntia.doc.gov/files/ntia/publications/fttn00.pdf [https://perma.cc/Y622-JUZY]. Upon the arrival of the George W. Bush Administration, the digital divide was no longer a key governmental concern. Instead of *Falling Through the Net*, the survey became *A Nation Online*. *See* NAT'L TELECOMMS. & INFO. ADMIN., U.S. DEP'T OF COMMERCE, A NATION ONLINE: HOW AMERICANS ARE EXPANDING THEIR USE OF THE INTERNET (2002); *see also* Yu, *supra* note 7, at 33–35 (noting the comparison made by Federal Communications Commission Chairman Michael Powell of the digital divide to the "Mercedes Divide").

18. *See, e.g.*, RANETA LAWSON MACK, THE DIGITAL DIVIDE: STANDING AT THE INTERSECTION OF RACE & TECHNOLOGY (2001); NORRIS, *supra* note 13; ANNE PEACOCK, HUMAN RIGHTS AND THE DIGITAL DIVIDE (2019); MASSIMO RAGNEDDA, THE THIRD DIGITAL DIVIDE: A WEBERIAN APPROACH TO DIGITAL INEQUALITIES (2017); THE DIGITAL DIVIDE: FACING A CRISIS OR CREATING A MYTH? (Benjamin M. Compaine ed., 2001); THE DIGITAL DIVIDE: THE INTERNET AND SOCIAL INEQUALITY IN INTERNATIONAL PERSPECTIVE (Massimo Ragnedda & Glenn W. Muschert eds., 2013); THEORIZING DIGITAL DIVIDES (Massimo Ragnedda & Glenn W. Muschert eds., 2018); VAN DIJK, *supra* note 13; VAN DIJK, *supra* note 16; MARK WARSCHAUER, TECHNOLOGY AND SOCIAL INCLUSION: RETHINKING THE DIGITAL DIVIDE (2003).

19. Symposium, *Bridging the Digital Divide: Equality in the Information Age*, 20 CARDOZO ARTS & ENT. L.J. 1 (2002); Symposium, *Digital Divide, Digital Opportunities*, 24 HASTINGS COMM. & ENT. L.J. 449 (2002).

20. *See, e.g.*, John Hendel, *Democrats Torch Trump Failures on Rural Digital Divide*, POLITICO (Aug. 17, 2019, 6:37 AM), https://www.politico.com/story/2019/08/17/rural-digital-divide-democratic-candidates-1655290 [https://perma.cc/Z32S-YDMJ] ("Several presidential candidates including Joe Biden, Elizabeth Warren and Pete Buttigieg have rolled out proposals for tens of billions in new federal dollars to bring fast broadband service to rural America, with Warren's $85 billion plan leading the spending pack.").

21. *See* sources cited *supra* note 10 (collecting sources that discuss the algorithmic or artificial intelligence divide).

digital divide.[22] Given the similarities, this Part draws on prior research in the digital divide literature to explore ways to systematically analyze the new algorithmic divide. Specifically, this Part utilizes the analytical framework that this Author developed in the early 2000s to examine the five attributes of the algorithmic divide: (1) awareness; (2) access; (3) affordability; (4) availability; and (5) adaptability.[23]

A. *Awareness*

While those on the unfortunate side of the digital divide can easily notice their being left out of the Internet revolution,[24] especially after the medium entered the mainstream in the mid-1990s, those on the unfortunate side of the algorithmic divide may have greater difficulty discovering their exclusion from machine learning and artificial intelligence.[25] Indeed, many individuals on this unfortunate side may not appreciate how the increased use of machine-learning algorithms and intelligent machines can impact their lives—both positively and negatively. Even among those who take note of these impacts, most will have a very limited understanding of how algorithms actually operate.[26]

In this age of artificial intelligence, individuals—in both developed and developing countries—will need to become more aware of the strengths and drawbacks of algorithm-enhanced technological products and services. While such enhancement enables individuals to do things that they otherwise could not accomplish with traditional computing technology, these new technologies could also backfire when biased

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22. *See, e.g.*, LEE RAINIE & JANNA ANDERSON, CODE-DEPENDENT: PROS AND CONS OF THE ALGORITHM AGE 13 (2017), https://www.pewresearch.org/internet/wp-content/uploads/sites/9/2017/02/PI_2017.02.08_Algorithms_FINAL.pdf [https://perma.cc/F8KA-CU6X] (linking to the digital divide the new divide between those "whose capabilities and perception of the world is augmented by sensors and processed with powerful AI and connected to vast amounts of data" and "those who don't have access to those tools or knowledge of how to utilize them" (quoting Ryan Hayes, Owner, Fit to Tweet)); Jarrett, *supra* note 10 ("There may be a new digital divide forming . . . . As artificial intelligence continues to grow and become more commonplace, some experts fear there may be significant disadvantages for companies—and their employees—who don't have access to AI resources."); Susarla, *supra* note 10 (noting in the title that "[t]he new digital divide is between people who opt out of algorithms and people who don't").

23. *See* Yu, *supra* note 7, at 8–16 (discussing these attributes). This typology has been used or endorsed by other scholars in the digital divide literature. *See, e.g.*, ROLF H. WEBER, SHAPING INTERNET GOVERNANCE: REGULATORY CHALLENGES 251–52 (2009) (recalling the five key prerequisites for bridging the digital divide articulated in the earlier article).

24. *See* Scott Louie, *The New Invisible Man*, YO! YOUTH OUTLOOK (Nov. 1, 1999) (describing experience as "the new millennium's Invisible Man" after unplugging the modem for a few days), *cited in* Yu, *supra* note 7, at 9 n.49.

25. *See* BRETT FRISCHMANN & EVAN SELINGER, RE-ENGINEERING HUMANITY 13 (2018) ("[T]echno-social engineering can mold us while going unnoticed and unchallenged . . . .").

26. *See infra* text accompanying note 116 (discussing the limited understanding of algorithmic operations).

algorithms steer individuals away from the active or equal participation in the new technological environment. The harm that these algorithms could cause may range from "biases and bugs"[27] to the dehumanizing aspect of algorithmic operations.[28]

B. *Access*

Access is the most widely discussed attribute of the algorithmic divide. While the use of algorithms can provide important individual and societal benefits, not everybody has access to algorithm-enhanced technological products and services. At the domestic level, individuals will be shut out because they cannot afford these products and services, cannot find them on the local market, or do not have the needed skills to use them effectively.[29]

At the global level, the access challenge has become even more acute, especially when one takes into consideration the limited access to computing, Internet, and sophisticated communication technologies in the developing world.[30] While the Internet-penetration rates for Japan, the United States, and the United Kingdom are over 90%, the corresponding rates for Burundi, the Central African Republic, Eritrea,

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27. ANDREW MCAFEE & ERIK BRYNJOLFSSON, MACHINE, PLATFORM, CROWD: HARNESSING OUR DIGITAL FUTURE 53 (2017).

28. *See* FRISCHMANN & SELINGER, *supra* note 25, at 1 ("[T]echno-social engineering of humans exists on an unprecedented scale and scope, and it is only growing more pervasive as we embed networked sensors in our public and private spaces, our devices, our clothing, and ourselves."); LEE, *supra* note 6, at 173 (noting that artificial intelligence will provide "a direct assault on [the] sense of identity and purpose" of many workers); RAINIE & ANDERSON, *supra* note 22, at 9–11, 42–56 (surveying views on the loss of humanity and human judgment when data and predictive modeling become paramount); Andrew C. Michaels, *Artificial Intelligence, Legal Change, and Separation of Powers*, 88 U. CIN. L. REV. (forthcoming 2020) (manuscript at 28), https://ssrn.com/abstract=3459069 [https://perma.cc/4J7P-48ME] ("[T]he arguments for AI judges underappreciate and undervalue the human aspects of law."); *see also* Guido Noto La Diega, *Against the Dehumanisation of Decision-Making—Algorithmic Decisions at the Crossroads of Intellectual Property, Data Protection, and Freedom of Information*, 9 J. INTELL. PROP. INFO. TECH. & ELECTRONIC COM. L. 3, 33 (2018) ("[W]e should trust our fellow human beings over the algorithms, despite developments in artificial intelligence allowing the deployment of increasingly refined legal applications.").

29. *See* discussion *infra* Sections I.C, I.D, I.E (discussing unaffordability, unavailability, and inadaptability).

30. *See* Maria De-Arteaga et al., *Machine Learning for the Developing World*, ACM TRANSACTIONS ON MGMT. INFO. SYS., Aug. 2018, at 9:1, 9:2 ("Availability of data, computational capacity, and Internet accessibility are often markedly more limited than in developed countries."); Yu, *supra* note 7, at 4–5 (discussing the alarming disparities between developed and developing countries in their access to information technology); *see also* Pratap Khedkar & Dharmendra Sahay, *Trends in Healthcare and Medical Innovation*, *in* THE GLOBAL INNOVATION INDEX 2019: CREATING HEALTHY LIVES—THE FUTURE OF MEDICAL INNOVATION 87, 87 (Soumitra Dutta et al. eds., 2019) (noting that "90% of the developed world and 41% of the developing world [are] on broadband").

and Western Sahara are around or below 5%.[31] As a result, access to algorithm-enhanced technological products and services in the developing world cannot be taken for granted. As stated in the final report of the United Nations Secretary-General's High-level Panel on Digital Cooperation, cochaired by Melinda Gates and Jack Ma:

> Well more than half the world's population still either lacks affordable access to the internet or is using only a fraction of its potential despite being connected. People who lack safe and affordable access to digital technologies are overwhelmingly from groups who are already marginalised: women, elderly people and those with disabilities; indigenous groups; and those who live in poor, remote or rural areas.[32]

To a large extent, much of the prior research on information and communication technology for development[33]—or "ICT4D" for short—can provide instructive lessons for addressing development-related challenges in the age of artificial intelligence.[34] Among the strategies proposed for developing countries are an increase in the ability to handle small and messy datasets, the development of intelligent data-acquisition strategies and compression algorithms, the creation of transfer-learning

31. *See Internet in Europe Stats*, INTERNET WORLD STATS, https://www.internetworldstats.com/stats4.htm [https://perma.cc/M6J6-P2Y7] (last updated July 24, 2019) (reporting the Internet-penetration rate for the United Kingdom at 94.6%); *Internet Usage in Asia*, INTERNET WORLD STATS, https://www.internetworldstats.com/stats3.htm [https://perma.cc/9Q4B-T3BW] (last updated Sept. 26, 2019) (reporting the Internet-penetration rate for Japan at 93.5%); *Internet Usage Statistics for All the Americas*, INTERNET WORLD STATS, https://internetworldstats.com/stats2.htm [https://perma.cc/A2EJ-2ZQ2] (last updated Sept. 10, 2019) (reporting the Internet-penetration rate for the United States at 95.6%); *Internet Users Statistics for Africa*, INTERNET WORLD STATS, https://internetworldstats.com/stats1.htm [https://perma.cc/5ZGM-ULSH] (last updated Nov. 6, 2019) (reporting the Internet-penetration rates for Burundi, the Central African Republic, Eritrea, and Western Sahara at 5.3%, 5.3%, 1.3%, and 4.8%, respectively).

32. U.N. Sec'y-Gen.'s High-level Panel on Digital Cooperation, *The Age of Digital Interdependence*, at 6 (June 10, 2019) [hereinafter *High-level Panel Report*] (footnote omitted).

33. *See* Amir Hatem Ali, Note, *The Power of Social Media in Developing Nations: New Tools for Closing the Global Digital Divide and Beyond*, 24 HARV. HUM. RTS. J. 185, 193 (2011) ("Proponents of addressing the digital divide argue that economic depravity, poor education, and deficient healthcare might be addressed on a structural level by providing developing nations with infrastructure and skills to compete in the national economy, in which ICT [information and communication technology] is undoubtedly an essential tool."). *See generally* Executive Board of U.N. Development Programme & U.N. Population Fund, *Role of UNDP in Information and Communication Technology for Development*, U.N. Doc. DP/2001/CRP.8 (June 8, 2001) (discussing the ICT4D efforts taken by the U.N. Development Programme).

34. *See generally* De-Arteaga et al., *supra* note 30 (examining the burgeoning literature on "machine learning for the developing world").

models[35] for low-resource languages, the facilitation of machine learning with limited computational capabilities, and the utilization of decision support systems.[36]

C. *Affordability*

Affordability goes hand in hand with access, yet the two attributes raise different considerations. While the lack of economic and technological resources may lead to inaccessibility, it could also determine the type of product and service that an individual could access and the frequency at which that individual could utilize the selected product or service. In addition, because affordability limits one's ability to "upgrad[e] the equipment, software, and training support,"[37] this attribute of the algorithmic divide will affect the overall quality of the products and services that the individual enjoys.

To a large extent, affordability determines not only individual access to machine learning and artificial intelligence but also one's ability to fully participate in the artificial intelligence revolution. The less access one can afford, the more limited benefits one will secure from algorithm-enhanced technological products and services, and the less likely one will be able to fully realize the promise of machine learning and artificial intelligence.

D. *Availability*

There is a general assumption that individuals will have the needed technological products or services if machine-learning capabilities become accessible and affordable. Yet, that assumption cannot always be supported given the differing individual needs for products and services.[38] It is not uncommon that the specific type of product or service needed by an individual does not exist. Even if it does, that product or service may feature algorithms designed by those who do not fully grasp the user's specific needs, interests, conditions, and priorities, especially those in the developing world. As Ralph Hamann lamented: "AI algorithms are developed almost entirely in developed regions. Thus they may not sufficiently reflect the contexts and priorities of developing countries."[39]

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35. For overviews of "transfer learning" in the deep learning context, see generally JOHN D. KELLEHER, DEEP LEARNING 236–37 (2019); Jason Brownlee, *A Gentle Introduction to Transfer Learning for Deep Learning*, MACHINE LEARNING MASTERY (Dec. 20, 2017), https://machinelearningmastery.com/transfer-learning-for-deep-learning/ [https://perma.cc/M9N8-9GVU].

36. De-Arteaga et al., *supra* note 30, at 9:9 to :10.

37. Yu, *supra* note 7, at 12.

38. *See id.* at 13 ("Even with Internet access, many people may not be able to find information that is relevant to their lives and communities.").

39. Hamann, *supra* note 8.

Since the mid-2010s, commentators have widely discussed the problem of algorithmic bias and discrimination,[40] which Section II.B will discuss in greater detail. While this problem has produced undesirable outcomes that harm select individuals, it could shut these individuals out of access entirely. Thus, regardless of whether they are intentional,[41] algorithmic bias and discrimination threaten to take away the benefits that machine learning and artificial intelligence provide to a large segment of the population.

E. *Adaptability*

If individuals are to succeed in the age of artificial intelligence, they will need to take advantage of the different algorithm-enhanced technological products and services. They will also need to adapt these new technologies to their individual needs.[42] Only after they have made successful adaptation can they realize the full potential of machine learning and artificial intelligence.

Adaptability, however, requires both knowledge and understanding (in addition to awareness). In this age of artificial intelligence, algorithmic literacy is just as important as algorithmic awareness. As Section III.A will discuss in greater detail, policy makers will need to put in place programs to enhance the algorithmic literacy of their constituencies.[43] Should those on the unfortunate side of the algorithmic

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40. *See generally* Nizan Packin & Yafit Lev-Aretz, *Learning Algorithms and Discrimination*, *in* RESEARCH HANDBOOK ON THE LAW OF ARTIFICIAL INTELLIGENCE 88 (Woodrow Barfield & Ugo Pagallo eds., 2018) (discussing discrimination in the context of machine-learning algorithms); Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CALIF. L. REV. 671 (2016) (discussing the disparate impact caused by the use of big-data analytics); Stephanie Bornstein, *Antidiscriminatory Algorithms*, 70 ALA. L. REV. 519 (2018) (examining algorithmic decision-making through an antistereotypical lens); Aziz Z. Huq, *Racial Equity in Algorithmic Criminal Justice*, 68 DUKE L.J. 1043 (2019) (discussing algorithm-generated racial inequity in the criminal justice system); Pauline T. Kim, *Data-Driven Discrimination at Work*, 58 WM. & MARY L. REV. 857 (2017) (discussing data-driven discrimination in the employment context); Andrew D. Selbst, *Disparate Impact in Big Data Policing*, 52 GA. L. REV. 109 (2017) (discussing the disparate impact caused by the use of big-data analytics to provide predictive policing); Tal Z. Zarsky, *Understanding Discrimination in the Scored Society*, 89 WASH. L. REV. 1375 (2014) (discussing discrimination in social-scoring systems).

41. *See* Balkin, *supra* note 12, at 1233 ("We can't argue that the algorithm itself has bad intentions. Rather, the algorithm is used by human beings who want to achieve some particular set of managerial goals, but in the process, end up harming various groups of people.").

42. *Cf.* Yu, *supra* note 7, at 15 ("Access to information technology and Internet content is . . . useful only if people are able to adapt to the changing technological environment and to use the new technological tools effectively.").

43. *See* discussion *infra* Section III.A (discussing the need to increase algorithmic literacy).

divide fail to adequately respond to this fast-evolving technological environment, they will likely be left behind.[44]

II. PROBLEMS

Although Part I focused on the five attributes of the algorithmic divide, it is important not to dismiss this divide as a mere theoretical construct. Instead, the divide has generated three real-life problems that will deeply affect whether and how individuals are to benefit from machine learning and artificial intelligence. While the first two problems—algorithmic deprivation and algorithmic discrimination—have primary impacts on those on the unfortunate side of the algorithmic divide, the last problem—algorithmic distortion—affects virtually everybody. Taken together, these three problems demonstrate how the emerging and ever-widening algorithmic divide will affect all users in some way regardless of whether they sit on the fortunate or unfortunate side.

A. *Algorithmic Deprivation*

As the previous Part noted, those who have no access to algorithm-enhanced technological products and services will be shut out of the benefits provided by machine learning and artificial intelligence. Although commentators have documented the various problems caused by algorithms and intelligent machines, one cannot overlook the many promises that these technologies provide,[45] especially in areas in which they have shown to have outperformed human actors.[46] Just like all other

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44. One commentator described the adaptation process as follows:

> Smart(er) new apps and platforms will require people to learn how to understand the nature of the new experience, learn how it is guided by software, and learn to interact with the new environment. That has tended to be followed by a catch-up by people who learn then to game the system, as well as navigate it more speedily and reject experiences that don't meet expectations or needs. The major risk is that less-regular users, especially those who cluster on one or two sites or platforms, won't develop that navigational and selection facility and will be at a disadvantage.

RAINIE & ANDERSON, *supra* note 22, at 63 (quoting Pete Cranston, Co-Dir., Euroforic Servs.).

45. *See* AMY PAUL ET AL., U.S. AGENCY FOR INT'L DEV., REFLECTING THE PAST, SHAPING THE FUTURE: MAKING AI WORK FOR INTERNATIONAL DEVELOPMENT 4 (2018), https://www.usaid.gov/sites/default/files/documents/15396/AI-ML-in-Development.pdf [https://perma.cc/Y8TT-AGEY] ("Emerging [machine-learning and artificial-intelligence] applications promise to reshape healthcare, agriculture, and democracy in the developing world. [These technologies] show tremendous potential for helping to achieve sustainable development objectives globally." (emphasis omitted)).

46. Examples abound in the health area:

new technologies, algorithm-enhanced technological products and services have their strengths and drawbacks.[47]

> AI technology has been utilized to improve the quality of medical diagnosis, especially in radiology, due to the large volumes of medical image data. A radiologist, Keith Dreyer at Harvard Medical School, claimed that "Meaningful AI will improve quality, efficiency, and outcomes." Esteva et al. trained deep convolutional neural networks (CNN) based on a dataset of 129,450 clinical images to diagnose skin cancer. The results demonstrated that this system is able to classify skin cancer at a comparable level to dermatologists. They hypothesized that smartphones might be a low-cost method of helping to extend the reach of dermatologists to improve access to diagnostic care. Liu from Google, Inc. reported a CNN framework to aid the pathological diagnosis of breast cancer metastasis in lymph nodes. The results showed that this system could improve the speed, accuracy, and consistency of diagnosis, as well as reduce the false negative rate to a quarter of the rate experienced by human pathologists.

Jonathan Guo & Li Bin, *The Application of Medical Artificial Intelligence Technology in Rural Areas of Developing Countries*, 2 HEALTH EQUITY 174, 175 (2018) (footnotes omitted); *see also Digital Decisions*, CTR. FOR DEMOCRACY & TECH., https://cdt.org/files/2018/09/Digital-Decisions-Library-Printer-Friendly-as-of-20180927.pdf [https://perma.cc/KVA8-BD5V] ("Algorithms can help doctors read and prioritize X-rays, and they are better and faster than humans at detecting credit card fraud." (footnote omitted)).

47. As Andrew McAfee and Erik Brynjolfsson observed in their new book, *Machine Platform Crowd*:

> We . . . see both a challenge and opportunity in the growing reliance on algorithmic decision making. The challenge is that this approach can embed and perpetuate unfair, harmful, and unwanted biases. What's worse, these biases may emerge despite the best intentions of the designers to create unbiased systems, and they may be difficult to identify without extensive testing. All system design must confront this challenge.
>
> The opportunity is that machine-based systems typically can be tested and improved. And once corrected, they are unlikely to make the same mistake again. In contrast, it is a lot harder to get humans to acknowledge their biases (how many avowed racists or sexists do you know?), let alone the hard work required to overcome them. The ultimate standard for adopting a decision-making system—whether based on machines, on humans, or on some combination of the two—cannot realistically be perfection. Any system is likely to make mistakes and have biases. Instead, the goal should be to choose an approach that minimizes biases and errors, and that allows them to be easily and quickly corrected.

MCAFEE & BRYNJOLFSSON, *supra* note 27, at 52–53; *see also* RAINIE & ANDERSON, *supra* note 22, at 2 ("Algorithms are aimed at optimizing everything. They can save lives, make things easier, and conquer chaos. Still, experts worry they can also put too much control in the hands of corporations and governments, perpetuate bias, create filter bubbles, cut choices, creativity and serendipity, and could result in greater unemployment." (emphasis omitted)); *id.* at 18 ("If we use machine learning models rigorously, they will make things better; if we use them to paper over injustice with the veneer of machine empiricism, it will be worse." (quoting Cory Doctorow, Thus far, commentators have identified a number of areas in which machine learning and artificial intelligence can help the poor, the vulnerable, and the disadvantaged.[48] To underscore the promise of these technologies, this Section highlights their benefits in the developing world. Even though these benefits also inure to those in the developed world,[49] the illustrations focus on developing countries for two reasons. First, because these countries contain some of the world's most disadvantaged populations, the illustrations' usefulness will go beyond the developing world. Second, as the digital divide literature has shown, more research has been, and will be, devoted to communications issues involving the poor and the disadvantaged in developed countries.[50] This Section therefore highlights developments that are unlikely to receive the needed attention from policy makers and commentators.[51]

The first area that provides an excellent illustration of the promise of machine learning and artificial intelligence is disaster relief. The oft cited example is Nepal, which suffered from a devastating earthquake in Kathmandu, its capital, in April 2015.[52] Shortly after that earthquake, machine learning and artificial intelligence were deployed, alongside drones and other automated devices, to facilitate the rescue, relief, and

Author)). One may recall similar "good or evil" analyses regarding other new media technologies, which range from film to television to the Internet. *See* NORRIS, *supra* note 13, at 232 ("Previous technological breakthroughs have commonly generated exaggerated hopes that machines can transform society and democracy. Luddites fear for the worse, but technophiles hope for the better."); RAGNEDDA, *supra* note 18, at 22 (noting the differing views of techno-optimists, techno-skeptics, and techno-pessimists concerning whether the Internet reduces or reinforces social inequalities).

48. *See* discussion *infra* text accompanying notes 52–70.

49. *See* EUBANKS, *supra* note 2, at 81–82 ("New high-tech tools allow for more precise measuring and tracking, better sharing of information, and increased visibility of targeted populations. In a system dedicated to supporting poor and working-class people's self-determination, such diligence would guarantee that they attain all the benefits they are entitled to by law."). *But see* NORRIS, *supra* note 13, at 10 ("Technological opportunities are often unevenly distributed, even in nations like Australia, the United States, and Sweden at the forefront of the information society.").

50. *See, e.g.*, MACK, *supra* note 18 (discussing the digital divide and the intersection of race and technology, with a focus on the United States); FALLING THROUGH THE NET IV, *supra* note 17 (providing the concluding report of the Clinton Administration's *Falling Through the Net* series).

51. For additional examples, see generally materials provided through the "AI for Good" Global Summit, organized by the International Telecommunication Union. AI FOR GOOD GLOBAL SUMMIT, https://aiforgood.itu.int/ [https://perma.cc/P9GN-NFNL].

52. *See* Mark Brown, *Nepal Earthquake Destroys Kathmandu Valley's Architectural Treasures*, GUARDIAN (Apr. 27, 2015, 2:30 PM), https://www.theguardian.com/world/2015/apr/27/nepal-earthquake-destroys-kathmandu-valleys-architecture-buildings-heritage [https://perma.cc/VT6V-9VL3] (reporting the earthquake).

reconstruction efforts.[53] As a Nepalese executive of a New York–based provider of artificial intelligence solutions and services recounted:

> [P]redictive models for disaster relief enable first responders to automatically analyze large-scale behavior and movement through multiple sources of data including social media platforms, web forums, news sources, etc. Based on collected data, responders can scale reconstruction efforts and distribute supplies in a timely manner. In 2015, when a major earthquake hit Nepal, more than 8 million people were affected. During the aftermath, drones were used to map and assess the destruction and speed up the rescue mission.
>
> The town of Sankhu, situated about 20 kilometers northeast of Kathmandu, was among the highly affected locations. In May 2018, my company Fusemachines and GeoSpatial Systems partnered with Sankhu's city officials to use drones and artificial intelligence in an effort to automatically estimate the reconstruction need. After processing data accumulated from a drone-powered aerial mapping of the region, the team fed this data to advanced machine learning algorithms. Combining drone imagery, digital mapping and machine learning, the team configured region modeling and infrastructure development with higher accuracy.[54]

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53. *See* Sameer Maskey, *AI for Humanity: Using AI to Make a Positive Impact in Developing Countries*, FORBES (Aug. 23, 2018, 7:30 AM), https://www.forbes.com/sites/forbestechcouncil/2018/08/23/ai-for-humanity-using-ai-to-make-a-positive-impact-in-developing-countries-2 [https://perma.cc/MED5-VPA3] (recounting the disaster rescue, relief, and reconstruction efforts in Nepal); *see also How AI Is Helping Undeveloped and Developing Countries*, DAY TRANSLATIONS (Nov. 30, 2018), https://www.daytranslations.com/blog/2018/11/how-ai-is-helping-undeveloped-and-developing-countries-12899/ [https://perma.cc/BV8C-MULL] ("The United Nations Office for the Coordination of Humanitarian Affairs . . . used artificial intelligence to pinpoint and map all social media posts related to the Nepal earthquake emergency needs, damage to infrastructure, and disaster response activities.").

54. Maskey, *supra* note 53. As another commentator explained:

> AI-assisted disaster response operations have become more efficient because of the smart consolidation of a myriad of information. It made it easy to find the best routes to take when going to a calamity-struck site as the AI system determined the infrastructure damaged and those that are still usable. Digital maps were generated to help aid workers in providing the needed help promptly and safely. It became easier to work on at least three types of data (texts, images, and videos).
>
> The system used by [the United Nations Office for the Coordination of Humanitarian Affairs] is referred to as AIDR (Artificial Intelligence for Disaster Response). It is capable of learning from how it is being used and the data

The second area that showcases the benefits of machine learning and artificial intelligence is public health. Because the ratio between doctors and patients in developing countries is always dramatically higher than the corresponding ratio in their developed counterparts,[55] the use of machine learning and artificial intelligence is badly needed to train doctors, nurses, and other health professionals as well as to provide medical assistance.[56] In recent years, developing countries have successfully utilized these technologies to improve healthcare. As noted in a contribution to the *Global Innovation Index 2019* report:

> China is turning to AI-based technologies to provide better healthcare, especially in rural areas where doctors are relying on perceptual senses, like vision and hearing, to gather information about patient health. In India, Arvind Eye Care is working with Google Brain to detect signs of diabetes-related eye disease by analyzing photographs.[57]

> inputted into it, allowing it to identify humanitarian aid needs automatically, sort data (according to the following categories: urgent needs, response efforts, and infrastructure damage), and disseminate accurate and useful information. The more AIDR is used, the better it gets.

How AI Is Helping Undeveloped and Developing Countries, *supra* note 53.

55. *See* Guo & Li, *supra* note 46, at 177 ("Due to the poor working environment, it is difficult to attract and retain high-quality healthcare providers in rural areas. To compensate for the shortage of physicians, many developing countries launch some abbreviated training programs for becoming a physician, or they authorize nurses to perform certain physician tasks."); Adebayo Alonge, *How AI Can Help Africa Get Universal Health Care Before America*, NEWSWEEK (Oct. 30, 2017, 11:56 AM), https://www.newsweek.com/artificial-intelligence-us-healthcare-africa-693849 [https://perma.cc/SRD2-UDEP] ("Across Africa, the ratio of doctors to patients is painfully low. The continent accounts for 25 percent of global disease cases, but has only 2–3 percent of the doctors in the world.").

56. As one commentator observed:

> In many places such as Nepal and Africa, human medical experts are rarely available. Physicians may need to consult with fellow doctors, particularly experts in specific fields. Artificial intelligence can fill the gap, providing the knowledge and analytical output doctors can use to come up with better diagnosis and treatment plans.

How AI Is Helping Undeveloped and Developing Countries, *supra* note 53; *see also* Guo & Li, *supra* note 46, at 175 ("Although clinical work cannot be completely replaced by AI robot doctors in the foreseeable future, medical AI technology will play a huge role in electronic health records . . . , diagnosis, treatment protocol development, patient monitoring and care, personalized medicine, robotic surgery, and health system management."); *id.* at 176 ("[T]elerobots can facilitate communication between patients with medical professionals; assistive walking devices can help with maneuvering, walking, standing, or sitting; and animal-like robots can communicate with and entertain patients. Robots can also be used in surgery as assistant surgeons." (footnote omitted)).

57. Khedkar & Sahay, *supra* note 30, at 91 (footnote omitted).

In Rwanda, "Zipline is using drones to deliver medical supplies and blood to hospitals and clinics that are difficult to access by car."[58]

The third area that demonstrates the potential of machine learning and artificial intelligence is food production. In developing countries, farmers often have to travel long distances to sell crops, produce, and animals.[59] With the information they secure through predictive algorithms, such as crop prices, they will be in much better positions than in the past to determine when to sell products.[60] Algorithm-enhanced technologies will also help them increase crop yield, telling them when to plant and fertilize and what seeds to use based on local climate and soil conditions.[61] To a large extent, the Internet has already greatly improved the livelihoods of

58. Maskey, *supra* note 53. This delivery "has dramatically impacted people living in remote parts of the country because they are able to get medical help when needed," and "[t]he drone system in Rwanda has . . . helped reduce waste of blood by 95%." *Id.*

59. *See* Marcel Fafchamps & Ruth Vargas Hill, *Selling at the Farmgate or Traveling to Market*, 87 AM. J. AGRIC. ECON. 717, 718 (2005) ("In contrast with farmers in developed countries who often . . . enjoy good institutions and infrastructure, most farmers in developing countries are . . . geographically isolated . . . and outside the reach of formal market institutions.").

60. *See* NITI AAYOG, NATIONAL STRATEGY FOR ARTIFICIAL INTELLIGENCE 20 (2018) (India), https://www.niti.gov.in/writereaddata/files/document_publication/NationalStrategy-for-AI-Discussion-Paper.pdf [https://perma.cc/A7D8-MCNW] (noting that artificial intelligence "has the potential to address challenges such as inadequate demand prediction" and has been used for the "prediction of crop prices to inform sowing practices").

61. As Bernard Marr observed:

> AI technology . . . can help researchers figure out the right genetic makeup to create seeds that generate the highest yield, the most nutrition, and the most disease-resistant strains of staple crops. There are 40,000 varieties of sorghum, a valuable cereal crop in developing countries such as Ethiopia and India. AI can be used to experiment with these varieties to develop the perfect crop. All the growth, genetic, and environmental data collected during research will be given to an AI model to process. AI algorithms are better able to review all the variables and varieties to identify patterns and insights faster than humans. Deep-learning AI will be able to comprehend the complex genetics of plants that will support better breeding of plants. Those more efficient plants will improve our food production.

Bernard Marr, *How Artificial Intelligence Can Help Fight World Hunger*, SAP INSIDER (Jan. 10, 2018), https://sapinsider.wispubs.com/Assets/Articles/2018/January/How-Artificial-Intelligence-Can-Help-Fight-World-Hunger [https://perma.cc/WUD8-4D7T]; *see also* PAUL ET AL., *supra* note 45, at 26 ("[A machine-learning] model can recommend crop management practices that are tailored to local soil type, plant varieties, and climate forecasts."); *How AI Is Helping Undeveloped and Developing Countries*, *supra* note 53 ("The [machine-generated] sowing advisories sent to farmers include information on the best time for land preparation, sowing date, and fertilizer application."); Maskey, *supra* note 53 ("Farmers monitor crops more effectively and make better predictions on planting, weeding and harvesting using AI tools. It can also be used to analyze one plant at a time and add pesticides only to infected plants and trees instead of spraying pesticides across large swaths of crops.").

farmers in developing countries.[62] The use of machine learning and artificial intelligence will provide further improvements by giving them more and better information and by strengthening their predictive abilities.

The fourth area that exemplifies the success provided by machine learning and artificial intelligence is education. Thus far, these technologies have been deployed to address the shortage of teachers and easily accessible schools.[63] Computers equipped with learning algorithms have also been used as tutors.[64] These "intelligent" tutors not only can track the participants' progress but will also be able to adjust teaching coverage and pace based on such progress. As Nizan Packin and Yafit Lev-Aretz observed:

> Intelligent tutoring systems (ITS) have rapidly moved from laboratory experimental stages to real everyday use. When learners work on a problem-solving task, ITS track mental steps to diagnose errors and appraise their understanding of the domain. Learners can also enjoy ITS's timely guidance, feedback and explanations, and be matched

62. *See* Charlie Mitchell, *Technology Hope for African Farmers*, FIN. TIMES (Oct. 15, 2018), https://www.ft.com/content/3316885c-b07d-11e8-87e0-d84e0d934341 [https://perma.cc/WT6N-FERU] ("[D]igital services allow smallholders to view real-time crop prices, raise capital and crowdfund on their computers and smart devices.").

63. As one commentator recounted:

> In most developing countries, schools lack experienced teachers and resources to enhance students' knowledge. As a result, many students still have to walk long distances to get to the nearest school, which has created education gaps, especially in rural areas. AI tools such as personalized learning assistants can simplify learning by making tutoring services and learning materials accessible to all students, wherever they are. Machines can be automated to help students learn basic concepts without a tutor . . . . This would allow students to learn at any time from anywhere.

Maskey, *supra* note 53; *see also* De-Arteaga et al., *supra* note 30, at 9:6 ("[T]eacher shortages are common in rural areas of the developing world. If machines could augment and support human teaching responsibilities, this could help increase literacy and sharpen STEM [science, technology, engineering, and mathematics] skills, paving a road to improve development." (citation omitted)). For the benefits of both developed and developing countries, teaching robots can cover not only the present but also the past. *See generally* Michal Shur-Ofry & Guy Pessach, *Robotic Collective Memory*, 97 WASH. U. L. REV. 975 (2019) (discussing issues raised by virtual witnesses who help convey memories from the Holocaust).

64. *See* U.N. EDUC., SCI. & CULTURAL ORG. [UNESCO], ARTIFICIAL INTELLIGENCE IN EDUCATION: CHALLENGES AND OPPORTUNITIES FOR SUSTAINABLE DEVELOPMENT 12 (2019) ("AI was part of the vision promising to transform education by creating tutor systems that could personalise learning.").

> with learning activities at an individually-tailored level of difficulty and interest.[65]

To better tailor the teaching and learning experiences to the participants' specific needs, interests, and capabilities, these tutors can utilize the growing amount of open-access courseware that has already appeared in both developed and developing countries.[66] Machine learning and artificial intelligence have also been utilized for grading and other purposes.[67]

The last area that illuminates the possibilities generated by greater use of machine learning and artificial intelligence involves policy analysis. As Maria De-Arteaga and her collaborators observed, "Whether it is through knowledge-discovery models that improve our understanding of a phenomenon, or through predictive models that inform proactive policies, [machine learning] can be integrated as an essential component of decision support systems."[68] For instance, scientists have utilized machine-learning capabilities, survey data, and satellite images of differential nighttime luminosity to map poverty levels in African countries where estimates of consumption expenditure and asset wealth have been incomplete or lacking.[69] A group of researchers at Development Seed also teamed up with the World Bank to utilize big-

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65. Packin & Lev-Aretz, *supra* note 40, at 108. A frequently cited example is Cape Town–based Daptio:

> Daptio [is] an adaptive learning platform that makes use of artificial intelligence to help students study remotely. It specializes in courses whose content, structure, and assessments are designed to adjust based on the strengths and weaknesses of the students. Daptio is designed to serve a learning model that is deemed best suited to a specific student.

How AI Is Helping Undeveloped and Developing Countries, *supra* note 53; *see also* UNESCO, *supra* note 64, at 14 (discussing Daptio).

66. A widely cited example is the open courseware provided by the Massachusetts Institute of Technology. *See* Mass. Inst. of Tech., MIT OPEN COURSEWARE, https://ocw.mit.edu/index.htm [https://perma.cc/94R5-TZFS].

67. *See* Packin & Lev-Aretz, *supra* note 40, at 108 ("[M]assive open online courses and other models of online education increasingly use AI. Many of the popular online education platforms, including EdX, Coursera, and Udacity, use [natural-language processing], machine learning, and crowdsourcing for grading students' assignments and programming tasks."); *see also* UNESCO, *supra* note 64, at 13 ("A dual-teacher model entailing a teacher and a virtual teaching assistant, which can take over the teacher's routine task, frees up teachers' time, enabling them to focus on student guidance and one-to-one communication.").

68. De-Arteaga et al., *supra* note 30, at 9:7.

69. Neal Jean et al., *Combining Satellite Imagery and Machine Learning to Predict Poverty*, 353 SCIENCE 790, 790 (2016); *see also* PAUL ET AL., *supra* note 45, at 50 ("One of the most well-developed use cases for [machine learning] in international development is the automated analysis of satellite imagery. . . . Satellite imagery can provide invaluable information about human settlement patterns, land use, and infrastructure.").

data analytics and machine-learning capabilities to analyze the urban dynamics in Ethiopian lowlands.[70] By providing greater, better, and more complete information, machine learning and artificial intelligence have put policy makers in better positions to design, evaluate, and improve policies.

Taken together, the examples in these five areas illustrate the many benefits that machine learning and artificial intelligence have provided to developing countries. They explain why it is just as urgent to bridge the algorithmic divide in developing countries as it is to bridge that divide in developed countries. The examples also show that different areas need varying levels of access to machine learning and artificial intelligence.[71] While some areas, such as public health, food production, and education, need large-scale access to these technologies, other areas, such as disaster relief and policy analysis, may require only access on the part of the government and some other key players.

As if the wide-ranging benefits that machine learning and artificial intelligence have provided to developing countries were not appealing enough, efforts to bridge the algorithmic divide in developing countries can generate three types of collateral benefits to developed countries. First, commentators have widely noted the network effects generated by the increased global use of information and communication technology,[72] which will create economy of both scale and scope. Second, as Mark Cooper observed in relation to Internet usage: "As the customer and geographic base spreads, the load on the system can be balanced, achieving higher overall utilization rates. Spreading the customer base across geographic areas would allow time zone differences to balance the load as well."[73] The same would apply to machine learning and artificial intelligence, especially regarding those algorithm-driven artificial intelligence systems that are usable in both developed and developing countries. Finally, because big-data analytics are increasingly deployed

70. Zhuangfang NaNa Yi, *Accurate Machine Learning in Data-Sparse Environments*, MEDIUM (Apr. 4, 2019), https://medium.com/devseed/accurate-machine-learning-in-data-sparse-environments-afad1101a928 [https://perma.cc/2Z9E-YZ5T].

71. Thanks to Chris Drahozal for pushing me on this point.

72. As Mark Cooper observed:

> At the core of the [digital-transformation] process is a virtuous circle that uniquely affects these industries. Improvements in computers and software can be used to produce further improvements in computers and software. Network effects mean that as more people use these products, the products become more valuable to each user, stimulating more people to join the network and use it more intensely.

Mark N. Cooper, *Inequality in the Digital Society: Why the Digital Divide Deserves All the Attention It Gets*, 20 CARDOZO ARTS & ENT. L.J. 73, 73 (2002).

73. *Id.* at 84–85.

in algorithm-enhanced technological products and services, having comprehensive datasets that include individuals on both sides of the algorithmic divide is imperative.[74] As Woodrow Hartzog wrote succinctly, "In the world of big data, more is always better."[75]

To be sure, the introduction of algorithm-enhanced technological products and services could lead to the problems of algorithmic discrimination and distortion, both of which the next two Sections will discuss in greater detail.[76] When introduced without much consideration of local contexts, these products and services could also generate unintended consequences.[77] As Chinmayi Arun lamented:

> Ideas of the past like one laptop per child have resulted in spectacular failure despite the bright-eyed optimism and laudable intentions with which they were created. Technology designed out of context may fail to take local resources, social norms and cultural context into account. "One day delivery" can mean very different things in Boston and Hyderabad even if the system designed for both cities is the same. Facebook can be fairly harmless in most countries and find itself weaponised in a country with Myanmar's socio-political context, to contribute to genocide. It can take effort for Google Maps to be able to account for the favelas of Rio de Janeiro.[78]

Notwithstanding the different problems that algorithm-enhanced technological products and services may generate, the many promises these technologies provide suggest that individuals will be, on balance, better off having the technologies than not having them in the first place.[79] In fact, the sooner those on the unfortunate side of the algorithmic

74. *See* discussion *infra* Section II.C (discussing algorithmic distortion).

75. WOODROW HARTZOG, PRIVACY'S BLUEPRINT: THE BATTLE TO CONTROL THE DESIGN OF NEW TECHNOLOGIES 51 (2018); *see also* VIKTOR MAYER-SCHÖNBERGER & KENNETH CUKIER, BIG DATA: A REVOLUTION THAT WILL TRANSFORM HOW WE LIVE, WORK, AND THINK 100 (2013) ("[I]n the age of big data, *all* data will be regarded as valuable, in and of itself.").

76. *See* discussion *infra* Sections II.B, II.C (discussing algorithmic discrimination and distortion).

77. *See generally* Chinmayi Arun, *AI and the Global South: Designing for Other Worlds*, *in* THE OXFORD HANDBOOK OF ETHICS OF AI (Markus D. Dubber et al. eds., forthcoming 2020), https://ssrn.com/abstract=3403010 [https://perma.cc/WCG7-PU7K] (noting the concerns raised by out-of-context design and deployment of artificial intelligence in the global South).

78. *Id.* (manuscript at 3) (footnotes omitted); *see also* WARSCHAUER, *supra* note 18, at 65–69 (discussing Brazil's People's Computer and India's simputer).

79. In their book, Brett Frischmann and Evan Selinger underscored the concern about the techno-social engineering of humans and called for "the freedom to be off, to be free from techno-social engineering, to live and develop within underdetermined techno-social environments." FRISCHMANN & SELINGER, *supra* note 25, at 269. While they made a convincing case about the need for this freedom, there is no freedom to speak of if those on the unfortunate side of the

divide can participate in the artificial intelligence revolution, the more quickly they will be able to begin shaping the new technological environment.[80] Such shaping, and reshaping, will make the environment more appealing and relevant to them in the long run.

Moreover, whether these products and services are beneficial or harmful will largely depend on the design and use of the algorithms involved. To help ensure proper design and usage, Part III will outline select remedial actions that implicate ethics, transparency, accountability, and competition.[81] As that discussion will show, solutions can be developed to maximize the benefits of algorithm-enhanced technological products and services while minimizing their shortcomings.

Finally, regardless of whether those on the unfortunate side of the algorithmic divide can secure ready and affordable access to these products and services, those on the other side of the divide will still actively deploy them. Such deployment will harm the technology poor by accelerating job displacement[82] while widening the gap between the technology haves and have-nots.[83] Given the sad reality that society

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algorithmic divide are forced to be off. Only after their services have been turned on can they have "the freedom to be off."

80. Manuel Castells lamented the impact of the digital divide on the Internet:

> The fact that the rise of the Internet took place in conditions of social inequality in access everywhere may have lasting consequences on the structure and content of the medium . . . . This is because users shape the Internet to an even greater extent than any other technology because of the speed of transmission of their feedback, and the flexibility of the technology. Thus, first users may have shaped the Internet for the latecomers, both in terms of content and of technology, in the same way that the pioneers of the Internet shaped the technology for the masses of users in the 1990s.

MANUEL CASTELLS, THE INTERNET GALAXY: REFLECTIONS ON THE INTERNET, BUSINESS, AND SOCIETY 255 (2001).

81. *See* discussion *infra* Sections III.C, III.D, III.E, III.F (proposing remedial actions relating to ethics, transparency, accountability, and competition).

82. *See* EXEC. OFFICE OF THE PRESIDENT, ARTIFICIAL INTELLIGENCE, AUTOMATION, AND THE ECONOMY 35 (2016) ("Job displacement is likely to be one of the most serious negative consequences of AI-driven automation, impacting entire industries and communities."); RAINIE & ANDERSON, *supra* note 22, at 70–73 (surveying views on the rise of unemployment); Hamann, *supra* note 8 (listing "worsening unemployment" as one of the key risks of technological advances associated with artificial intelligence). As far as job displacement is concerned, the level of displacement by machine learning and artificial intelligence will likely vary from sector to sector and from country to country. *See generally* ERIK BRYNJOLFSSON & ANDREW MCAFEE, THE SECOND MACHINE AGE: WORK, PROGRESS, AND PROSPERITY IN A TIME OF BRILLIANT TECHNOLOGIES (2014) (examining the transformative impacts of emerging digital technologies on jobs and the economy); Cynthia Estlund, *What Should We Do After Work? Automation and Employment Law*, 128 YALE L.J. 254 (2018) (advancing reforms to address the future impact of automation on jobs).

83. *See* Hamann, *supra* note 8 (listing "increasing concentration of economic power and wealth" as another key risk of technological advances associated with artificial intelligence).

cannot easily shelter the technology poor from the actions of the technology rich—whether in developed or developing countries—facilitating greater use of algorithm-enhanced technological products and services is, to a large extent, a choice that everybody has to embrace. This choice is similar to how individuals needed to adapt to the Internet in the late 1990s and the early 2000s despite the medium's many documented shortcomings.[84]

B. *Algorithmic Discrimination*

In the past few years, commentators have highlighted the different problems caused by algorithms, which range from errors to biases and from discrimination to dehumanization.[85] While Frank Pasquale lamented how we now live in a "Black Box Society,"[86] Cathy O'Neil referred to machine-learning algorithms as "Weapons of Math Destruction."[87]

In February 2017, the Pew Research Center and the Imagining the Internet Center at Elon University released their joint study, canvassing more than 1000 "technology experts, scholars, corporate practitioners and government leaders" for their views on the pros and cons of the algorithmic age.[88] Opening that report is a list containing some widely reported problems generated by seemingly out-of-whack algorithms:

> - The British pound dropped 6.1% in value in seconds on Oct. 7, 2016, partly because of currency trades triggered by algorithms.
>
> - Microsoft engineers created a Twitter bot named "Tay" . . . in an attempt to chat with Millennials by

84. *See* NORRIS, *supra* note 13, at 68 ("The chief concern about the digital divide is that the underclass of info-poor may become further marginalized in societies where basic computer skills are becoming essential for economic success and personal advancement, entry to good career and educational opportunities, full access to social networks, and opportunities for civic engagement."); FALLING THROUGH THE NET IV, *supra* note 17, at 89 ("We are approaching the point where not having access to [computers and the Internet] is likely to put an individual at a competitive disadvantage and in a position of being a less-than-full participant in the digital economy."); Yu, *supra* note 7, at 16–17 ("Information technology is no longer a luxury, but a development tool and a critical means of information exchange in the New Economy." (footnote omitted)).

85. *See supra* text accompanying notes 27, 28, 40. In addition to discrimination, Jack Balkin identified the following algorithmic harms: (1) harms to reputation; (2) normalization or regimentation; (3) manipulation; and (4) lack of due process, transparency, or interpretability. Balkin, *supra* note 12, at 1238–39.

86. FRANK PASQUALE, THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION (2015).

87. CATHY O'NEIL, WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY (Broadway Books 2017) (2016).

88. RAINIE & ANDERSON, *supra* note 22, at 4.

responding to their prompts, but within hours it was spouting racist, sexist, Holocaust-denying tweets based on algorithms that had it "learning" how to respond to others based on what was tweeted at it.

- Facebook tried to create a feature to highlight Trending Topics from around the site in people's feeds. First, it had a team of humans edit the feature, but controversy erupted when some accused the platform of being biased against conservatives. So, Facebook then turned the job over to algorithms only to find that they could not discern real news from fake news.[89]

As if these examples were not disturbing enough, in 2015, Google "publicly apologize[d] after its object recognition algorithm tagged two black users of Google Photo as 'gorillas.'"[90] Likewise, "Hewlett-Packard (HP) suffered a serious public relations crisis when it was revealed that its implementation of what was probably a bottom-up feature-based face localization algorithm did not detect Black people as having a face," due largely to the fact that the "[c]ameras on new HP computers did not track the faces of Black people in some common lighting conditions."[91] In a speech, Ben Bernanke also relayed a story about how his request to refinance a mortgage had been denied shortly after stepping down from being the chair of the Federal Reserve.[92] As a *New York Times* report explained, "[I]n the thoroughly automated world of mortgage finance, having recently changed jobs makes [him] a steeper credit risk."[93]

Taken together, these examples show that algorithms can be error prone, biased, or both. While algorithmic errors affect everybody having access to algorithm-enhanced technological products and services, algorithmic bias is particularly problematic for those on the unfortunate side of the algorithmic divide. Indeed, many commentators fear that algorithmic bias will have a disproportionate impact on the poor, the disadvantaged, and the vulnerable.[94]

89. *Id.* at 2–3.

90. Omer Tene & Jules Polonetsky, *Taming the Golem: Challenges of Ethical Algorithmic Decision-Making*, 19 N.C. J.L. & TECH. 125, 154 (2017).

91. Christian Sandvig et al., *When the Algorithm Itself Is a Racist: Diagnosing Ethical Harm in the Basic Components of Software*, 10 INT'L J. COMM. 4972, 4973 (2016) (citations omitted).

92. Neil Irwin, *Why Ben Bernanke Can't Refinance His Mortgage*, N.Y. TIMES (Oct. 2, 2014), https://www.nytimes.com/2014/10/03/upshot/why-ben-bernanke-cant-refinance-his-mortgage.html [https://perma.cc/F64T-QDXZ].

93. *Id.*

94. As Cathy O'Neil explained:

Although algorithmic bias can be introduced intentionally through overt discriminatory practices,[95] most of the time biases enter algorithms through covert actions—whether intentional or not.[96] First, biases can enter algorithms through what commentators have referred to as "masking."[97] By utilizing complex algorithms, algorithm designers or

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> [Algorithm-driven weapons of math destruction] tend to punish the poor. This is, in part, because they are engineered to evaluate large numbers of people. They specialize in bulk, and they're cheap. That's part of their appeal. The wealthy, by contrast, often benefit from personal input. A white-shoe law firm or an exclusive prep school will lean far more on recommendations and face-to-face interviews than will a fast-food chain or a cash-strapped urban school district. The privileged, we'll see time and again, are processed more by people, the masses by machines.

O'NEIL, *supra* note 87, at 8; *see also* EUBANKS, *supra* note 2, at 12 ("Automated decision-making shatters the social safety net, criminalizes the poor, intensifies discrimination, and compromises our deepest national values."); RAINIE & ANDERSON, *supra* note 22, at 63–65 (surveying views on whether the disadvantaged will lag behind even further in this algorithmic age).

95. *See* Joshua A. Kroll et al., *Accountable Algorithms*, 165 U. PA. L. REV. 633, 682 (2017) ("A prejudiced decisionmaker could skew the training data or pick proxies for protected classes with the intent of generating discriminatory results.").

96. Anupam Chander noted the unlikelihood of overt discrimination on the part of algorithm designers:

> First, because much of societal discrimination is subconscious or unconscious, it is less likely to be encoded into automated algorithms than the human decisionmakers that the algorithms replace. . . .
>
> . . . .
>
> Second, even for programmers or companies who intend to discriminate, the process of coding itself is likely to cause programmers to shy away from actually encoding the discrimination. Even absent compelled disclosure through litigation, there is the danger that a hard-coded discrimination will be revealed later by hackers or by insiders disgusted by the discrimination. Moreover, because code writing is likely to involve teams of programmers sharing code, with different persons reviewing and debugging code, consciously coding discrimination will likely require obtaining the cooperation of multiple persons, which is likely to be a fraught task.

Anupam Chander, *The Racist Algorithm?*, 115 MICH. L. REV. 1023, 1028–29 (2017) (footnotes omitted).

97. For discussions of the masking of discriminatory practices, see generally Barocas & Selbst, *supra* note 40, at 712–14; Huq, *supra* note 40, at 1089–90; Zarsky, *supra* note 40, at 1389–90. For illustrative purposes, "a system forbidden to use race as a variable might use other data, such as media consumption or purchases of hair care products, to infer race and adjust the offered pricing or services accordingly, and it might use factors that themselves reflect preexisting patterns of discrimination, such as lower scores on standardized tests or longer commuting distances to the site of a new job, as decision-making proxies." JULIE E. COHEN, BETWEEN TRUTH AND POWER: THE LEGAL CONSTRUCTIONS OF INFORMATIONAL CAPITALISM 247 (2019).

their employers can mask discriminatory practices.[98] As Aziz Huq showed, masked discrimination in algorithmic design can be very difficult to prove:

> A discriminatory algorithm designer will leverage such knowledge to fashion instruments that yield the disparate racial effects they believe to be warranted *a priori*. Without knowing the full spectrum of features that could, conceivably, have been included in the training data—which can be "enormous"—it will be difficult or impossible to diagnose this kind of conduct absent direct evidence of discriminatory intent. It will, moreover, be especially difficult to show that, but for race, a specific feature would or would not have been included, as the doctrine requires. A basic principle of "feature selection" instructs that one should keep the important features and discard the unimportant ones. To the extent that masking occurs, therefore, it seems clear that the litigation process would rarely yield evidence of such intentional manipulation of the algorithm's design.[99]

Second, implicit biases can enter algorithms in two ways. First, these biases can originate from algorithm designers who are neutral or well-intentioned, or who genuinely care about those on the unfortunate side of the algorithmic divide.[100] Second, the algorithms can rely on problematic

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98. *See* Tene & Polonetsky, *supra* note 90, at 167 ("The profound capability of computers to identify patterns in endless piles of unstructured data facilitates the masking of illegitimate discrimination behind mirrors and proxies. Decision-making, automated or not, based on such criteria should be banned." (footnote omitted)); Nicholas Diakopoulos et al., *Principles for Accountable Algorithms and a Social Impact Statement for Algorithms*, FAT/ML, https://www.fatml.org/resources/principles-for-accountable-algorithms [https://perma.cc/W8XL-P3UK] ("'The algorithm did it' is not an acceptable excuse if algorithmic systems make mistakes or have undesired consequences, including from machine-learning processes." (emphasis omitted)); *see also* Cynthia Dwork & Deirdre K. Mulligan, *It's Not Privacy, and It's Not Fair*, 66 STAN. L. REV. ONLINE 35, 35 (2013), https://review.law.stanford.edu/wp-content/uploads/sites/3/2016/08/DworkMullliganSLR.pdf [https://perma.cc/996Z-XVWW] ("While many companies and government agencies foster an illusion that classification is (or should be) an area of absolute algorithmic rule—that decisions are neutral, organic, and even automatically rendered without human intervention—reality is a far messier mix of technical and human curating.").

99. Huq, *supra* note 40, at 1089–90 (footnotes omitted); *see also* Barocas & Selbst, *supra* note 40, at 712–14 (discussing the problem of masking and the related difficulty in proving disparate treatment).

100. Kate Crawford described this problem as artificial intelligence's "white guy problem":

> Like all technologies before it, artificial intelligence will reflect the values of its creators. So inclusivity matters—from who designs it to who sits on the company boards and which ethical perspectives are included. Otherwise, we risk

historical online[101] or offline data.[102] With inappropriate data fed as either input or training data,[103] these algorithms will be caught in so-called

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> constructing machine intelligence that mirrors a narrow and privileged vision of society, with its old, familiar biases and stereotypes.

Kate Crawford, *Artificial Intelligence's White Guy Problem*, N.Y. TIMES (June 25, 2016), https://www.nytimes.com/2016/06/26/opinion/sunday/artificial-intelligences-white-guy-problem.html [https://perma.cc/8N73-MW2J]; *see also* RAINIE & ANDERSON, *supra* note 22, at 12 ("The algorithms will be primarily designed by white and Asian men—with data selected by these same privileged actors—for the benefit of consumers like themselves." (quoting Justin Reich, Exec. Dir., MIT Teaching Sys. Lab)); Katyal, *supra* note 2, at 59 ("[A]lgorithmic models are . . . the product of their fallible creators, who may miss evidence of systemic bias or structural discrimination in data or may simply make mistakes. These errors of omission—innocent by nature—risk reifying past prejudices, thereby reproducing an image of an infinitely unjust world." (footnote omitted)); Andrea M. Matwyshyn, *Silicon Ceilings: Information Technology Equity, the Digital Divide and the Gender Gap Among Information Technology Professionals*, 2 NW. J. TECH. & INTELL. PROP. 35, 55 (2003) ("Software reflects the biases of its creators, and tends to be biased in favor of what are perceived by many to be boys' interests." (footnote omitted)); Hamann, *supra* note 8 (lamenting how "AI algorithms are developed almost entirely in developed regions" and "may not sufficiently reflect the contexts and priorities of developing countries"); Mariya Yao, *Fighting Algorithmic Bias and Homogenous Thinking in A.I.*, FORBES (May 1, 2017, 12:02 PM), https://www.forbes.com/sites/mariyayao/2017/05/01/dangers-algorithmic-bias-homogenous-thinking-ai [https://perma.cc/ZRW4-9DG2] ("When Timnit Gebru attended a prestigious AI research conference last year, she counted 6 black people in the audience out of an estimated 8,500. And only one black woman: herself.").

101. As Nizan Packin and Yafit Lev-Aretz observed:

> It is questionable how accurate and reliable Internet sources truly are. Especially, as they are prone to data cleaning processes—a phenomenon that is more typical in the case of social media data—as well as other types of outages, random errors and gaps. The cleaning processes, errors, and outages raise questions as to whether Internet sources and online data can represent an objective truth or is any interpretation necessarily biased by some subjective filter given the way that data is cleaned. Similarly, data loss, another frequent occurrence, refers to the situation when information is destroyed by failures or neglect in storage, transmission, or processing. Originating in Internet sources, such errors, outages, and losses in large datasets are amplified when multiple datasets are pulled together.

Packin & Lev-Aretz, *supra* note 40, at 91.

102. *See* Anthony J. Casey & Anthony Niblett, *A Framework for the New Personalization of Law*, 86 U. CHI. L. REV. 333, 349 (2019) ("The question of whether an algorithm can achieve the objective of the law turns on the *quality* of the data that a lawmaker relies on."); Katyal, *supra* note 2, at 79 ("[W]hen algorithms train on imperfect data, or are designed by individuals who may be unconsciously biased in some manner, the results often reflect these biases, often to the detriment of certain groups."); Kim, *supra* note 40, at 861 ("Algorithms that are built on inaccurate, biased, or unrepresentative data can in turn produce outcomes biased along lines of race, sex, or other protected characteristics."); Zarsky, *supra* note 40, at 1392–94 (discussing the reliance on tainted datasets and data collection methods).

103. Ajay Agrawal, Joshua Gans, and Avi Goldfarb distinguished between three types of

"garbage in, garbage out" situations, causing the outcomes to be biased against the excluded populations.[104]

While the existence of algorithmic bias alone is bad enough, the problem can be exacerbated by the fact that machines learn themselves by feeding the newly generated data back into the algorithms. Because these data will become the new training and feedback data, algorithms that are improperly designed or that utilize problematic data could amplify real-world biases by creating self-reinforced feedback loops.[105] As time passes, the biases generated through these loops will become much worse than the biases found in the original algorithmic designs or the initial training data.

C. *Algorithmic Distortion*

The first two problems—algorithmic deprivation and discrimination—affect primarily those on the unfortunate side of the algorithmic divide. By contrast, the third problem—the distortion created by improperly designed algorithms or a lack of appropriate data—affects all users that rely on algorithms to develop policies or to understand, manage, or improve the world.

For instance, when machine-learning algorithms are used to predict economic developments at the national or global level, such algorithms are unlikely to produce accurate analyses if the training data exclude

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data that enter artificial intelligence systems: "Input data is used to power [the machine] to produce predictions. Feedback data is used to improve it. . . . Training data is used at the beginning to train an algorithm, but once the prediction machine is running, it is not useful anymore." AJAY AGRAWAL ET AL., PREDICTION MACHINES: THE SIMPLE ECONOMICS OF ARTIFICIAL INTELLIGENCE 163 (2018).

104. *See* Peter K. Yu, *Fair Use and Its Global Paradigm Evolution*, 2019 U. ILL. L. REV. 111, 157 (defining the "garbage in, garbage out" situation as one "in which incorrect input ends up producing faulty output").

105. As Ronald Yu and Gabriele Spina Alì observed:

> [T]here is a strong risk that AI may reiterate and even amplify the biases and flaws in datasets, even when these are unknown to humans. In this sense, AI has a self-reinforcing nature, due to the fact that the machine's outputs will be used as data for future algorithmic operations.

Ronald Yu & Gabriele Spina Alì, *What's Inside the Black Box? AI Challenges for Lawyers and Researchers*, 19 LEGAL INFO. MGMT. 2, 4 (2019); *see also* Sofia Grafanaki, *Autonomy Challenges in the Age of Big Data*, 27 FORDHAM INTELL. PROP. MEDIA & ENT. L.J. 803, 827 (2017) ("[A]lgorithmic self-reinforcing loops are now present across many spheres of our daily life (e.g., retail contexts, career contexts, credit decisions, insurance, Google search results, news feeds) . . . ."); Katyal, *supra* note 2, at 69 ("Bad data . . . can perpetuate inequalities through machine learning, leading to a feedback loop that replicates existing forms of bias, potentially impacting minorities as a result."); *Digital Decisions*, *supra* note 46 ("Unreliable or unfair decisions that go unchallenged can contribute to bad feedback loops, which can make algorithms even more likely to marginalize vulnerable populations.").

those on the unfortunate side of the algorithmic divide, which make up a large segment of the population. Because biases in machine-generated analyses can amplify themselves by feeding these biases into future analyses, the unreliability of those analyses that omit data from the unfortunate side of the algorithmic divide will increase over time. Such analyses will eventually become much more unreliable than the initial skewing caused by a lack of training data concerning that unfortunate side.

At the global level, analyses that omit data from the technology poor will become even more problematic. Oftentimes, big-data analytics, machine learning, and artificial intelligence are deployed to address global problems—be they reduction of poverty, improvement on public health, enhancement on basic education, or relief to climate change.[106] In the area of climate change, for example, machine learning and artificial intelligence have been actively utilized to track natural disasters,[107] highlight alarming trends, and prevent man-made environmental damage.[108] Without the inclusion of information from the world's most vulnerable populations that are on the unfortunate side of the algorithmic divide, any algorithmically generated analyses will likely be of limited or no use to addressing these problems.

To be sure, in terms of the scope of the problem and the severity of its impact, the problem of algorithmic distortion is no comparison to the problem of algorithmic deprivation or discrimination. Nevertheless, in terms of the scale of that impact, such distortion can be quite damaging, as algorithmic distortion will prevent all users—on both sides of the divide—from realizing the full potential of machine learning and artificial intelligence.

Given the strong likelihood that the algorithmic divide will continue to distort outcomes generated by algorithms, it is worth exploring when such distortion warrants human intervention.[109] Anthony Casey and Anthony Niblett, for instance, noted the continuous role of humans in algorithmic development:

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106. *See* discussion *supra* Section II.A.

107. *See* Maskey, *supra* note 53 (noting the artificial intelligence program that "accurately predicts seismic events and is . . . working on solutions for floods, wildfires and hurricanes").

108. *See* De-Arteaga et al., *supra* note 30, at 9:4 ("[V]iolence in the developing world often occurs in difficult to access rural areas. In order to prevent such atrocities, 'crisis mapping' provides spatio-temporal analyses of . . . environmental disasters." (quoting Jen Ziemke, *Crisis Mapping: The Construction of a New Interdisciplinary Field?*, 8 J. MAP & GEOGRAPHY LIBR. 101, 101 (2012))).

109. Article 22(3) of the EU General Data Protection Regulation requires a data controller to "implement suitable measures to safeguard the data subject's rights and freedoms and legitimate interests, at least the right to obtain human intervention on the part of the controller, to express his or her point of view and to contest [a decision based solely on automated processing, including profiling]." Council Regulation 2016/679, art. 22(3), 2016 O.J. (L 119) 1, 46.

> Algorithmic decision-making does not mean that humans are shut out of the process. Even after the objective has been set, there is much human work to be done. Indeed, humans are involved in all stages of setting up, training, coding, and assessing the merits of the algorithm. If the objectives of the algorithm and the objective of the law are perfectly aligned at the ex ante stage, one must ask: Under what circumstances should a human ignore the algorithm's suggestions and intervene *after* the algorithm has made the decision?[110]

Notwithstanding the need for and benefit of human intervention or "supervision,"[111] deciding when humans should intervene is not always easy. As Professors Casey and Niblett continued:

> Algorithms will often identify counterintuitive connections that may appear erroneous to humans even when accurate. Humans should be careful in those cases not to undo the very value that was added by the algorithm's ability to recognize these connections. This is especially true when the benefit of the algorithm was that it reduced human bias and behavioral errors.[112]

III. SOLUTIONS

The previous Part identified three distinct problems, each of which may call for the development of different solutions. Yet, these problems overlap to some extent and at times may warrant common solutions. To help bridge the algorithmic divide, this Part proposes seven non-

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110. Casey & Niblett, *supra* note 102, at 354.

111. Machine learning can generally be separated into supervised and unsupervised learning, with the latter having no predefined output. *See generally* ETHEM ALPAYDIN, MACHINE LEARNING: THE NEW AI 38–42, 111–18 (2016) (discussing supervised and unsupervised learning); KELLEHER, *supra* note 35, at 26–30 (discussing supervised, unsupervised, and reinforcement learning). Supervision, in this case, will be to set parameters for the algorithmic operation or to add predefined outputs to constrain that operation. Although unsupervised learning has become increasingly attractive, due to its unlimited potential, most artificial intelligence systems combine supervised- and unsupervised-learning techniques. *See generally* David Lehr & Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. DAVIS L. REV. 653 (2017) (providing an accessible overview of machine learning for lawyers).

112. Casey & Niblett, *supra* note 102, at 354; *see also* RAINIE & ANDERSON, *supra* note 22, at 40 ("People often confuse a biased algorithm for an algorithm that doesn't confirm their biases. If Facebook shows more liberal stories than conservative, that doesn't mean something is wrong. It could be a reflection of their user base, or of their media sources, or just random chance." (quoting an anonymous principal of a consulting firm)); Harry Surden & Mary-Anne Williams, *Technological Opacity, Predictability, and Self-Driving Cars*, 38 CARDOZO L. REV. 121, 158 (2016) ("[I]t is not uncommon for pilots in the cockpit to be surprised or confused by an automated activity undertaken by an autopilot system."). *See generally* Andrew D. Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085 (2018) (documenting the limitations of intuition while noting the need to address inscrutability).

exhaustive clusters of remedial actions. Featuring law, communications policy, ethical principles, institutional mechanisms, and business practices, the wide variety of actions proposed in this Part aim to fashion a holistic response to the multidimensional problems precipitated by the algorithmic divide.

A. *Literacy*

From the individuals' lack of awareness of algorithm-related problems to their inability to adapt to machine learning and artificial intelligence,[113] increasing algorithmic literacy is crucial if a large majority of the world's population is to reap the benefits of these new technologies.[114] These individuals will need to know not only the impact of machine learning and artificial intelligence on their daily lives but also what it means to live in a society driven heavily by algorithms and intelligent machines.[115] Greater algorithmic literacy will help these

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113. *See* discussion *supra* Sections I.A, I.E, II.B (discussing the need for awareness of and adaptability to machine learning and artificial intelligence and the problem of algorithmic discrimination).

114. *See* INST. ELEC. & ELEC. ENG'RS, *supra* note 14, at 142 ("Improving digital literacy of citizens should be a high priority for the government and other organizations."); PAUL ET AL., *supra* note 45, at 74 ("Strengthening training programs for data science and machine learning in local development contexts can help create a pipeline of individuals who are 'bilingual' in the sense of understanding local context and having the technical skills to take an active role in developing [machine-learning] tools."); RAINIE & ANDERSON, *supra* note 22, at 74–76 (surveying views on the need for algorithmic literacy); UNESCO, *supra* note 64, at 6–7 ("[T]eachers must learn new digital skills to use AI in a pedagogical and meaningful way . . . ."); *id.* at 29 (identifying the new competencies needed by teachers to make more effective use of artificial intelligence-enabled technologies); *see also* EXEC. OFFICE OF THE PRESIDENT, *supra* note 82, at 32 (noting the need to "build[] on the President's *Computer Science for All* initiative, which seeks to give all students at the K–12 level access to coursework in computing and computational thinking").

115. The International Society for Technology in Education and the Computer Science Teachers Association provided the following operational definition of computational thinking:

> Computational thinking (CT) is a problem-solving process that includes (but is not limited to) the following characteristics:
>
> - Formulating problems in a way that enables us to use a computer and other tools to help solve them[]
> - Logically organizing and analyzing data
> - Representing data through abstractions such as models and simulations
> - Automating solutions through algorithmic thinking (a series of ordered steps)
> - Identifying, analyzing, and implementing possible solutions with the

individuals realize the full potential of machine learning and artificial intelligence. It will also assist them in choosing away from undesirable technological products and services that fail to protect privacy or other individual rights.

In addition, a greater understanding of algorithmic operations will allow individuals to develop human-generated responses to ensure more successful engagement with algorithm-enhanced technological products and services and the rapidly changing technological environment. While most of these individuals are unlikely to be able to fully understand the operation of the algorithms involved[116]—or, in some cases, no individual will ever be able to develop such a full understanding—research has shown that individuals are capable of developing responses that would

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> goal of achieving the most efficient and effective combination of steps and resources
>
> - Generalizing and transferring this problem solving process to a wide variety of problems[.]

INT'L SOC'Y FOR TECH. IN EDUC. & COMPUT. SCI. TEACHERS ASS'N, OPERATIONAL DEFINITION OF COMPUTATIONAL THINKING FOR K–12 EDUCATION (n.d.), https://id.iste.org/docs/ct-documents/computational-thinking-operational-definition-flyer.pdf?sfvrsn=2 [https://perma.cc/5M9N-SBL2]; *see also* RAGNEDDA, *supra* note 18, at 101 ("Digital literacy . . . should not be confused with technological skills; rather, it is an umbrella term that includes several skills, including: information-finding skills; Internet skills; effective communication skills; functional skills; collaboration skills; creative skills; shared knowledge; critical-thinking skills; social-networking skills; career skills; and identity management skills."); WARSCHAUER, *supra* note 18, at 113 ("Information literacies involve both computer-specific knowledge (e.g., mastery of browsing software and search tools) and broader critical literacy skills (e.g., analysis and evaluation of information sources)."). *See generally* PETER J. DENNING & MATTI TEDRE, COMPUTATIONAL THINKING (2019) (providing an overview of computational thinking).

116. As Pedro Domingos lamented:

> When algorithms become too intricate for our poor human brains to understand, when the interactions between different parts of the algorithm are too many and too involved, errors creep in, we can't find them and fix them, and the algorithm doesn't do what we want. Even if we somehow make it work, it winds up being needlessly complicated for the people using it and doesn't play well with other algorithms, storing up trouble for later.

DOMINGOS, *supra* note 2, at 5; *see also* EUBANKS, *supra* note 2, at 184–85 ("The software, algorithms, and models that power [the algorithm-driven digital poorhouse] are complex and often secret."); RAINIE & ANDERSON, *supra* note 22, at 19 ("Only the programmers are in a position to know for sure what the algorithm does, and even they might not be clear about what's going on. In some cases there is no way to tell exactly why or how a decision by an algorithm is reached." (quoting Doc Searls, Dir., Project VRM, Berkman Klein Ctr. for Internet & Soc'y, Harvard Univ.)); Chander, *supra* note 96, at 1040 ("[T]he algorithm may be too complicated for many others to understand, or even if it is understandable, too demanding, timewise, to comprehend fully."); Kroll et al., *supra* note 95, at 638 ("The source code of computer systems is illegible to nonexperts. In fact, even experts often struggle to understand what software code will do, as inspecting source code is a very limited way of predicting how a computer program will behave.").

"trick" algorithms into providing more desirable results.[117] Facebook users, for example, have provided different information to improve algorithmic outcomes.[118] Research has also shown that users change their behaviors in response to undesirable outcomes.[119] Having strong algorithmic literacy will therefore be crucial to making adjustments in this new technological environment.

Finally, as policy makers and commentators have widely noted, the age of artificial intelligence will result in massive job losses,[120] especially in developing countries.[121] If individuals are to successfully transition to

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117. The ability to manipulate results or game the system is often used to justify the nondisclosure of algorithms. *See* Chander, *supra* note 96, at 1040 ("[T]ransparency invites manipulations by those who game those algorithms."); Kroll et al., *supra* note 95, at 639 ("The process for deciding which tax returns to audit, or whom to pull aside for secondary security screening at the airport, may need to be partly opaque to prevent tax cheats or terrorists from gaming the system.").

118. *See* Caleb Garling, *Tricking Facebook's Algorithm*, ATLANTIC (Aug. 8, 2014), https://www.theatlantic.com/technology/archive/2014/08/tricking-facebooks-algorithm/375801/ [https://perma.cc/8BKJ-56WQ] (discussing the experience of tricking Facebook to elevate the author's post); Susarla, *supra* note 10 ("A study of Facebook usage found that when participants were made aware of Facebook's algorithm for curating news feeds, about 83% of participants modified their behavior to try to take advantage of the algorithm, while around 10% decreased their usage of Facebook."); *see also* Jane Bambauer & Tal Zarsky, *The Algorithm Game*, 94 NOTRE DAME L. REV. 1, 12–14 (2018) (listing avoidance, altered conduct, altered input, and obfuscation among the dominant gaming strategies deployed by users on Internet platforms).

119. *See* Dan L. Burk, *Algorithmic Fair Use*, 86 U. CHI. L. REV. 283, 295 (2019) ("Audiences will inevitably alter their behavior under the influence of the algorithms they depend on, and these behavioral changes then impact the data and data relationships that form the inputs to the same algorithms, a mirrored parallel to the cycles of anticipation in design."); *see also* Gillespie, *supra* note 2, at 183–88 (discussing the algorithms' entanglement with user behavior); Peter K. Yu, *Can Algorithms Promote Fair Use?*, 14 FIU L. REV. (forthcoming 2020) (manuscript at 4–5), https://ssrn.com/abstract=3403712 [https://perma.cc/QYY9-PSKE] (discussing the potential changes in creative choices and practices when algorithms are deployed to promote fair use in copyright law).

120. *See supra* text accompanying note 82 (discussing how machine learning and artificial intelligence would displace jobs).

121. As Lee Kai-fu observed:

> AI-driven automation in factories will undercut the one economic advantage developing countries historically possessed: cheap labor. Robot-operated factories will likely relocate to be closer to their customers in large markets, pulling away the ladder that developing countries like China and the "Asian Tigers" of South Korea and Singapore climbed up on their way to becoming high-income, technology-driven economies. The gap between global haves and have-nots will widen, with no known path toward closing it.

LEE, *supra* note 6, at 20–21. Similarly, the Institute of Electrical and Electronics Engineers noted the following in its draft guiding document:

> The risk of unemployment for developing countries is more serious than for

this new technological environment, they will need to acquire a high level of algorithmic literacy. To a large extent, the lack of such literacy will harm individuals the same way as the lack of computing or Internet-related skills at the turn of this millennium, or even today.[122] In the age of artificial intelligence, policy makers should be well prepared to train, and retrain, a large portion of their constituents to better adapt to the new technological demands and challenges.

B. *Amelioration*

Just like how the changing technological environment could affect an individual's career opportunities, policy makers can easily anticipate and sufficiently ameliorate the problems of algorithmic deprivation and algorithmic discrimination. Not only will these policy makers need to better understand the changing technological environment—through the literacy-based solutions discussed above[123]—but they will also need to take proactive actions to preempt or quickly address problems that the algorithmic divide will precipitate. Successful responses to these problems will generate algorithmic opportunities that will allow their constituencies to fully participate in the artificial intelligence revolution.[124]

Ameliorating algorithmic deprivation will require laws and policies that facilitate greater technology diffusion to those in need. To a large extent, the laws and policies needed in this area resemble those that were

> developed countries. The industry of most developing countries is labor intensive. While labor may be cheap(er) in developing economies, the ripple effects will be felt much more than in the developed economies as more and more jobs will be gradually replaced along with the development of robots or [autonomous and intelligent systems].

INST. ELEC. & ELEC. ENG'RS, *supra* note 14, at 133–34.

122. *See* RAGNEDDA, *supra* note 18, at 101 ("A lack of basic ability in using computers and surfing the net puts individuals in a disadvantaged position."); *see also* WARSCHAUER, *supra* note 18, at 111–19 (noting the need for computer, information, multimedia, and computer-mediated communication literacy); Ali, *supra* note 33, at 194 ("In today's global economy, where computers and the Internet are so fundamental to production and participation, it is clear that if the right to development is to be taken seriously, that right must encompass the development of ICT infrastructure and skills.").

123. *See* discussion *supra* Section III.A (discussing the need to increase algorithmic literacy).

124. *Cf.* B. Keith Fulton, *AOL Time Warner Foundation: Extending Internet Benefits to All*, 20 CARDOZO ARTS & ENT. L.J. 181, 181 (2002) ("[W]orld leaders, captains of industry, local politicians, community advocates and others have begun to embrace the notion of 'digital opportunity' as a better way to quickly frame domestic and international efforts to extend the benefits of the digital age to all."); Yu, *supra* note 7, at 21–22 (discussing the Digital Opportunity Taskforce established at the G-8 Summit in Okinawa, Japan, in July 2000). In addition to digital opportunity, the term "digital dividend" has also been widely used to refer to the benefits provided by digital technology. *See, e.g.*, *High-level Panel Report*, *supra* note 32, at 6 ("Digital dividends co-exist with digital divides.").

already introduced a decade or two ago to address the digital divide.[125] In the telecommunications field, for instance, policy makers have relied on the introduction of universal service,[126] such as the E-rate Program.[127] Some European countries, such as "Estonia, Finland, Greece, and Spain, have also mandated universal broadband access or recognized a right to broadband services."[128]

To be sure, there is a significant distinction between addressing algorithmic deprivation and providing access to the Internet or other basic telecommunications services. While the latter requires the provision of free or affordable service, the former requires adaptation to a new technological environment. Nevertheless, many capabilities relating to machine learning and artificial intelligence have already been built into easy-to-use technological products and services. For example, it does not take much effort or knowledge to figure out how to use the auto-complete feature in a software[129] or to wait patiently for a self-learning computer to provide better results. From that vantage point, facilitating access to new algorithm-enhanced technological products and services is quite similar to increasing one's ability to utilize basic telecommunications services.

Compared with efforts to tackle algorithmic deprivation, addressing algorithmic discrimination requires different solutions. To begin with, policy makers should introduce laws, policies, and institutional mechanisms to prevent intentional algorithmic discrimination.[130] In the workplace, for instance, Title VII of the Civil Rights Act of 1964[131] prohibits discrimination based on "race, color, religion, sex, or national

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125. *See* NORRIS, *supra* note 13, at 10 (identifying the measures taken by the Clinton Administration to address the digital divide); VAN DIJK, *supra* note 13, at 205–17 (outlining the concrete measures for closing the digital divide and preventing structural inequality, with a focus on motivational, material, skills, and usage access).

126. *See generally* Milton Mueller, *Telecommunications Access in the Age of Electronic Commerce: Toward a Third-Generation Universal Service Policy*, 49 FED. COMM. L.J. 655 (1997) (discussing the evolution of the universal-service policy in light of the changing demands and expectations brought about by electronic commerce).

127. *See* Yu, *supra* note 7, at 10 n.53 (providing sources discussing the E-rate Program).

128. Peter K. Yu, *The Graduated Response*, 62 FLA. L. REV. 1373, 1422 (2010) (footnote omitted).

129. Notwithstanding its benefits, this feature can also cause significant harm to individual users. *See generally* Anne S.Y. Cheung, *Defaming by Suggestion: Searching for Search Engine Liability in the Autocomplete Era*, *in* COMPARATIVE PERSPECTIVES ON THE FUNDAMENTAL FREEDOM OF EXPRESSION 467 (András Koltay ed., 2015) (discussing the defamatory results generated by Google's search algorithm).

130. *See* Tene & Polonetsky, *supra* note 90, at 135 ("[A]lgorithms that implement discriminatory criteria are unlawful and/or unethical and must be purged.").

131. Pub. L. No. 88-352, §§ 701–716, 78 Stat. 241, 253–68 (codified as amended at 42 U.S.C. §§ 2000e–2000e-17 (2018)).

origin."[132] While commentators have noted the complications caused by diverging legal standards and interpretations—such as those addressing the difference between "disparate treatments" and "disparate impacts"[133]—the biggest challenge in the age of artificial intelligence will likely be the increased ability for those in support of discriminatory practices to hide behind algorithms and machines—the masking problem mentioned in Section II.B.[134]

Equally daunting is to address algorithmic discrimination that neutral or well-intentioned efforts have caused. As the previous Part noted, algorithm-enhanced technological products and services are often biased or discriminatory because they are designed with implicit bias or rely on problematic data.[135] To address this complication, the next four Sections will focus on remedial actions that implicate ethics, transparency, accountability, and competition.[136] Cumulatively these actions will help address such unintentional discriminatory practices and outcomes.

Finally, addressing algorithmic distortion—and, to an equal extent, algorithmic discrimination—requires the development of a more inclusive environment.[137] Such an environment needs to be diverse not only in terms of those designing algorithms and related technological products and services but also in terms of the training and feedback data that are being fed into the algorithms. The lack of diversity in either

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132. 42 U.S.C. § 2000e-2(a).

133. *See, e.g.*, Barocas & Selbst, *supra* note 40, at 694–712 (discussing the distinction between disparate treatment and disparate impact in the context of big data); Zarsky, *supra* note 40, at 1384–1404 (discussing disparate treatment and disparate impact in the context of social-scoring systems).

134. *See supra* text accompanying notes 97–99 (discussing the masking problem).

135. *See* discussion *supra* Section II.B (discussing algorithmic discrimination).

136. *See* discussion *infra* Sections III.C, III.D, III.E, III.F (proposing remedial actions relating to ethics, transparency, accountability, and competition).

137. As Amy Webb, CEO of the Future Today Institute, declared:

> The only way to address algorithmic discrimination in the future is to invest in the present. The overwhelming majority of coders are white and male. Corporations must do more than publish transparency reports about their staff—they must actively invest in women and people of color, who will soon be the next generation of workers. And when the day comes, they must choose new hires both for their skills and their worldview. Universities must redouble their efforts not only to recruit a diverse body of students—administrators and faculty must support them through to graduation. And not just students. Universities must diversify their faculties, to ensure that students see themselves reflected in their teachers.

RAINIE & ANDERSON, *supra* note 22, at 23 (quoting Amy Webb, Chief Exec. Officer, Future Today Inst.); *see also* MEREDITH BROUSSARD, ARTIFICIAL UNINTELLIGENCE: HOW COMPUTERS MISUNDERSTAND THE WORLD 154 (2018) ("Th[e] willful blindness on the part of some technology creators is why we need inclusive technology . . . .").

direction will likely perpetuate the many historical biases that originate in the offline world.

To respond to this need for inclusivity, commentators have called for policies and practices to facilitate greater inclusion in the new technological environment.[138] For example, in its final report, the United Nations Secretary-General's High-level Panel on Digital Cooperation underscored the importance of developing "[a]n inclusive digital economy and society."[139] Greater emphasis on inclusivity will help move society closer to tackling the problems of both algorithmic discrimination and algorithmic distortion.[140]

C. *Ethics*

As the previous Section noted, well-intentioned efforts can sometimes lead to discriminatory outcomes. Efforts in an algorithmic society are no different. As a result, policy makers and commentators should devote greater time, effort, and energy to developing ethical standards that should be built into the design, usage, and improvement of algorithms and intelligent machines.[141]

To ensure the compliance of high ethical standards, responses should be developed both inside and outside the design process. Within the process, those involved in algorithmic design should devote greater attention to developing best practices or codes of conduct concerning how best to avoid or alleviate the problems of algorithmic discrimination and distortion.[142] Letting designers develop best practices and codes of

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138. *See* Mark Warschauer, *Reconceptualizing the Digital Divide*, FIRST MONDAY (July 1, 2002), https://www.firstmonday.org/ojs/index.php/fm/article/view/967/888 [https://perma.cc/QX69-E5WW] ("A framework of technology for social inclusion allows us to re-orient the focus from that of gaps to be overcome by provision of equipment to that of social development to be enhanced through the effective integration of ICT into communities and institutions.").

139. *High-level Panel Report*, *supra* note 32, at 29–30.

140. *See* discussion *supra* Section II.C (discussing algorithmic distortion).

141. As the Obama Administration declared in its white paper on artificial intelligence:

> Ethical training for AI practitioners and students is a necessary part of the solution. Ideally, every student learning AI, computer science, or data science would be exposed to curriculum and discussion on related ethics and security topics. However, ethics alone is not sufficient. Ethics can help practitioners understand their responsibilities to all stakeholders, but ethical training should be augmented with technical tools and methods for putting good intentions into practice by doing the technical work needed to prevent unacceptable outcomes.

COMM. ON TECH., NAT'L SCI. & TECH. COUNCIL, PREPARING FOR THE FUTURE OF ARTIFICIAL INTELLIGENCE 3 (2016) [hereinafter PREPARING FOR THE FUTURE], https://obamawhitehouse.archives.gov/sites/default/files/whitehouse_files/microsites/ostp/NSTC/preparing_for_the_future_of_ai.pdf [https://perma.cc/24P5-FKYD].

142. *See* Katyal, *supra* note 2, at 108–11 (discussing codes of conduct for designing artificial intelligence systems).

conduct can be highly effective because they understand the technological challenges and are in good positions to anticipate problems that improperly designed algorithms and data practices could cause.

Thus far, there has been a growing push for the development of fair and explainable algorithms.[143] Pauline Kim explained the benefits of "explainability" as follows:

> When a model is interpretable, debate may ensue over whether its use is justified, but it is at least possible to have a conversation about whether relying on the behaviors or attributes that drive the outcomes is normatively acceptable. When a model is not interpretable, however, it is not even possible to have the conversation.[144]

In January 2017, the U.S. Public Policy Council of the authoritative Association for Computing Machinery (ACM) released its *Statement on Algorithmic Transparency and Accountability* (*ACM Statement*).[145] Principle 4 states explicitly that "[s]ystems and institutions that use algorithmic decision-making are encouraged to produce explanations regarding both the procedures followed by the algorithm and the specific decisions that are made."[146] Later that year, the Institute of Electrical and Electronics Engineers (IEEE) also released the second draft of its guiding document entitled *Ethically Aligned Design: A Vision for Prioritizing Human Well-being with Autonomous and Intelligent Systems*.[147] Included in that document was a recommendation calling on software engineers to "document all of their systems and related data flows, their performance, limitations, and risks," with emphases on "auditability, accessibility, meaningfulness, and readability."[148] Apart from the ACM and the IEEE, every year FAT/ML, which stands for "Fairness, Accountability, and Transparency in Machine Learning," "[brings] together a . . . community of researchers and practitioners" with similar interests and concerns.[149] Like the two other organizations, FAT/ML has adopted principles that are designed to help make algorithms fair, explainable, ethical, and transparent.[150]

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143. *See infra* text accompanying notes 179–182.

144. Kim, *supra* note 40, at 922–23.

145. ACM STATEMENT, *supra* note 1.

146. *Id.* at 2; *see also* Diakopoulos et al., *supra* note 98 ("Ensure that algorithmic decisions as well as any data driving those decisions can be explained to end-users and other stakeholders in non-technical terms.").

147. INST. ELEC. & ELEC. ENG'RS, *supra* note 14.

148. *Id.* at 68.

149. *Fairness, Accountability, & Transparency in Machine Learning*, FAT/ML, https://www.fatml.org/ [https://perma.cc/2B24-PZ3G].

150. *See* Diakopoulos et al., *supra* note 98 (delineating principles laid down by the FAT/ML).

Even though trusting designers to come up with best practices and codes of conduct can be highly promising, there also needs to be external responses. At the domestic level, laws should be put in place to ensure greater ethical standards in the design and use of algorithms. At the international level, treaties,[151] soft law recommendations,[152] or other normative documents can be utilized to help facilitate the development of internationally acceptable standards. As consensus emerges at the international level, these standards will slowly translate into domestic laws and practices.

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151. The area that has caught immediate attention concerns human rights. *See* INST. ELEC. & ELEC. ENG'RS, *supra* note 14, at 22–23 (proposing Principle 1 to ensure that autonomous and intelligent systems "do not infringe upon human rights"); PEACOCK, *supra* note 18, at 108–84 (discussing the positive human rights obligations to facilitate access to the Internet and the possibility of using human rights to provide support for the overall goal of bridging the digital divide); Lorna McGregor et al., *International Human Rights Law as a Framework for Algorithmic Accountability*, 68 INT'L & COMP. L.Q. 309, 313 (2019) ("[A] human rights-based approach to algorithmic accountability offers an organizing framework for the design, development and deployment of algorithms . . . ."); Rohinton P. Medhora, *AI & Global Governance: Three Paths Towards a Global Governance of Artificial Intelligence*, UNITED NATIONS U. CTR. POL'Y RES. (Oct. 28, 2018), https://cpr.unu.edu/ai-global-governance-three-paths-towards-a-global-governance-of-artificial-intelligence.html [https://perma.cc/5TBZ-ZP4A] ("[A]lgorithms should be subordinated to the same kind of universal ethics regime that governs human and state behavior: something similar to the Universal Declaration of Human Rights."). As Lorna McGregor, Daragh Murray, and Vivian Ng elaborated:

> First, [international human rights law] may rule out the use of algorithms in certain decision-making processes. Second, it may require modifications or the building in of additional safeguards in order to ensure rights compliance and thus may create a delay in deployment. Third, it may shift debates on the unpredictability of algorithms, particularly in the future where greater autonomy is anticipated, from a perceived reduced responsibility to a greater responsibility for actors that deploy algorithms in the knowledge that they cannot predict effects, including to human rights. While these three findings act as restrictions on the use of algorithms, in our view, they constitute appropriate checks and balances. They are not intended to be "anti-innovation". Instead algorithmic decision-making is addressed in the same way as human decision-making. The objective is to ensure that algorithms contribute to society, while safeguarding against risks.

McGregor et al., *supra*, at 314–15.

152. Target 9.C of U.N. Sustainable Development Goal 9 provides: "Significantly increase access to information and communications technology and strive to provide universal and affordable access to the Internet in least developed countries by 2020." G.A. Res. 70/1, Transforming Our World: The 2030 Agenda for Sustainable Development, at 21 (Oct. 21, 2015).

D. *Transparency*

Commentators have noted how algorithms have resulted in the creation of an inscrutable "black box."[153] In response to this problem, Frank Pasquale outlined various legal strategies to provide checks against some of the worst "black box" abuses while "mak[ing] the case for a new politics and economics of reputation, search, and finance, based on the ideal of an intelligible society."[154] Commentators have also noted the importance of accountability by design.[155] In the privacy area, for instance, Woodrow Hartzog advanced "a design agenda for privacy law," explaining why "the design of popular technologies is critical to privacy, and the law should take it more seriously."[156] In addition, commentators have underscored the need for greater transparency in the design and use of algorithms, including the disclosure of technological choices made by algorithm designers.[157] Some experts and organizations have also called

153. In his widely cited book, Frank Pasquale noted the dual meaning of the term "black box": "The term 'black box' . . . can refer to a recording device, like the data-monitoring systems in planes, trains, and cars. Or it can mean a system whose workings are mysterious; we can observe its inputs and outputs, but we cannot tell how one becomes the other." PASQUALE, *supra* note 86, at 3; *see also* DOMINGOS, *supra* note 2, at xvi ("When a new technology is as pervasive and game changing as machine learning, it's not wise to let it remain a black box."); EUBANKS, *supra* note 2, at 5 ("[T]hat's the thing about being targeted by an algorithm: you get a sense of a pattern in the digital noise, an electronic eye turned toward *you*, but you can't put your finger on exactly what's amiss."); RAINIE & ANDERSON, *supra* note 22, at 19 ("There is a larger problem with the increase of algorithm-based outcomes beyond the risk of error or discrimination—the increasing opacity of decision-making and the growing lack of human accountability." (quoting Marc Rotenberg, Exec. Dir., Elec. Privacy Info. Ctr.)).

154. PASQUALE, *supra* note 86, at 15; *see also id.* at 140–218 (outlining the legal strategies to curb "black box" abuses and calling for the development of "an intelligible society").

155. *See, e.g.*, Kroll et al., *supra* note 95, at 640 ("[I]n order for a computer system to function in an accountable way—either while operating an important civic process or merely engaging in routine commerce—accountability must be part of the system's design from the start.").

156. HARTZOG, *supra* note 75, at 7.

157. *See, e.g.*, Danielle Keats Citron, *Open Code Governance*, 2008 U. CHI. LEGAL F. 355 (calling for an open code model to improve the quality and legitimacy of decisions made by administrative agencies); Sonia K. Katyal, *The Paradox of Source Code Secrecy*, 104 CORNELL L. REV. 1183, 1250–79 (2019) (calling for the controlled disclosure of source code).

on these designers to provide social impact statements[158] or periodic assessments.[159]

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158. As the FAT/ML's *Principles for Accountable Algorithms and a Social Impact Statement for Algorithms* declare:

> In order to ensure their adherence to these principles and to publicly commit to associated best practices, we propose that algorithm creators develop a Social Impact Statement using the above principles as a guiding structure. This statement should be revisited and reassessed (at least) three times during the design and development process:
>
> - design stage,
> - pre-launch,
> - and post-launch.
>
> When the system is launched, the statement should be made public as a form of transparency so that the public has expectations for social impact of the system.

Diakopoulos et al., *supra* note 98; *see also* Katyal, *supra* note 2, at 111–17 (discussing human impact statements in the artificial intelligence context); Selbst, *supra* note 40, 169–82 (advancing a regulatory proposal based on the requirement of algorithmic impact statements); Selbst & Barocas, *supra* note 112, at 1134–35 (discussing algorithmic impact statements).

159. Article 35(1) of the EU General Data Protection Regulation provides:

> Where a type of processing in particular using new technologies, and taking into account the nature, scope, context and purposes of the processing, is likely to result in a high risk to the rights and freedoms of natural persons, the controller shall, prior to the processing, carry out an assessment of the impact of the envisaged processing operations on the protection of personal data.

Council Regulation 2016/679, *supra* note 109, art. 35(1); *see also* INST. ELEC. & ELEC. ENG'RS, *supra* note 14, at 98 ("A system to assess privacy impacts related to [autonomous and intelligent systems] needs to be developed, along with best practice recommendations, especially as automated decision systems spread into industries that are not traditionally data-rich."); McGregor et al., *supra* note 151, at 330 (discussing impact assessments in an algorithmic context); Diakopoulos et al., *supra* note 98 (calling for assessment "(at least) three times during the design and development process: design stage, pre-launch, and post-launch"). As Lorna McGregor, Daragh Murray, and Vivian Ng explained:

> During the design and development stage, impact assessments should evaluate how an algorithm is likely to work, ensure that it functions as intended and identify any problematic processes or assumptions. This provides an opportunity to modify the design of an algorithm at an early stage, to build in human rights compliance—including monitoring mechanisms—from the outset, or to halt development if human rights concerns cannot be addressed. Impact assessments should also be conducted at the deployment stage, in order to monitor effects during operation. . . . [T]his requires that, during design and development, the focus should not only be on testing but steps should also be taken to build in effective oversight and monitoring processes that will be able to identify and

While improving transparency in algorithmic design is of paramount importance, algorithmic transparency alone does not suffice. As Anupam Chander rightly noted, in the age of artificial intelligence, data used in, and outcomes generated by, the algorithms should also be transparent.[160] The importance of data transparency is obvious, considering that the training and feedback data fed into the algorithms are key ingredients sustaining the algorithmic operation. Even if the algorithms used are properly designed, the inclusion of problematic data could heavily skew the algorithmic outcomes.[161]

Indeed, in this age of artificial intelligence, scrutinizing algorithms alone may not reveal the full extent of a problem.[162] As Kartik Hosanagar and Vivian Jair observed:

> [M]achine learning algorithms—and deep learning algorithms in particular—are usually built on just a few hundred lines of code. The algorithms logic is mostly learned from training data and is rarely reflected in its source code. Which is to say, some of today's best-performing algorithms are often the most opaque.[163]

> respond to human rights violations once the algorithm is deployed. This ability to respond to violations is key as [international human rights law] requires that problematic processes must be capable of being reconsidered, revised or adjusted.

McGregor et al., *supra* note 151, at 330.

160. *See* Chander, *supra* note 96, at 1024–25 ("What we need instead is a *transparency of inputs and results*, which allows us to see that the algorithm is generating discriminatory impact."); *see also* O'NEIL, *supra* note 87, at 229 ("We have to learn to interrogate our data collection process, not just our algorithms.").

161. *See supra* text accompanying notes 101–104 (discussing the biases and errors created by problematic data).

162. *See* Kroll et al., *supra* note 95, at 641 ("[W]ithout full transparency—including source code, input data, and the full operating environment of the software—even the disclosure of audit logs showing what a program did while it was running provides no guarantee that the disclosed information actually reflects a computer system's behavior."); *see also id.* at 657–60 (discussing the limits to transparency in the algorithmic context).

163. Kartik Hosanagar & Vivian Jair, *We Need Transparency in Algorithms, but Too Much Can Backfire*, HARV. BUS. REV. (July 23, 2018), https://hbr.org/2018/07/we-need-transparency-in-algorithms-but-too-much-can-backfire [https://perma.cc/3NVS-FNWP]; *see also* Daniel Gervais, *Exploring the Interfaces Between Big Data and Intellectual Property Law*, 10 J. INTELL. PROP. INFO. TECH. & ELECTRONIC COM. L. 3, 5 (2019) ("[A]ny human contribution to the output of deep learning systems is 'second degree.'"). As a government report on artificial intelligence explained:

> Deep learning uses structures loosely inspired by the human brain, consisting of a set of units (or "neurons"). Each unit combines a set of input values to produce an output value, which in turn is passed on to other neurons downstream. For

Thus, in cases involving self-learning algorithms, closely scrutinizing the algorithms alone will unlikely provide the information needed to fully understand the algorithmic operations.[164] Such scrutiny will be even less useful when algorithms begin designing new algorithms.[165] In those scenarios, the related designers' ability to explain the algorithms involved and the related technological choices will be much more limited than their ability to explain the choices involved in the original algorithmic designs.

Like data transparency, the transparency of algorithmic outcomes is also very important. Without knowing the outcomes, it will be difficult for individual users or outside reviewers to determine the satisfactoriness of the algorithms involved. The lack of outcome transparency also harms users by reducing their ability to choose away from undesirable products and services.[166] Such a lack will also make it difficult for policy makers, consumer advocates, and the public at large to document the problems in

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> example, in an image recognition application, a first layer of units might combine the raw data of the image to recognize simple patterns in the image; a second layer of units might combine the results of the first layer to recognize patterns-of-patterns; a third layer might combine the results of the second layer; and so on.

PREPARING FOR THE FUTURE, *supra* note 141, at 9. For discussions of deep learning, see generally ALPAYDIN, *supra* note 111, at 104–09; KELLEHER, *supra* note 35; JOHN D. KELLEHER & BRENDAN TIERNEY, DATA SCIENCE 121–30 (2018); THIERRY POIBEAU, MACHINE TRANSLATION 181–95 (2017).

164. As Ronald Yu and Gabriele Spina Alì observed:

> Deep learning machines can self-reprogram to the point that even their programmers are unable to understand the internal logic behind AI decisions. In this context, it is difficult to detect hidden biases and to ascertain whether they are caused by a fault in the computer algorithm or by flawed datasets.

Yu & Spina Ali, *supra* note 105, at 5; *see also* Chander, *supra* note 96, at 1040 ("[I]n the era of self-enhancing algorithms, the algorithm's human designers may not fully understand their own creation: even Google engineers may no longer understand what some of their algorithms do."). Likewise, Joshua Kroll and his collaborators explained:

> Machine learning . . . is particularly ill-suited to source code analysis because it involves situations where the decisional rule itself emerges automatically from the specific data under analysis, sometimes in ways that no human can explain. In this case, source code alone teaches a reviewer very little, since the code only exposes the machine learning method used and not the data-driven decision rule.

Kroll et al., *supra* note 95, at 638 (footnote omitted).

165. *See* DOMINGOS, *supra* note 2, at 6 ("Learning algorithms—also known as learners—are algorithms that make other algorithms. With machine learning, computers write their own programs, so we don't have to.").

166. *See* Chander, *supra* note 96, at 1025 ("If we know that the results of an algorithm are systematically discriminatory, then we know enough to seek to . . . distrust its results.").

the questionable products and services as well as for technology developers to come up with improvements.[167]

To be sure, it can be cost-prohibitive to collect or disclose all algorithmic outcomes, not to mention the lack of incentives for technology developers to reveal the algorithms used or to make algorithmic outcomes available for public scrutiny.[168] While intellectual property laws call into question the acceptability of demands to reveal source codes used to develop algorithms, privacy laws caution against the release of all algorithmic outcomes to the public.[169]

As a compromise, technology developers could provide a representative, anonymized sample of the different algorithmic outcomes to enable the public to determine for itself the satisfactoriness of algorithm-enhanced technological products and services.[170] This sample could be made available to the public or be provided to external auditors,[171] ombudspersons,[172] or oversight bodies.[173] If privacy concerns

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167. *See id.* ("If we know that the results of an algorithm are systematically discriminatory, then we know enough to seek to redesign the algorithm . . . .").

168. *See* Yu & Spina Alì, *supra* note 105, at 6 ("Commercial providers could be reluctant to share information on their models or have their systems openly compared to their competitors.").

169. *See* ACM STATEMENT, *supra* note 1, at 2 (Principle 5) ("[C]oncerns over privacy, protecting trade secrets, or revelation of analytics that might allow malicious actors to game the system can justify restricting access to qualified and authorized individuals."); Pauline T. Kim, *Auditing Algorithms for Discrimination*, 166 U. PA. L. REV. ONLINE 189, 191–92 (2017), https://scholarship.law.upenn.edu/cgi/viewcontent.cgi?article=1212&context=penn_law_review_online [https://perma.cc/4A9B-B2MC] ("[T]ransparency is often in tension with other important interests, such as protecting trade secrets, ensuring the privacy of sensitive personal information, and preventing strategic gaming of automated decision systems.").

170. As Frank Pasquale declared:

> Just as the "fair use" doctrine has deterred the overpropertization of expression, generally recognized fair information practices should include large and powerful data holders' obligation to surrender some sample of their data to entities entrusted to audit and assess the data holders' activities. Objective audits will help restore confidence in automated authority.

Frank Pasquale, *Restoring Transparency to Automated Authority*, 9 J. ON TELECOMM. & HIGH TECH. L. 235, 238–39 (2011) (footnote omitted).

171. *See infra* text accompanying notes 191–195 (discussing algorithmic audits and the need for institutional oversight).

172. *See* McGregor et al., *supra* note 151, at 332 ("Independent oversight bodies established to monitor State surveillance activity and analysis of their effectiveness may . . . provide points of reference and comparison. Other models being proposed include dedicated ombuds for the AI sector or the expansion of the mandate of existing ombuds to address these issues as well as industry regulatory bodies." (footnote omitted)).

173. *See* INST. ELEC. & ELEC. ENG'RS, *supra* note 14, at 70 ("An independent, internationally coordinated body should be formed to oversee whether [autonomous and intelligent systems] actually meet ethical criteria, both when deployed, and considering their evolution after deployment and interaction with other products."); Pasquale, *supra* note 170, at 247 ("[P]erhaps

are significant, these developers could instead offer algorithmic outcomes based on test data provided by consumer advocacy groups. The provision of these samples is important because they would support external audits even without providing access to the algorithms involved.[174]

In recent years, commentators have also paid greater attention to the so-called right to explanation, especially when it relates to the new European Union (EU) General Data Protection Regulation.[175] Although this right can be traced back to the 1995 EU Data Protection Directive,[176]

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a trusted advisory committee within the Federal Trade Commission could help courts and agencies adjudicate coming controversies over search engine practices."); *see also* Katyal, *supra* note 157, at 1250–79 (calling for the controlled disclosure of source code); Rebecca Wexler, *Life, Liberty, and Trade Secrets: Intellectual Property in the Criminal Justice System*, 70 STAN. L. REV. 1343, 1419–20 (2018) (discussing the disclosure of source code under protective orders in the criminal setting). While disclosure to regulatory authorities makes great policy sense, governments increasingly push for provisions in bilateral, regional, and plurilateral trade agreements that ban laws requiring the disclosure or transfer of software source code. *See, e.g.*, Trans-Pacific Partnership Agreement art. 14.17.1, Feb. 4, 2016, https://ustr.gov/trade-agreements/free-trade-agreements/trans-pacific-partnership/tpp-full-text [https://perma.cc/2UHR-LSQ5] ("No Party shall require the transfer of, or access to, source code of software owned by a person of another Party, as a condition for the import, distribution, sale or use of such software, or of products containing such software, in its territory."). *See also* Mira Burri, *The Governance of Data and Data Flows in Trade Agreements: The Pitfalls of Legal Adaptation*, 51 U.C. DAVIS L. REV. 65, 115 (2017) (discussing this provision).

174. Rob Kitchin outlined six distinct ways to conduct research on algorithms: (1) "[e]xamining pseudo-code [or] source code"; (2) "[r]eflexively producing code"; (3) "[r]everse engineering"; (4) "[i]nterviewing designers or conducting an ethnography of a coding team"; (5) "[u]npacking the full socio-technical assemblage of algorithms"; and (6) "[e]xamining how algorithms do work in the world." Rob Kitchin, *Thinking Critically About and Researching Algorithms*, 20 INFO. COMM. & SOC'Y 14, 22–26 (2017).

175. *See* Council Regulation 2016/679, *supra* note 109, recital 71, at 14 (stating that the automated processing of personal data "should be subject to suitable safeguards, which should include specific information to the data subject and the right to obtain human intervention, to express his or her point of view, to obtain an explanation of the decision reached after such assessment and to challenge the decision"); *id.* art. 13.2(f), at 41 (requiring the data controller to provide to the data subject information about "the existence of automated decision-making, including profiling, . . . and, at least in those cases, meaningful information about the logic involved, as well as the significance and the envisaged consequences of such processing for the data subject"); *id.* art. 14.2(g), at 42 (requiring the same). For discussions of what commentators have referred to as the right to explanation, see generally Isak Mendoza & Lee A. Bygrave, *The Right Not to Be Subject to Automated Decisions Based on Profiling*, *in* EU INTERNET LAW: REGULATION AND ENFORCEMENT 77 (Tatiani-Eleni Synodinou et al. eds., 2017); 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 (2017); Margot E. Kaminski, *The Right to Explanation, Explained*, 34 BERKELEY TECH. L.J. 189 (2019); Andrew D. Selbst & Julia Powles, *Meaningful Information and the Right to Explanation*, 7 INT'L DATA PRIVACY L. 233 (2017); Bryce Goodman & Seth Flaxman, *European Union Regulations on Algorithmic Decision Making and a "Right to Explanation,"* AI MAG., Fall 2017, at 50.

176. *See* Council Directive 95/46, art. 12, 1995 O.J. (L 281) 31, 42 (EC) ("Member States

which preceded the new regulation,[177] commentators have now devoted greater energy and effort to understanding this emerging right, due in large part to the increasing need to explain how data are being collected and used in technological platforms that are heavily driven by algorithms.

In this age of artificial intelligence, the right to explanation is important not only because of the data used in the algorithms but also because of the algorithmic designs. Considering the not-too-distant future when algorithms will actively design new algorithms, building explainability into algorithmic designs as part of best practices or codes of conduct will likely be highly important.[178] It is indeed no surprise that some commentators have emphasized the need to develop explainable algorithms, even though they acknowledge the continuous challenge of fully explaining the design and operation of algorithms.[179]

For example, the U.S. Department of Defense has launched the Explainable AI (XAI) program that "aims to create a suite of machine learning techniques that [(1)] [p]roduce more explainable models, while maintaining a high level of learning performance (prediction accuracy); and [(2)] [e]nable human users to understand, appropriately trust, and effectively manage the emerging generation of artificially intelligent partners."[180] As a program manager at the Defense Advanced Research Projects Agency Program explained:

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shall guarantee every data subject the right to obtain from the controller . . . knowledge of the logic involved in any automatic processing of data concerning him at least in the case of the automated decisions . . . ."); *id.* art. 15.1, at 43 ("Member States shall grant the right to every person not to be subject to a decision which produces legal effects concerning him or significantly affects him and which is based solely on automated processing of data intended to evaluate certain personal aspects relating to him, such as his performance at work, creditworthiness, reliability, conduct, etc.").

177. *See* Edwards & Veale, *supra* note 175, at 20 (noting that a remedy similar to the right to explanation "had existed in the EU Data Protection Directive . . . which preceded the [General Data Protection Regulation], since 1995" (footnote omitted)).

178. *See* Yu & Spina Alì, *supra* note 105, at 7 ("[U]nderstanding AI internal logic is a first step towards ensuring full accountability for computational legal research and automated legal decisions.").

179. *See* ACM STATEMENT, *supra* note 1, at 1 ("Decisions made by predictive algorithms can be opaque because . . . []the algorithm may not lend itself to easy explanation[] . . . ."); PREPARING FOR THE FUTURE, *supra* note 141, at 9 ("Because trained models have a very large number of adjustable parameters—often hundreds of millions or more—training may yield a model that 'works,' in the sense of matching the data, but is not necessarily the simplest model that works."); Noto La Diega, *supra* note 28, at 23 (suggesting that "a technical document which includes the algorithm used and the mere explanation of the logic in mathematical terms will not in itself meet the legal requirement [for the right to explanation]" and that this requirement "should be interpreted as the disclosure of the algorithm with an explanation in non-technical terms of the rationale of the decision and criteria relied upon").

180. Matt Turek, *Explainable Artificial Intelligence (XAI)*, DEF. ADVANCED RES. PROJECTS AGENCY, https://www.darpa.mil/program/explainable-artificial-intelligence [https://perma.cc/8BPN-7N4K].

> New machine-learning systems will have the ability to explain their rationale, characterize their strengths and weaknesses, and convey an understanding of how they will behave in the future. The strategy for achieving that goal is to develop new or modified machine-learning techniques that will produce more explainable models. These models will be combined with state-of-the-art human-computer interface techniques capable of translating models into understandable and useful explanation dialogues for the end user . . . .[181]

Likewise, private technology developers and research institutions have engaged in efforts to train intelligent machines to document their algorithms and internal logic. As Ronald Yu and Gabriele Spina Alì recounted:

> [A] team at Microsoft is trying to teach AI to show how it weighted every single variable in evaluating mortality risk factors. Similarly, a team at Rutgers University is working on a deep neural network that provides users with examples that demonstrates why it took a specific algorithmic decision. Another project at the University of Berkeley involves lashing two neural networks together, tasking one to describe the inner procedures running inside the other. Finally, an international team consisting, among the others, of researchers from Facebook, Berkeley and the University of Amsterdam has taught an image recognition software to show the evidence he relied upon to reach its decisions.[182]

E. *Accountability*

As important as transparency is, it should not be equated with accountability.[183] As political processes have repeatedly demonstrated, one could have a highly transparent process that involves checks and balances, different rounds of open consultations, and a large number of publicly available documents, yet the outcomes remain heavily captured by industries and are of limited public accountability.[184] To address the

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181. *Id.*

182. Yu & Spina Alì, *supra* note 105, at 7 (footnotes omitted).

183. *See* Maayan Perel & Niva Elkin-Koren, *Black Box Tinkering: Beyond Disclosure in Algorithmic Enforcement*, 69 FLA. L. REV. 181, 184 (2017) ("Normally, with human decision-making, oversight is principally achieved through transparency—so much so that the terms 'transparency' and 'accountability' are often used interchangeably. In the realm of algorithmic enforcement, however, transparency alone is insufficient to generate accountability, for algorithms—due to their inherent traits—lack critical reflection.").

184. *See generally* MONICA HORTEN, A COPYRIGHT MASQUERADE: HOW CORPORATE LOBBYING THREATENS ONLINE FREEDOMS (2013) (discussing how legislative capture by the

problems that the emerging and ever-widening algorithmic divide causes, transparency-based solutions should be separated from accountability-based solutions.

As noted earlier, civil rights and antidiscrimination laws already exist to ensure accountability.[185] These laws will address the problems caused by those who have designed algorithms intentionally to facilitate individual deprivation or discrimination. Indeed, the need for public accountability in the artificial intelligence context is not that different from similar needs in other contexts, or in the offline world. Principle 3 of the *ACM Statement* expressly states that "[i]nstitutions should be held responsible for decisions made by the algorithms that they use, even if it is not feasible to explain in detail how the algorithms produce their results."[186] That statement states further: "Policymakers should hold institutions using analytics to the same standards as institutions where humans have traditionally made decisions and developers should plan and architect analytical systems to adhere to those standards when algorithms are used to make automated decisions or as input to decisions made by people."[187]

In most situations, however, the discrimination or distortion originates in neutral or well-intentioned efforts. As a result, accountability will have to manifest in the form of remediation, rather than punishment. Such remediation-based accountability will require technology developers to quickly correct the problems once they have been notified of these problems[188]—similar, perhaps, to the "notice and takedown"

copyright industries has undermined online freedom); BRINK LINDSEY & STEVEN TELES, THE CAPTURED ECONOMY: HOW THE POWERFUL ENRICH THEMSELVES, SLOW DOWN GROWTH, AND INCREASE INEQUALITY 64–89 (2017) (discussing capture in the intellectual property area).

185. *See* Tene & Polonetsky, *supra* note 90, at 166 ("Antidiscrimination laws typically govern decisions on credit, housing, and employment, and restrict the use of categories such as race, gender, disability, or age."); *supra* text accompanying notes 131–132.

186. ACM STATEMENT, *supra* note 1, at 2 (Principle 3); *see* INST. ELEC. & ELEC. ENG'RS, *supra* note 14, at 27 (proposing Principle 3 to "assure that designers, manufacturers, owners, and operators of [autonomous and intelligent systems] are responsible and accountable"); *see also id.* at 27–28 (providing recommendations under proposed Principle 3).

187. ACM STATEMENT, *supra* note 1, at 1.

188. *See id.* at 2 (Principle 2) ("Regulators should encourage the adoption of mechanisms that enable questioning and redress for individuals and groups that are adversely affected by algorithmically informed decisions."); Diakopoulos et al., *supra* note 98 ("Make available externally visible avenues of redress for adverse individual or societal effects of an algorithmic decision system, and designate an internal role for the person who is responsible for the timely remedy of such issues."); *see also* Chander, *supra* note 96, at 1025 ("[I]f we believe that the real-world facts, on which algorithms are trained and operate, are deeply suffused with invidious discrimination, then our prescription to the problem of racist or sexist algorithms is *algorithmic affirmative action*." (footnote omitted)); Kate Crawford & Jason Schultz, *Big Data and Due Process: Toward a Framework to Redress Predictive Privacy Harms*, 55 B.C. L. REV. 93, 126–

arrangements now found in copyright law.[189] Indeed, as technology becomes increasingly complicated and inscrutable, ensuring quick correction of the problem will likely be more constructive than punishing those who have allowed the problems to surface in the first place, often unintentionally.

It will also be important to provide institutional oversight of the design and use of algorithms that have far-reaching political, social, economic, and cultural impacts or that deeply affect the public interest.[190] Such oversight—and the enforcement power with which it comes—is particularly urgent if problems have already been documented.

Finally, it will be useful to require regular algorithmic audits to hold technology developers accountable.[191] As Pauline Kim explained:

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27 (2014) ("Once notice is available, the question then becomes how one might challenge the fairness of the predictive process employed. We believe that the most robust mechanism for this is the opportunity to be heard and, if necessary, correct the record.").

189. *See* 17 U.S.C. § 512(c) (2018) (requiring online service providers to "respond[] expeditiously to remove, or disable access to, the material that is claimed to be infringing or to be the subject of infringing activity" once these providers have been notified of copyright infringement or obtained knowledge or awareness of such infringement); *see also* Peter K. Yu, *Digital Copyright Reform and Legal Transplants in Hong Kong*, 48 U. LOUISVILLE L. REV. 693, 709–13 (2010) (providing an overview of the "notice and takedown" procedure in copyright law).

190. *See* TREASURY BD. OF CAN. SECRETARIAT, RESPONSIBLE ARTIFICIAL INTELLIGENCE IN THE GOVERNMENT OF CANADA 33 (2018) (Can.) (Version 2.0) ("[Potential] models of governance that could provide the necessary oversight and guidance to Federal institutions . . . can range from an *ad hoc* federal 'Automation Advisory Board' comprising of internal and external experts to a more formal and permanent body with staff."); Katyal, *supra* note 2, at 109 (noting the need for "regulatory participation" to provide effective ethical safeguards); McGregor et al., *supra* note 151, at 330–31 ("The establishment of internal monitoring and oversight bodies can play an important role in coordinating and overseeing the implementation of regular impact assessments and ensuring that findings are addressed."); Katelyn Ringrose, *Law Enforcement's Pairing of Facial Recognition Technology with Body-Worn Cameras Escalates Privacy Concerns*, 105 VA. L. REV. ONLINE 57, 66 (2019), http://www.virginialawreview.org/sites/virginialawreview.org/files/04.%20Final%20Ringrose.pdf [https://perma.cc/8CTV-Q2Z4] (underscoring the need to "establish independent oversight ensuring police accountability and mitigation of facial-recognition misidentification errors likely to have a racially disparate impact").

191. As the Center for Democracy and Technology noted on its website:

> Audits are one method to provide explanations and redress without compromising the intellectual property behind the business model. Designing algorithmic systems that can be easily audited increases accountability and provides a framework to standardize best practices across industries. While explanations can help individuals understand algorithmic decision making, audits are necessary for systemic and long-term detection of unfair outcomes. They also make it possible to fix problems when they arise.

Digital Decisions, *supra* note 46; *see also* Deven R. Desai & Joshua A. Kroll, *Trust but Verify: A Guide to Algorithms and the Law*, 31 HARV. J.L. & TECH. 1, 37–42 (2017) (discussing ways to test and evaluate algorithms). *But see* Kroll et al., *supra* note 95, at 660–61 (discussing the limits to auditing in the algorithmic context).

> When the goal is nondiscrimination, auditing could involve techniques to ensure that an algorithm follows a specified rule—for example, sorting must not occur based on race or sex. Alternatively, auditing for discrimination could take the form of examining inputs and outputs to detect when a decision process systematically disadvantages particular groups. The latter form of auditing does not involve direct examination of the decision process, but is useful in detecting patterns.[192]

Principle 6 of the *ACM Statement* specifically requires that "[m]odels, algorithms, data, and decisions be recorded so that they can be audited in cases where harm is suspected."[193] Principle 7 further states: "Institutions should use rigorous methods to validate their models and document those methods and results. In particular, they should routinely perform tests to assess and determine whether the model generates discriminatory harm. Institutions are encouraged to make the results of such tests public."[194]

Although algorithmic audits can be done internally, it is often important for government regulators, ombudspersons, or outside auditors to independently review the algorithms and data used.[195] Indeed, past experience has shown that outsiders are sufficiently motivated and well equipped[196] to find bugs and other vulnerabilities in computer programs

192. Kim, *supra* note 169, at 190.

193. ACM STATEMENT, *supra* note 1, at 2 (Principle 6); *see also* INST. ELEC. & ELEC. ENG'RS, *supra* note 14, at 53 ("To maximize effective evaluation by third parties (e.g., regulators, accident investigators), [autonomous and intelligent systems] should be designed, specified, and documented so as to permit the use of strong verification and validation techniques for assessing the system's safety and norm compliance . . . ."); Diakopoulos et al., *supra* note 98 ("Identify, log, and articulate sources of error and uncertainty throughout the algorithm and its data sources so that expected and worst case implications can be understood and inform mitigation procedures."); *Digital Decisions*, *supra* note 46 ("An effective audit requires institutions to maintain internal documentation of the logic or circumstance behind significant design choices and procedures governing who is responsible for making changes. These systems are best installed as a product develops, rather than retroactively.").

194. ACM STATEMENT, *supra* note 1, at 2 (Principle 7).

195. *See id.* (Principle 5) ("Public scrutiny of the data provides maximum opportunity for corrections."); Diakopoulos et al., *supra* note 98, at 2 ("Enable interested third parties to probe, understand, and review the behavior of the algorithm through disclosure of information that enables monitoring, checking, or criticism, including through provision of detailed documentation, technically suitable [application programming interfaces], and permissive terms of use."); *see also* MAYER-SCHÖNBERGER & CUKIER, *supra* note 75, at 180–82 (discussing the need for external and internal algorithmists); Annie Lee, Note, *Algorithmic Auditing and Competition Under the CFAA: The Revocation Paradigm of Interpreting Access and Authorization*, 33 BERKELEY TECH. L.J. 1307, 1309–10 (2018) ("Algorithmic auditors largely consist of academics, computer scientists from nonprofits, and journalists who scrutinize online websites powered by algorithms for bias and discrimination." (footnotes omitted)).

196. Some users will no doubt discover these bugs and vulnerabilities by accident.

or systems.[197] To provide support for external audits that do not involve regulatory authorities, adjustments will have to be made to those laws that have posed barriers to external reviews of source code and computer systems,[198] such as the Computer Fraud and Abuse Act[199] and the Digital Millennium Copyright Act.[200]

F. *Competition*

Competition is imperative if society is to develop more efficient, more effective, and less biased algorithms.[201] Such competition is particularly needed when algorithmic choices are increasingly difficult, or time

197. *See* Peter K. Yu, *Anticircumvention and Anti-anticircumvention*, 84 DENV. U. L. REV. 13, 24 (2006) (discussing SunnComm's threat to sue a computer science graduate student who figured out on his own how to disarm its copy-protection technology by pushing the shift key when loading a CD into a computer); *see also* Universal City Studios, Inc. v. Reimerdes, 111 F. Supp. 2d 294, 311 (S.D.N.Y. 2000) (involving a Norwegian teenager who cowrote the DeCSS program that circumvented the copy-protection technology used by the U.S. motion picture industry), *aff'd sub nom*. Universal City Studios, Inc. v. Corley, 273 F.3d 429 (2d Cir. 2001).

198. The Digital Millennium Copyright Act of 1998 (DMCA), Pub. L. No. 105-304, 112 Stat. 2860 (codified as amended in scattered sections of 17 U.S.C. and 28 U.S.C. § 4001 (2018)), for example, provides a limited exception for encryption research. *See* 17 U.S.C. § 1201(g). This exception, however, has been criticized for failing to support such research. *See* Joseph P. Liu, *The DMCA and the Regulation of Scientific Research*, 18 BERKELEY TECH. L.J. 501, 503 (2003) ("[E]ven though academic encryption researchers can continue to conduct and publish some of their research under the DMCA without significant practical risk of criminal or civil liability, the DMCA significantly affects the manner in which that research is conducted."); Pamela Samuelson, *Intellectual Property and the Digital Economy: Why the Anti-Circumvention Regulations Need to Be Revised*, 14 BERKELEY TECH. L.J. 519, 524 (1999) (arguing that the DMCA "should be amended to provide a general purpose 'or other legitimate purposes' provision to avert judicial contortions in interpreting the statute"); Peter K. Yu, *Is Anti-Piracy Law Stifling Cybersecurity Innovation?*, LEGAL TIMES, Mar. 29, 2004, at 20 (discussing how the DMCA has undermined cryptography and cybersecurity).

199. 18 U.S.C. § 1030 (2018). As Sonia Katyal observed:

> [T]he ACLU sued on behalf of four researchers who maintained that [this statute] actually prevented them from scraping data from sites, or from creating fake profiles to investigate whether algorithmic discrimination led some employment and real estate sites to fail to display certain listings on the basis of race or gender. The concern was that the law permitted researchers to be held criminally accountable because the research might involve violating one of the sites' Terms of Service, something that could carry both prison and fines. As one researcher observed, these laws have the perverse effect of "protecting data-driven commercial systems from even the most basic external analysis."

Katyal, *supra* note 2, at 122 (footnotes omitted); *see also* Lee, *supra* note 195, at 1311–38 (discussing how the Computer Fraud and Abuse Act has discouraged algorithmic auditors from exposing questionable business practices and has fostered a hostile market for legitimate competitors).

200. Pub. L. No. 105-304, 112 Stat. 2860.

201. *See* Lee, *supra* note 195, at 1310 ("Online competitors . . . promote fair online practices by providing users with a choice between competitive products . . . .").

consuming, to explain.[202] Indeed, without competition, it would be hard to identify problems within an algorithm or to determine whether that algorithm has provided the best solution in light of the existing technological conditions and constraints. Moreover, because a wide variety of algorithms exist to achieve the same goal, competition will be greatly needed to accommodate the different trade-offs preferred by either algorithm designers or consumers.[203]

In the past decade, commentators have already explained why competition is badly needed in a data-pervasive world, the Internet of Things, and the Fourth Industrial Revolution.[204] In the artificial intelligence context, for instance, commentators have examined the challenge of using antitrust or competition law to foster competition among the dominant players.[205] In the past few years, European competition authorities have also actively explored ways to address the

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202. *See supra* text accompanying notes 162–165 (noting the growing challenges to explaining algorithms in the artificial intelligence context).

203. *See* AGRAWAL ET AL., *supra* note 103, at 189 ("There is often no single right answer to the question of which is the best AI strategy or the best set of AI tools, because AIs involve trade-offs: more speed, less accuracy; more autonomy, less control; more data, less privacy.").

204. As Timo Minssen and Justin Pierce observed:

> While there are issues to be resolved between Big Data and [intellectual property rights], there is a growing awareness of the importance of data and specifically Big Data by market authorities. Antitrust agencies, those in the United States and competition agencies in Europe, are taking note of Big Data, and there is an increasing trend to examine closely the collection, use, and access of Big Data for anticompetitive effects.

Timo Minssen & Justin Pierce, *Big Data and Intellectual Property Rights in the Health and Life Sciences*, *in* BIG DATA, HEALTH LAW, AND BIOETHICS 311, 320 (I. Glenn Cohen et al. eds., 2018); *see also* MAYER-SCHÖNBERGER & CUKIER, *supra* note 75, at 182–84 (discussing the use of competition law to govern the data barons); Josef Drexl, *Designing Competitive Markets for Industrial Data—Between Propertisation and Access*, 8 J. INTELL. PROP. INFO. TECH. & ELECTRONIC COM. L. 257, 280–85 (2017) (discussing the application of EU competition law to address refusals to grant access to data); Peter K. Yu, *Data Producer's Right and the Protection of Machine-Generated Data*, 93 TUL. L. REV. 859, 927 (2019) (noting that competition law is "a critical area relating to data governance").

205. *See generally* Rupprecht Podszun & Stefan Kreifels, *Data and Competition Law*, *in* RESEARCH HANDBOOK IN DATA SCIENCE AND LAW 183 (Vanessa Mak et al. eds., 2018) (discussing the uneasy relationship between data and competition law); Maurice E. Stucke & Ariel Ezrachi, *Antitrust, Algorithmic Pricing and Tacit Collusion*, *in* RESEARCH HANDBOOK ON THE LAW OF ARTIFICIAL INTELLIGENCE, *supra* note 40, at 624, 628–32 (discussing the complications regarding algorithmic tacit collusion); Clark D. Asay, *Artificial Stupidity*, 61 WM. & MARY L. REV. (forthcoming 2020) (manuscript at 51–53), https://ssrn.com/abstract=3399170 [https://perma.cc/F7TR-Y4N6] (discussing the pros and cons of using antitrust to thwart consolidation in the artificial intelligence industry); Maurice E. Stucke, *Should We Be Concerned About Data-opolies?*, 2 GEO. L. TECH. REV. 275 (2018) (discussing "data-opolies" in the antitrust context and the harm they cause).

anticompetitive effects generated by U.S. technology giants, such as Google and Facebook.[206]

The issues relating to competition are complicated because big-data analytics require the existence of large, comprehensive datasets.[207] The more competition there is, the more fragmentary datasets will become, and the less likely that the full potential of artificial intelligence will be realized. Nevertheless, policy makers and commentators have increasingly looked for laws, policies, and institutional mechanisms to facilitate data sharing, portability, and interoperability.[208] After all, the better coordinated the data usage is, the more benefits algorithmic competition will provide. Greater competition in this area will also make it easier to identify problems in algorithms, especially those utilizing identical or substantially identical training and feedback data.[209]

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206. *See* Stucke, *supra* note 205, at 275–77 (discussing the actions taken by the European competition authorities against Google, Apple, Facebook, and Amazon); *see also* Peter K. Yu & John Cross, *Why Are the Europeans Going After Google?*, NEWSWEEK (May 18, 2015, 2:31 PM), https://www.newsweek.com/why-are-europeans-going-after-google-332775 [https://perma.cc/MB8M-8m69] (discussing the EU antitrust probe of Google).

207. *See* MAYER-SCHÖNBERGER & CUKIER, *supra* note 75, at 30 ("[B]ig data relies on all the information, or at least as much as possible . . . .").

208. *See* Council Regulation 2016/679, *supra* note 109, art. 20, at 45 (introducing the right to data portability); *see also* MAYER-SCHÖNBERGER & CUKIER, *supra* note 75, at 183 ("We should enable data transactions, such as through licensing and interoperability."); Drexl, *supra* note 204, at 292 ("The functioning of the data economy will also depend on the interoperability of digital formats and the tools of data collecting and processing."); Wolfgang Kerber, *A New (Intellectual) Property Right for Non-Personal Data? An Economic Analysis*, 65 GEWERBLICHER RECHTSSCHUTZ UND URHEBERRECHT INTERNATIONALER TEIL [GRUR INT] 989, 997 (2016) (Ger.) ("[S]upporting portability, interoperability and standardization in regard to data is seen as pivotal policy measures for improving the governance of data in the digital economy."); Yu, *supra* note 204, at 889 ("[I]f we are to maximize our ability to undertake big data analyses, such analyses may require greater sharing of data—which, in turn, calls for greater data portability and interoperability.").

209. As Professor Kitchin suggested:

> [R]esearchers might search Google using the same terms on multiple computers in multiple jurisdictions to get a sense of how its PageRank algorithm is constructed and works in practice, or they might experiment with posting and interacting with posts on Facebook to try and determine how its EdgeRank algorithm positions and prioritises posts in user time lines, or they might use proxy servers and feed dummy user profiles into e-commerce systems to see how prices might vary across users and locales.

Kitchin, *supra* note 174, at 24 (citations omitted); *see also* Yu & Spina Alì, *supra* note 105, at 7 (calling on legal researchers to "compare outputs from different programs to detect flaws in the AI utilized and increase research accuracy").

G. *Perspective*

If society is to truly understand how the remedial actions proposed in this Article can properly address the emerging and ever-widening algorithmic divide, it needs to have realistic goals. As appealing as it is to foster equality in the age of artificial intelligence, society should recognize that such equality takes time to achieve, if achievable at all. Indeed, much of the inequality perpetuated by algorithms and intelligent machines may be historical and may therefore have limited relation to algorithmic designs and data practices. If so, the solution to the problem lies elsewhere.

Two decades ago, when policy makers were actively searching for ways to bridge the digital divide, commentators reminded us of the importance of focusing on relative, as opposed to absolute, inequality in the information society.[210] In her widely cited book on the digital divide, Pippa Norris observed:

> Despite the more exaggerated hopes of some cyber-optimists, the Internet is not going to suddenly eradicate the fundamental and intractable problems of disease, debt, and disadvantage facing developing countries. The more interesting question, with important implications for understanding the new media, concerns the *relative* inequality of opportunities. Is it easier or more difficult to go online in different societies, compared with inequalities of access to other types of communication technologies, such as telephones and televisions?[211]

Considering that the real world is far from equal, inequality will always find its way to the technological environment. Having a more realistic perspective will certainly be conducive to developing workable solutions to help bridge the algorithmic divide.

After all, the extent of this divide may have been influenced by the existence of other divides, such as those relating to disparities in power, wealth, or education.[212] As Omer Tene and Jules Polonetsky rightly

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210. *See* NORRIS, *supra* note 13, at 49–54 (discussing relative inequalities in the information society); VAN DIJK, *supra* note 13, at 4 ("[One] misunderstanding might be the impression that the [digital] divide is about absolute inequalities, such as between those included and those excluded. In reality, most inequalities of access to digital technology are of a more relative kind."); Tene & Polonetsky, *supra* note 90, at 164 ("[T]o avoid throwing the baby out with the bathwater, critics should compare the consequences of algorithmic decisions to the prevailing status quo.").

211. NORRIS, *supra* note 13, at 49.

212. *See High-level Panel Report*, *supra* note 32, at 6 ("Many existing inequalities—in wealth, opportunity, education, and health—are being widened further [by the digital divide]."); INT'L TELECOMM. UNION, *supra* note 6, at v ("AI may widen gaps between countries, reinforcing the current digital divide. Countries may need different strategies and responses because AI

observed, "In many cases, criticisms of algorithmic decisions in fact reflect broader concerns about a digital divide or even a general condemnation of an unequal society."[213] One of the authors' illustrations concerns the Boston-based Street Bump app, which uses Global Positioning System coordinates and motion-sensing capabilities in smartphones to automatically report potholes to municipal authorities.[214] While innovative and socially beneficial, that app has been criticized for reporting more potholes in wealthy neighborhoods than poorer areas, due in large part to the higher concentration of smartphone usage in the reported neighborhoods.[215] Anticipating these and other similar complications, well-meaning governmental authorities frequently struggle with the difficult dilemma concerning whether to introduce new technological solutions that would address urban problems but at the

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adoption levels vary." (footnote omitted)); VAN DIJK, *supra* note 13, at 6 ("[Digital d]ivides *are* byproducts of old inequalities, digital technology *is* intensifying inequalities, and new inequalities *are* appearing."); *see also* Kate Crawford & Ryan Calo, *There Is a Blind Spot in AI Research*, NATURE (Oct. 13, 2016), https://www.nature.com/news/there-is-a-blind-spot-in-ai-research-1.20805 [https://perma.cc/MGQ4-H2MQ] ("[I]n some current contexts, the downsides of AI systems disproportionately affect groups that are already disadvantaged by factors such as race, gender and socio-economic background."). The converse is also true: bridging the digital divide could help cabin or reduce other divides. *See* Yu, *supra* note 7, at 35 ("[S]olutions to the digital divide and other, more traditional divides can work together to reinforce each other.").

213. Tene & Polonetsky, *supra* note 90, at 137.

214. As the authors described:

> In 2013, Boston adopted an innovative solution to combat the common municipal problem of road potholes. The city introduced "Street Bump," an app using the motion-sensing capabilities of smartphones to automatically report information to [the] municipal government about the condition of the streets users drive on. When a user's car hit a pothole, their phone recorded the shock and sent it to a data hub, which combined the information from many other phones to pinpoint problem areas on streets to be repaired.

Id. at 158.

215. As the authors explained:

> Despite being presented as evidence for the risks of algorithmic decision-making, the Boston Street Bump app had little to do with data-driven discrimination. If the app were programmed to apportion greater weight to reports coming from wealthier neighborhoods than poorer ones, for example, critics could rightly blame it for class-based discrimination. But that was not the case with Street Bump, which simply created a seamless way to report and help fix a common urban flaw. In this case, where a higher density of smartphone users in wealthier neighborhoods created the concentration of reports, critics were not really faulting the app but rather the city's socio-economic fabric. Like many large American cities, Boston has racial, ethnic, and socio-economic fault lines, which transcend ownership and use of smartphones and apps.

Id. at 159.

same time perpetuate existing inequities. Reflecting on this dilemma, the authors asked:

> Should cities avoid deploying new apps just because they help part, but not all, of their population? And against which backdrop should municipal leaders assess Street Bump's disparate impact? Perhaps the previous pothole reporting system—mailing complaints through the post or calling them in on the phone—was unbalanced as well? More generally, in an unequal society, every time an institution acts to improve a system, improving life for some citizens, it can be criticized for increasing—or at least not diminishing—existing disparities with persons who are worse off. Does that imply that until all disparities are purged urban systems should not improve?[216]

These questions are important, because the overarching goal of efforts to bridge the algorithmic divide is not to close the divide—an arguably impossible feat—but to expand access to machine learning and artificial intelligence to those who would otherwise be disenfranchised.[217]

Finally, as rhetorically attractive as the term "algorithmic divide" may have been, one should recall the fact that emphasizing a binary divide often blurs the distinction between the different levels of algorithmic inclusion based on age, gender, ethnicity, income, education, geography, and many other variables. To some extent, the term "algorithmic divide" faces the same problem as the term "digital divide," which implies "a bipolar societal split."[218] As Mark Warschauer observed with respect to the latter:

> [T]here is not a binary division between information haves and have-nots, but rather a gradation based on different degrees of access to information technology. Compare, for example, a professor at UCLA with a high-speed connection in her office, a student in Seoul who occasionally uses a cyber cafè, and a rural activist in Indonesia who has no computer or phone line but whose colleagues in the nongovernmental organization . . . with whom she is

216. *Id.*

217. *Cf.* WARSCHAUER, *supra* note 18, at 211 ("The overall policy challenge is not to overcome a digital divide but rather to expand access to and use of ICT for promoting social inclusion.").

218. *Id.* at 6; *see also* RAGNEDDA, *supra* note 18, at 55 ("[T]he digital divide indicates not a gap in terms of a binary division, but rather a continuum based on different degrees of possession and level of use of technologies of information."); VAN DIJK, *supra* note 16, at 3 ("If any delineation is required, a tripartite society might be a better definition than a two-tiered one. At one extreme we perceive an information elite and at the other the digitally illiterate or the fully excluded. In between are the majority of the population, having access in one way or another and using digital technology to a certain extent." (citation omitted)).

> working download and print out information for her. This example illustrates just three degrees of possible access a person can have to online material.[219]

Likewise, Henry Jenkins declared: "The rhetoric of the digital divide holds open this division between civilized tool-users and uncivilized nonusers. As well-meaning as it is as a policy initiative, it can be marginalizing and patronizing in its own terms."[220]

To make things even more complicated, an individual can be on one side of the digital divide based on select categories but on the other side based on other categories. As Jan van Dijk observed:

> Take, for instance, a relatively poor, young, single, female, Jamaican teacher living in the United Kingdom. Her inclusion in the categories of educational workers, young people, and inhabitants of a developed country would put her on the "right" side of the digital divide . . . . However, being a female with relatively low income, perhaps living alone without a partner or children to share a computer or Internet connection, and being part of an ethnic minority means that she would most likely be on the "wrong" side of the divide.[221]

In sum, society needs to keep its perspective in check when developing solutions to bridge the algorithmic divide. Like the digital divide, the algorithmic divide has many dimensions and covers many different areas. Neither an emphasis on absolute equality nor a focus on the binary split will help society develop the laws, policies, and institutional mechanisms needed to address such a critical challenge in the age of artificial intelligence.

CONCLUSION

The emerging and ever-widening algorithmic divide has threatened to take away the many political, economic, social, cultural, educational, and career opportunities that machine learning and artificial intelligence have provided to a large segment of the population—whether national or global. While this divide is only at the emerging stage, it is quickly widening,[222] just like how the digital divide started two decades ago with

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219. WARSCHAUER, *supra* note 18, at 6–7.

220. Jeffrey R. Young, *Does "Digital Divide" Rhetoric Do More Harm than Good?*, CHRON. HIGHER EDUC. (Nov. 9, 2001), https://www.chronicle.com/article/Does-Digital-Divide-Rhetoric/3058 [https://perma.cc/9X67-ZCQ9], *cited in* WARSCHAUER, *supra* note 18, at 7.

221. VAN DIJK, *supra* note 13, at 13.

222. To make tracking the algorithmic divide more difficult, algorithms evolve over time. *See* Kitchin, *supra* note 174, at 16 ("What constitutes an algorithm has changed over time and

a focus on the lack of access to information technology before quickly expanding to encompass the lack of access to digital content and skills.[223]

This Article takes stock of this algorithmic divide and the three problems that the divide has precipitated: algorithmic deprivation, algorithmic discrimination, and algorithmic distortion. To fashion a holistic response to these problems, the Article utilizes a multidisciplinary approach and proposes seven clusters of remedial actions. While these actions are by no means exhaustive, they provide useful starting points for policy makers and commentators to start thinking about how laws, policies, institutions, and business practices can be harnessed to bridge the algorithmic divide. By proposing these actions, this Article aims to foster greater equality in the age of artificial intelligence.

they can be thought about in a number of ways: technically, computationally, mathematically, politically, culturally, economically, contextually, materially, philosophically, ethically and so on.").

223. *See* RAGNEDDA, *supra* note 18, at 4–5 (discussing the evolution of the three levels of the digital divide); Yu, *supra* note 7, at 29–32 (noting the ever-changing definition of the digital divide); *see also* Mira Burri, *Re-Conceptualizing the Global Digital Divide*, 2 J. INTELL. PROP. INFO. TECH. & ELECTRONIC COM. L. 217, 219–21 (2011) (discussing the digital divide as impeded access to content).