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## AI, Equity, and the IP Gap

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# AI, EQUITY, AND THE IP GAP

Daryl Lim\*

## ABSTRACT

*Artificial intelligence (AI) has helped determine vaccine recipients, prioritize emergency room admissions, and ascertain individual hires, sometimes doing so inequitably. As we emerge from the Pandemic, technological progress and efficiency demands continue to press all areas of the law, including intellectual property (IP) law, toward incorporating more AI into legal practice. This may be good when AI promotes economic and social justice in the IP system. However, AI may amplify inequity as biased developers create biased algorithms with biased inputs or rely on biased proxies. This Article argues that policymakers need to take a thoughtful and concerted approach to graft AI into IP law and practice if social justice principles of access, inclusion, and empowerment flow from their union. It explores what it looks like to obtain AI justice in the IP context and focuses on two areas where IP law impedes equitable AI-related outcomes. The first involves the civil rights concerns that stem from trade secrets blocking access and deflecting accountability in biased algorithms or data. The second concerns the patent and copyright doctrine biases perpetuating historical inequity in AI-augmented processes. The Article also addresses how equity by design should look and provides a roadmap for implementing equity audits to mitigate bias. Finally, it briefly examines how AI would assist with adjudicating equitable IP law doctrines, which also tests the outer limits of what bounded AI processes can do.*

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## I. INTRODUCTION

IN the past two years, artificial intelligence (AI) has helped determine vaccine recipients,<sup>1</sup> prioritize emergency room admissions,<sup>2</sup> and ascertain individual hires,<sup>3</sup> sometimes doing so inequitably.<sup>4</sup> However, like feathers from a ripped pillow, we can do little to reverse AI's relentless march.<sup>5</sup> As we emerge from the Pandemic, technological progress and the demands of efficiency continue to press all areas of the law, including intellectual property (IP) law, toward incorporating more AI into legal practice.<sup>6</sup> For example, AI systems inform governmental decision-making.<sup>7</sup> This may be good when AI promotes economic and social justice in the IP system.<sup>8</sup> However, AI may also amplify inequity as biased

1. See Rebecca Kelly Slaughter, Janice Kopec & Mohamad Batal, *Algorithms and Economic Justice: A Taxonomy of Harms and A Path Forward for the Federal Trade Commission*, 23 YALE J.L. & TECH. 1, 4 (2021).

2. See Thomas Valley, Michael Sjoding & Susan Dorr Goold, *More Health Inequality: Black People Are 3 Times More Likely to Experience Pulse Oximeter Errors*, CONVERSATION (Jan. 15, 2021, 4:30 PM), <https://theconversation.com/more-health-inequality-black-people-are-3-times-more-likely-to-experience-pulse-oximeter-errors-152359> [<https://perma.cc/LS68-KZJT>]. Pulse oximeters overestimate oxygen levels three times more frequently in Black people compared to White people. *Id.* This disparity risks Blacks being sent home on the mistaken conclusion that their blood-oxygen levels are within a safe range when they are not. *Id.*

3. See Adam S. Forman, Nathaniel M. Glasser & Christopher Lech, *INSIGHT: Covid-19 May Push More Companies to Use AI as Hiring Tool*, BLOOMBERG L. NEWS (May 1, 2020, 3:00 AM), <https://news.bloomberglaw.com/daily-labor-report/insight-covid-19-may-push-more-companies-to-use-ai-as-hiring-tool> [<https://perma.cc/79R7-F3CZ>].

4. See Miriam Vogel, *COVID-19 Could Bring Bias in AI to Pandemic Level Crisis*, THRIVE GLOB. (June 14, 2020), <https://thriveglobal.com/stories/covid-19-could-bring-bias-in-ai-to-pandemic-level-crisis> [<https://perma.cc/A67Q-RBF5>].

5. See Richard M. Re & Alicia Solow-Niederman, *Developing Artificially Intelligent Justice*, 22 STAN. TECH. L. REV. 242, 246 (2019) (“This emerging pattern is already visible in recent headlines as governments the world over reach for technological means of increasing their courts’ efficiency, accessibility, and consistency.”).

6. See Daryl Lim, *AI & IP: Innovation & Creativity in an Age of Accelerated Change*, 52 AKRON L. REV. 813, 814, 854 (2018).

7. See Danielle Keats Citron, *Open Code Governance*, 2008 U. CHI. LEGAL F. 355, 361–63 (2008).

8. See Andrew D. Selbst, Response, *A Mild Defense of Our New Machine Overlords*, 70 VAND. L. REV. EN BANC 87, 88–89 (2017) (arguing that we need a realistic picture of

developers create biased algorithms with biased inputs or when they rely on biased proxies.<sup>9</sup>

To hedge against biased outcomes, our best recourse is to focus on proper regulation. Specifically, policymakers face the challenge of mitigating bias by considering implementing a model of what I term “equity by design.” If done right, AI disruption will not only improve efficiency in the law but also offer an opportunity to examine how our IP laws have baked in racial, gender, and other biases, which, if not addressed, would become amplified by the wave of accelerated change AI will bring.

We benefit from thoughtful scholarship providing an important doctrinal framework on how IP law entrenches social divisions and disparities.<sup>10</sup> Examples include biases in patent law doctrines<sup>11</sup> and patent claiming practices;<sup>12</sup> copyright law doctrine disadvantaging or exploiting creators based on race and culture;<sup>13</sup> and trademark doctrines reinforcing caricatures of people of color.<sup>14</sup> These examples invite us to pause and consider the sort of data points developers would have on hand to train their algorithms.

Unfortunately, IP scholarship does not comprehensively address how AI perpetuates inequity in IP law, nor does it provide policymakers with comprehensive solutions to address such inequity. Instead, IP scholars tend to offer thoughtful but piecemeal discussions of specific areas of IP law.<sup>15</sup> This Article fills that gap. At its core, this Article argues that

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what humans and machines can accomplish, which includes being aware of machines’ defects but also seeing where machines can improve human decision-making); cf. Andrew Tutt, *An FDA for Algorithms*, 69 ADMIN. L. REV. 83, 92–106 (2017) (discussing the advantages, disadvantages, and likely future implications of using algorithms).

9. See Sonia K. Katyal, *Private Accountability in the Age of Artificial Intelligence*, 66 UCLA L. REV. 54, 69 (2019) (“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.”).

10. See, e.g., Peter Lee, *Toward a Distributive Agenda for U.S. Patent Law*, 55 HOUS. L. REV. 321 (2017); Margaret Chon, *Intellectual Property Equality*, 9 SEATTLE J. SOC. JUST. 259 (2010); Kara W. Swanson, *Intellectual Property and Gender: Reflections on Accomplishments and Methodology*, 24 AM. U. J. GENDER SOC. POL’Y & L. 175 (2015).

11. See Jonathan Kahn, *Race-ing Patents/Patenting Race: An Emerging Political Geography of Intellectual Property in Biotechnology*, 92 IOWA L. REV. 353, 384–86 (2007); see also Dan L. Burk, *Diversity Levers*, 23 DUKE J. GENDER L. & POL’Y 25, 30 (2015) (describing how patent law doctrines “incorporate social biases against other marginalized classes”).

12. See Shubha Ghosh, *Race-Specific Patents, Commercialization, and Intellectual Property Policy*, 56 BUFF. L. REV. 409, 417–48 (2008) (identifying racially charged language in patent claims and patent specifications).

13. See Elizabeth L. Rosenblatt, *Copyright’s One-Way Racial Appropriation Ratchet*, 53 U.C. DAVIS L. REV. 591, 594 (2019); Robert Brauneis, *Copyright, Music, and Race: The Case of Mirror Cover Recordings 2*, 7–8 (Geo. Wash. L. Sch. Pub. L. Working Paper, Paper No. 2020-56, 2020), [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3591113#](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3591113#) [<https://perma.cc/TXJ4-K4M8>]; K.J. Greene, “Copynorms,” *Black Cultural Production, and the Debate Over African-American Reparations*, 25 CARDOZO ARTS & ENT. L.J. 1179, 1180–82, 1200–07 (2008).

14. See K.J. Greene, *Trademark Law and Racial Subordination: From Marketing of Stereotypes to Norms of Authorship*, 58 SYRACUSE L. REV. 431, 435–37 (2008); Dan L. Burk, *Racial Bias in Algorithmic IP*, 106 MINN. L. REV. HEADNOTES 270, 276 (2022).

15. See *infra* Part III (discussing examples in trade secret, patent, and copyright law).

policymakers need to take a thoughtful and concerted approach to graft AI into IP law and practice if social justice principles of access, inclusion, and empowerment flow from their union.<sup>16</sup>

Part II explores what it looks like to obtain AI justice in the IP context. It begins with the promises of algorithmic justice, proceeds to explain the significance of equity-focused reform in both IP doctrine and AI development, and finally identifies three bugs in the system—algorithmic failure, data bias, and implementation flaws—that could impede or derail progress toward a more equitable system of justice for all.

Part III focuses on two areas where IP law impedes equitable AI-related outcomes. The first involves the civil rights concerns that stem from trade secrets blocking access and deflecting accountability in biased algorithms or data. The second concerns the patent and copyright doctrine biases that perpetuate historical inequity in AI-augmented processes.

Part IV focuses on how equity by design should look. It first asks what kind of goals we should set for training data—more, less, or better data? It depends. Part IV then provides a roadmap for implementing equity audits to mitigate bias and concludes by briefly examining how AI would assist with adjudicating equitable IP law doctrines, which test the outer limits of what bounded AI processes can do.

## II. JUSTICE AT A KIOSK

For almost a century, judges have employed data and algorithms in making parole determinations.<sup>17</sup> Since then, technology has made stunning strides in augmenting the administration of justice.<sup>18</sup> First, Section A discusses the promises of implementing AI in general legal and IP practice. Next, Section B discusses the distinction between equity and equality. Finally, Section C identifies three bugs in the system—algorithmic failure, data bias, and implementation flaws.

### A. FIVE PROMISES FOR IP

In Singapore, motorists in an accident can receive a damages estimate within ten minutes based on multiple-choice questions they answer.<sup>19</sup>

16. For an overview of social justice principles in IP, see Steven D. Jamar, *A Social Justice Perspective on IP Protection for Artificial Intelligence Programs*, in *CAMBRIDGE HANDBOOK ON INTELLECTUAL PROPERTY AND SOCIAL JUSTICE* (Steven D. Jamar & Lateef Mtima eds., forthcoming 2022).

17. See K.N.C., *Algorithms Should Take Into Account, Not Ignore, Human Failings*, *ECONOMIST* (Apr. 8, 2019), <https://www.economist.com/open-future/2019/04/08/algorithms-should-take-into-account-not-ignore-human-failings> [<https://perma.cc/5LRY-3YLT>] (“Data and algorithms have been used in the judicial system for almost a century, the first examples dating back to 1920s America.”).

18. See *id.*

19. See Clement Yong, *How Much Can I Claim? Traffic Accident Claims Simulator Launched to Help Motorists Settle Out of Court*, *STRAITS TIMES* (Mar. 21, 2022, 6:48 PM), <https://www.straitstimes.com/singapore/how-much-can-i-claim-traffic-accident-claims-simulator-launched-to-help-motorists-settle-out-of-court> [<https://perma.cc/85TL-QBHL>] (“[The simulator] can determine how liable a person is, depending on where the accident took

Codeveloped with Singapore's judiciary, the online AI traffic accident claims simulator uses current law and case precedent to help motorists decide whether to sue or settle by giving them a realistic assessment of their legal position.<sup>20</sup> Importantly, the AI outcomes are nonbinding.<sup>21</sup> Rather, the simulator simply speeds up claims and frees up court resources to deal with more complex controversies.<sup>22</sup>

In American courtrooms, AI assists judges and, in some cases, replaces them.<sup>23</sup> For instance, IBM's Watson AI technology powers "ROSS," an artificially intelligent attorney that collects information from cases and statutes, asks for clarification to assist in determining whether the information was helpful, learns from those responses, and produces legal memoranda.<sup>24</sup> AI also assists the U.S. Patent and Trademark Office (USPTO) as it examines patent and trademark applications.<sup>25</sup> AI may soon power IP litigation.<sup>26</sup> As AI penetrates IP law, parties might consult an algorithm for freedom of action or infringement matters.<sup>27</sup> In short, AI will adjudicate disputes and administer copyright, trademark, and patent registrations at a scale and speed beyond that which courts and agencies could achieve today.<sup>28</sup>

There are high fixed costs involved in priming AI systems with training

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place and the relative positions of the two vehicles, and how much a victim suffering from a specific type of injury can claim.").

20. *Id.*

21. *Id.*

22. *See id.* ("The same amount of (court) resources is dedicated to motor accident claims regardless of whether they are \$5,000 or \$50,000 . . . . Other civil issues such as defamation suits and more complex issues, including contractual dispute, would arguably require more attention and resources.").

23. *See Aziz Z. Huq, Racial Equity in Algorithmic Criminal Justice*, 68 DUKE L.J. 1043, 1068, 1072–76 (2019) ("Algorithmic tools are used now in three main criminal justice contexts: policing, bail decisions, and post-conviction matters.").

24. *See* Catherine Nunez, Comment, *Artificial Intelligence and Legal Ethics: Whether AI Lawyers Can Make Ethical Decisions*, 20 TUL. J. TECH. & INTELL. PROP. 189, 192–93 (2017); Katherine Medianik, Note, *Artificially Intelligent Lawyers: Updating the Model Rules of Professional Conduct in Accordance with the New Technological Era*, 39 CARDOZO L. REV. 1497, 1498 (2018).

25. *See* Drew Hirshfeld, *Artificial Intelligence Tools at the USPTO*, U.S. PAT. & TRADEMARK OFF.: DIR.'S BLOG (Mar. 18, 2021, 10:12 AM), <https://www.uspto.gov/blog/director/entry/artificial-intelligence-tools-at-the> [<https://perma.cc/Z6D5-EMTQ>] ("We are incorporating AI tools into two critical areas of patent examination: search and classification.").

26. *See* Adi Libson & Gideon Parchomovsky, *Toward the Personalization of Copyright Law*, 86 U. CHI. L. REV. 527, 529–30, 544–45 (2019) (using predictive analytics to determine copyright infringement and "vary statutory damages awards based on the personal characteristics of infringers" like their willingness to pay). AI could be used in "the calculation of actual damages or reasonable royalties in patent enforcement. Thus, every indication is that AI systems will likely become as ubiquitous in the development and administration of intellectual property as they are becoming across myriad other activities." Burk, *supra* note 14, at 274.

27. *See generally* Daryl Lim, *Confusion, Simplified*, 36 BERKELEY TECH. L.J. (forthcoming 2022).

28. *See* Re & Solow-Niederman, *supra* note 5, at 255 ("An algorithmic decision procedure that draws on [machine learning] could resolve an indefinite number of cases and would not be limited by time and space in the way that a human judge or team of human decision-makers would be.").

data.<sup>29</sup> However, cost savings ride on reducing the number of legal professionals, so judges and attorneys can review more cases per day and focus on those requiring more time and effort to resolve.

First, AI will be more cost-efficient in the long run. With the legal industry under pressure to cut performance costs, AI will evolve into an arbiter of choice. AI could be cheaper than training and retaining judges and attorneys, especially since marginal costs are spread over many parties who will benefit during the algorithm's lifetime—this is the essence of mechanized mass production techniques that undergird today's economy.<sup>30</sup> Government entities and others can reinvest savings into improving algorithmic accuracy in a virtuous upward spiral.<sup>31</sup>

This adds algorithmic muscle to tasks in ways that “surpass human abilities.”<sup>32</sup> Well-developed AI can automate intellectual tasks,<sup>33</sup> organize and characterize massive amounts of data, and extrapolate upon attributes to serve as proxies for desired outcomes.<sup>34</sup> Moreover, as developments refine AI techniques over time, cost-efficiency will nudge law firms, agencies, and courts to deploy them on a greater scale to guide legal decision-making.<sup>35</sup> And cost is only one factor that will drive AI's adoption.

Second, algorithmic adjudication promises to offer impartiality by codifying justice and prioritizing standardization over discretion.<sup>36</sup> Even with the best intentions, humans are prone to biases and inconsistencies.<sup>37</sup> AI can help humans reduce errors and promises a fairer and more transparent justice system.<sup>38</sup> Human judges adopting more rule-like frameworks can reach more consistent outcomes.<sup>39</sup> Having a single AI guidance system minimizes judges' arbitrariness.<sup>40</sup>

Third, AI is effective. Neural networks can detect data patterns from past cases and match them to the facts before the court without formal

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29. See Will Knight, *AI's Smarts Now Come with a Big Price Tag*, WIRE (Oct. 14, 2021, 7:00 AM), <https://www.wired.com/story/ai-smarts-big-price-tag> [https://perma.cc/GPT7-DVHZ].

30. See A. Michael Froomkin, Ian Kerr & Joelle Pineau, *When AIs Outperform Doctors: Confronting the Challenges of a Tort-Induced Over-Reliance on Machine Learning*, 61 ARIZ. L. REV. 33, 64 (2019).

31. See Re & Solow-Niederman, *supra* note 5, at 256; see also Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249, 1252 (2008) (providing that cost savings is an argument made by proponents of automated decision-making systems).

32. Ignacio N. Cofone, *Algorithmic Discrimination Is an Information Problem*, 70 HASTINGS L.J. 1389, 1391 (2019).

33. See FRANÇOIS CHOLLET, DEEP LEARNING WITH PYTHON 4–5 (Toni Arritola, Jerry Gaines, Aleksandar Dragosavljević & Tiffany Taylor eds., 2018).

34. See Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CALIF. L. REV. 671, 677–78 (2016).

35. See Re & Solow-Niederman, *supra* note 5, at 258.

36. See *id.* at 246.

37. See *id.* at 257–58; e.g., Arthur Rizer & Caleb Watney, *Artificial Intelligence Can Make Our Jail System More Efficient, Equitable, and Just*, 23 TEX. REV. L. & POL. 181, 195–96 (2018).

38. See Re & Solow-Niederman, *supra* note 5, at 257–58.

39. See *id.* at 253–54.

40. See *id.* at 256.

programming defining legal rules or standards.<sup>41</sup> For instance, AI can determine with high probability whether the law would deem the use of copyrighted content to be fair.<sup>42</sup> AI can make conclusions faster than humans through simulations and modeling to independently learn to navigate novel data configurations and achieve those outcomes.<sup>43</sup>

Fourth, AI also promises to advance justice and equity by making IP more accessible to marginalized groups. For example, algorithms could provide courts and even members of the public with preliminary assessments on freedom of action searches, fair use, likelihood of confusion, or patent infringement. The progress of technology also benefits the marginalized. Scholars have boldly imagined ways for algorithmic adjudication “to provide low-cost determinations to a large number of people who otherwise may not be able to afford” legal assistance.<sup>44</sup> In copyright law, these low-cost determinations can allow content users to test legal boundaries in their creative pursuits while adhering to AI’s low-cost compliance.<sup>45</sup>

AI promises to promote access for litigants with limited means.<sup>46</sup> Most litigants who appear in court pro se do so because they cannot afford counsel.<sup>47</sup> Automated document preparation programs can help low-income individuals access the justice system.<sup>48</sup> This is particularly true if low-income individuals can access legal services through their smartphones, which they must frequently rely upon to access the internet.<sup>49</sup>

In Singapore, low-cost access to the IP system is already a reality. For example, a small business owner who wants a trademark can simply download an app on their mobile device and apply for one.<sup>50</sup> The app is

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41. See Dan L. Burk, *Algorithmic Fair Use*, 86 U. CHI. L. REV. 283, 293 (2019).

42. See Peter K. Yu, *Can Algorithms Promote Fair Use?*, 14 FIU L. REV. 329, 352–53 (2020).

43. See *id.* at 345–46. Analysis of copyright outcomes “will be even better if the machines can collect additional market information that is currently not in the possession of copyright holders, users, or technology platforms.” *Id.*

44. *Id.* at 349.

45. See *id.*; Burk, *supra* note 41, at 289 (“Automated identification and removal, whether accurate or mistaken, is relatively cheap, whereas legal and institutional engagement is comparatively expensive.”).

46. See Katherine L.W. Norton, *The Middle Ground: A Meaningful Balance Between the Benefits and Limitations of Artificial Intelligence to Assist with the Justice Gap*, 75 U. MIA. L. REV. 190, 232–47 (2020).

47. LEGAL SERVS. CORP., DOCUMENTING THE JUSTICE GAP IN AMERICA: THE CURRENT UNMET CIVIL LEGAL NEEDS OF LOW-INCOME AMERICANS 23–24 (2009), [https://www.lsc.gov/sites/default/files/LSC/pdfs/documenting\\_the\\_justice\\_gap\\_in\\_america\\_2009.pdf](https://www.lsc.gov/sites/default/files/LSC/pdfs/documenting_the_justice_gap_in_america_2009.pdf) [<https://perma.cc/S7CW-7WE3>].

48. See Norton, *supra* note 46, at 238–39.

49. See *id.* at 252. “Examples of apps successfully designed to provide these types of automated limited legal services include legal triage apps, intake apps, criminal expunge-drafting and review apps, and apps to help prepare for unemployment hearings.” *Id.*

50. See Eileen Yu, *Singapore Lets Firms Apply for Trademarks via Mobile App*, ZDNET (Aug. 20, 2019), <https://www.zdnet.com/article/singapore-lets-firms-apply-for-trademarks-via-mobile-app> [<https://perma.cc/7SCF-D34H>] (noting that trademark applicants can use the “IPOS Go” app to “track their registration status, receive notification about important updates, and submit trademark renewals via the app”).



integrated with AI to identify similar trademarks in Singapore's national trademark register.<sup>51</sup> In addition, the AI-driven app removes the need for small businesses and individuals to rely on attorneys, making the trademark system more accessible at little or no cost.

Fifth, AI systems can correct errors faster than human-driven justice systems.<sup>52</sup> For "even when AI adjudicators fail, developers can argue for greater research and perfection that no human judge can offer."<sup>53</sup> In the copyright context, Professor Yu questions what would happen "should a court find out months, or years, later that an earlier automated fair use determination was incorrect."<sup>54</sup> Correcting those errors becomes a matter of pushing an update through the system.<sup>55</sup>

In sum, AI offers five benefits to IP law and practice. First, AI will be more cost-efficient in the long run. Second, algorithmic adjudication promises to offer impartiality by codifying justice and prioritizing standardization over discretion. Third, AI is effective. Fourth, AI promises to advance justice and equity by making the IP system more accessible to marginalized groups. Finally, AI systems can correct errors faster within human-driven justice systems. The improvements that AI offers to IP law and what is at stake for equity are, in a word, world-changing.

## B. EQUITY AND EQUALITY

Like the rest of us, judges are susceptible to subconscious biases, which can make judicial decision-making inconsistent and random.<sup>56</sup> Unlike human judges, algorithms are consistent; they always give the same answer when presented with the same facts.<sup>57</sup> The power of algorithms lies in making standardized, data-based estimates about "the occurrence of an event or existence of a fact."<sup>58</sup>

Standardization minimizes human bias but may not lead to equal or fair outcomes since algorithmic consistency comes at the cost of flexibility to case-specific nuances.<sup>59</sup> AI may produce disparate outcomes, but that

51. *Id.*

52. See Sibel Nicholson, *AI Proves To Be 10% Faster and More Accurate than Top Human Lawyers*, INTERESTING ENG'G (Feb. 27, 2018), <https://interestingengineering.com/innovation/ai-proves-to-be-10-faster-and-more-accurate-than-top-human-lawyers> [https://perma.cc/7H2R-VR7D].

53. See Re & Solow-Niederman, *supra* note 5, at 258. "For many, the pitch to invest in 'better, faster, cheaper' justice will prove irresistible." *Id.*

54. Yu, *supra* note 42, at 356.

55. See Re & Solow-Niederman, *supra* note 5, at 268–69.

56. See generally Daryl Lim, *Retooling the Patent-Antitrust Intersection: Insights from Behavioral Economics*, 69 BAYLOR L. REV. 124, 135–39 (2017).

57. K.N.C., *supra* note 17 ("[T]he algorithm will always give exactly the same answer when presented with the same set of circumstances.")

58. Steven M. Bellovin, Renée M. Hutchins, Tony Jebara & Sebastian Zimmeck, *When Enough Is Enough: Location Tracking, Mosaic Theory, and Machine Learning*, 8 N.Y.U. J.L. & LIBERTY 555, 590 (2014) ("Machine learning works best when given a large training set of observations (ideally drawn in some independent manner) with which it estimates models. These models are then used to make predictions on future data outputting a probability measure for the occurrence of an event or existence of a fact.")

59. See Re & Solow-Niederman, *supra* note 5, at 256 n.43.

disparity may be acceptable if error rates are equal for different groups.<sup>60</sup> To be clear, unequal outcomes are not necessarily unfair.<sup>61</sup> The difference between them is the difference between equity and equality.

Equality means that “each individual or group is given the same resources or opportunities, regardless of their circumstances.”<sup>62</sup> In contrast, “[e]quity recognizes [that] each person has different circumstances and needs” and allocates resources and opportunities accordingly in order to improve different groups’ outcomes.<sup>63</sup> Even with equal support, access may remain unequal and outcomes inequitable.<sup>64</sup> The equitable solution allocates what each person needs to enjoy the same positive outcomes as the favored group.<sup>65</sup>

The law must decide if the trade-offs are justified, but that assumes it can detect those disparities and know what to do with them. For this reason, equity loomed large in the Singapore judiciary’s initiative. As the court’s spokesperson acknowledged, the traffic accident claims simulator “may raise issues about whether [AI] would affect the public’s confidence in the judicial process.”<sup>66</sup> In particular, “AI may not be equipped to come up with a ‘fair’ outcome having regard to the human element—sympathy and compassion—or non-tangible factors.”<sup>67</sup>

Equity and equality also loom large in the IP context. IP law seeks to optimize innovation and creativity while uplifting the national economy.<sup>68</sup> In 2019, 41% of domestic economic activity was IP-related, and “IP-intensive industries accounted for 63 million jobs, or 44% of all U.S. employment.”<sup>69</sup> Moreover, workers across all IP-intensive industries

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60. See Nicol Turner Lee, Paul Resnick & Genie Barton, *Algorithmic Bias Detection and Mitigation: Best Practices and Policies to Reduce Consumer Harms*, BROOKINGS (May 22, 2019), <https://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms> [https://perma.cc/6843-RWFP].

61. See *id.*

62. *Equity vs. Equality: What’s the Difference – Examples & Definitions*, UNITED WAY NAT’L CAP. AREA (June 22, 2021), <https://unitedwaynca.org/blog/equity-vs-equalityw> [https://perma.cc/4V8S-9TS3].

63. *Id.*

64. *Equity vs. Equality: What’s the Difference?*, GW ONLINE PUB. HEALTH (Nov. 5, 2020), <https://onlinepublichealth.gwu.edu/resources/equity-vs-equality> [https://perma.cc/F4MC-KAJ7].

65. *Id.*

66. Yong, *supra* note 19.

67. *Id.*

68. See Laura Possesky, *Cultivating the Economic Benefits of Creativity: Finding the Right Balance in IP Laws*, A.B.A. (Apr. 1, 2020), [https://www.americanbar.org/groups/intellectual\\_property\\_law/publications/landslide/2019-20/march-april/cultivating-economic-benefits-creativity-finding-right-balance-ip-laws](https://www.americanbar.org/groups/intellectual_property_law/publications/landslide/2019-20/march-april/cultivating-economic-benefits-creativity-finding-right-balance-ip-laws) [https://perma.cc/2YLH-BUKH]; see also U.S. CONST. art. I, § 8, cl. 8 (granting Congress the power “[t]o promote the Progress of Science and useful Arts, by securing for limited Times to Authors and Inventors the exclusive Right to their respective Writings and Discoveries”).

69. Eileen McDermott, *USPTO Report Says IP-Intensive Industries Account for 44% of All U.S. Employment, Pay 60% More*, IPWATCHDOG (Mar. 17, 2022, 4:15 PM), <https://www.ipwatchdog.com/2022/03/17/uspto-report-says-ip-intensive-industries-account-44-us-employment-pay-60-more/id=147675> [https://perma.cc/7CDX-UUNM].

earned 60% more per week than workers in other industries.<sup>70</sup> In addition, workers in IP industries are more likely to be at larger companies with 500 employees or more, participate in employer-sponsored health insurance, and have employer-sponsored retirement plans.<sup>71</sup>

While it is tempting to think that “if we get incentives right, the optimal level of innovation should follow,” the evidence is inconclusive despite the near canonical faith in this narrative.<sup>72</sup> The fact is that the IP system is unequal because women and minorities remain underrepresented in IP-intensive industries.<sup>73</sup> In 2019, the female workforce gap was the starkest in patent-intensive industries.<sup>74</sup>

The IP system is also inequitable; it is not value-neutral concerning equity.<sup>75</sup> Instead, it has “reward[ed] specific demographics for so long that the system’s outcomes may appear unintentional but [they] are actually rooted discriminatory practices and beliefs.”<sup>76</sup> IP doctrines and concepts can entrench and perpetuate biases.<sup>77</sup> Since IP “is a product of its social milieu,” society bakes in “assumptions about race, class, gender, [and] other socially constructed norms.”<sup>78</sup>

The legal problem stems from inequity in participation in the IP system.<sup>79</sup> Criteria and doctrines in IP law that developed over the years the participation of marginalized groups are now bereft of those groups’ insights, experiences, and viewpoints.<sup>80</sup> If the IP system fails to incentivize artistic and scientific works specific to underrepresented groups, it results in a qualitative deficit.<sup>81</sup> Section II.C discusses this issue in greater detail.

70. *Id.* (“Workers in non-IP-intensive industries earned an average of \$947 per week in 2019. Utility patent-intensive industries saw an average of \$1,869 per week.”).

71. *Id.*

72. Stephanie Plamondon Bair, *Impoverished IP*, 81 OHIO ST. L.J. 523, 559–60 (2020); see also Mark A. Lemley, *Faith-Based Intellectual Property*, 62 UCLA L. REV. 1328, 1335 (2015) (“[W]e have gone out, collected the evidence, and found that it is far from clear that IP is doing the world more good than harm.”); e.g., GLYNN LUNNEY, *COPYRIGHT’S EXCESS: MONEY AND MUSIC IN THE US RECORDING INDUSTRY* 193–94 (2018) (providing that increased revenue from more copyright protection has led to a decrease in high-quality music output).

73. See McDermott, *supra* note 69 (“Women comprised 43.7% of the workforce in IP-intensive industries, versus 54% in non-IP-intensive industries. Blacks and Hispanics respectively comprised 8.9% and 13% of the workforce in IP-intensive industries, versus 13.9% and 19.5% in non-IP-intensive industries.”).

74. *Id.*

75. See Burk, *supra* note 11, at 29.

76. See *Equity vs. Equality: What’s the Difference?*, *supra* note 64; e.g., Carys J. Craig, *Reconstructing the Author-Self: Some Feminist Lessons for Copyright Law*, 15 AM. U. J. GENDER SOC. POL’Y & L. 207, 240 (2007).

77. See Dan L. Burk, *Do Patents Have Gender?*, 19 AM. U. J. GENDER SOC. POL’Y & L. 881, 885–88 (2011) (discussing bias in the patent system specifically with respect to gender).

78. Burk, *supra* note 11, at 29.

79. See, e.g., Burk, *supra* note 77, at 887; Bair, *supra* note 72, at 536–37.

80. Burk, *supra* note 14, at 278.

81. See Bair, *supra* note 72, at 554–55 (“[R]elying disproportionately on particular demographic groups for our innovation may result in insufficiently varied output—both in terms of the types of works being created, and in the content of those works, as the substance of innovative works generally reflects the individual backgrounds and experiences of their creators.”).

The result is an IP system that perpetuates inequity when elite groups own an increasingly large share of IP rights.<sup>82</sup> For instance, in the recording industry from 1962–2015, a few top artists received most copyright royalties but felt little need to keep producing new music.<sup>83</sup> Moreover, as Section II.C shows, copyright law’s European-focused doctrines fail to account for how other cultures create music.<sup>84</sup> Similarly, in 2016, the top 1% of patent owners received over half of new patent grants, up from 38% in 1986.<sup>85</sup> This symptom is evidence that the system over-incentivizes certain groups, which are generally wealthy, mostly White, and mostly male, at the expense of other groups.<sup>86</sup>

The link between equity and innovation invites us to ask how distributive justice could complement the current IP system to increase participation of marginalized groups and, in doing so, course-correct AI systems running on biased data.<sup>87</sup> This reimagining of what I call “equity-focused IP” offers a more effective paradigm to promote innovation inclusively rather than simply equally. The time for this idea has come.

With “the right structures, ethics[,] and incentives, . . . scientific and social progress could be truly incredible.”<sup>88</sup> One study found that if “women, minorities, and children from lower-income families were to invent at the same rate as [W]hite men from high-income (top-quintile) families, the total number of inventors in the economy would quadruple.”<sup>89</sup> Suboptimal innovation robs society of the collective benefits of these creations and the jobs and economic growth they would otherwise spur.<sup>90</sup>

One obstacle to this progress is the risk that humans become lulled into giving more deference to the algorithm than they should. AI may produce predictions that we feel obliged to accept based on what we perceive to be a more expert risk predictor.<sup>91</sup> Some in behavioral psychology argue that “people will be inordinately influenced by it.”<sup>92</sup> On the other hand, stakeholders may feel that AI-based conclusions would be more

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82. *Id.* at 552; see Colleen Chien, *Inequality, Innovation, and Patents* 39–40 (Santa Clara Univ. Sch. of L., Legal Stud. Rsch. Paper, Working Paper No. 2018-03), [https://www.law.nyu.edu/sites/default/files/upload\\_documents/Colleen%20Chien.pdf](https://www.law.nyu.edu/sites/default/files/upload_documents/Colleen%20Chien.pdf) [<https://perma.cc/J76L-YRA8>].

83. See LUNNEY, *supra* note 72, at 193 (“[A]s revenues increased, earnings for our top artists rose sharply; as they did, our top artists started producing fewer hit songs.”).

84. See Rosenblatt, *supra* note 13, at 618–19.

85. Chien, *supra* note 82, at 5.

86. See Bair, *supra* note 72, at 554.

87. See *id.* at 560–61.

88. Mustafa Suleyman, *AI Offers a Unique Opportunity for Social Progress*, *ECONOMIST* (Sept. 20, 2018), <https://www.economist.com/open-future/2018/09/20/ai-offers-a-unique-opportunity-for-social-progress> [<https://perma.cc/BA4K-4W53>].

89. Alex Bell, Raj Chetty, Xavier Jaravel, Neviana Petkova & John Van Reenen, *Who Becomes an Inventor in America? The Importance of Exposure to Innovation*, 134 *Q.J. ECON.* 647, 653 (2019).

90. See Bair, *supra* note 72, at 555.

91. See Re & Solow-Niederman, *supra* note 5, at 245.

92. K.N.C., *supra* note 17 (“People are often quite lazy. We like taking the easy way out—we like handing over responsibility, we like being offered shortcuts that mean we don’t have to think.”).

reliable and withstand scrutiny by judges on appeal. When that happens, people will become blind to bugs in the system. Resource-strapped courts may happily rely on the conclusions and fail to take the appropriate steps or have the technical know-how to constantly monitor, update, and validate the algorithmically generated options.

Even flawed decision-making systems may be acceptable if they can compensate by delivering fast, low-cost determinations that enable nimble corporate decision-making. For example, pseudoscience claims that human character can be objectively assessed through handwriting analysis and lie-detector polygraphs.<sup>93</sup> In the same vein, Rebecca Kelly Slaughter, Janice Kopec, and Mohamad Batal warn that claims involving AI “can be more pernicious than their analog counterparts because they might encounter less skepticism even though opacity in algorithms can prevent objective analysis of their inputs and conclusions.”<sup>94</sup> The good news is that we can resist that complacency if we remain aware of the bugs in the system.

### C. BUGS IN THE SYSTEM

The AI revolution developed through improved algorithms, powerful computing muscles, and big data.<sup>95</sup> However, as demonstrated above, AI does not make things fairer unless deliberately designed to do so.<sup>96</sup> Biased conclusions undergird fears about technology “fueled by failures in experimental design.”<sup>97</sup> Those failures take three key forms: algorithmic failure, data bias, and implementation flaws. This Section addresses each one.

#### 1. Algorithmic Failure

Technology reflects the values of its creators and AI is no exception.<sup>98</sup> Programmers are instructed to code legal policy objectives into algorithms that sort data, targeting variables of interest and class labels.<sup>99</sup> Target variables can range from binary outcomes, like whether a defendant

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93. Slaughter, Kopec & Batal, *supra* note 1, at 13.

94. *Id.*

95. See Lim, *supra* note 6, at 830.

96. See, e.g., Andre M. Perry & Nicol Turner Lee, *AI Is Coming to Schools, and If We're Not Careful, So Will Its Biases*, BROOKINGS (Sept. 26, 2019), <https://www.brookings.edu/blog/the-avenue/2019/09/26/ai-is-coming-to-schools-and-if-were-not-careful-so-will-its-biases/> [<https://perma.cc/LG3H-TWC9>] (“Developers must intentionally build AI systems through a lens of racial equity if the technology is going to disrupt the status quo.”).

97. See Slaughter, Kopec & Batal, *supra* note 1, at 10.

98. Kate Crawford, Opinion, *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/XR42-YTEJ>]; see also Katyal, *supra* note 9, 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.”).

99. Bradfield E.A. Biggers, *Curbing Widespread Discrimination by Artificial Intelligence Hiring Tools: An Ex Ante Solution*, 2020 B.C. INTELL. PROP. & TECH. F. 1, 5.

infringed a patent claim, to more abstract concepts, like whether an ornamental feature is separable from its functional purpose and thus protectable under copyright law.<sup>100</sup> In contrast, class labels are discrete categories of target variables organized by degrees.<sup>101</sup>

In writing the code for AI systems, well-intentioned developers may produce biased outcomes.<sup>102</sup> Professors Kate Crawford and Ryan Calo's work points to the way algorithms "disproportionately affect groups that are already disadvantaged by factors such as race, gender[,] and socioeconomic background."<sup>103</sup> Cathy O'Neil warned that AI systems "tend to punish the poor . . . because they are engineered to evaluate large numbers of people. They specialize in bulk, and they're cheap."<sup>104</sup>

Further, minorities are conspicuously missing from the algorithmic design process.<sup>105</sup> In a 2019 article, a group of medical professionals cited an algorithm that uses healthcare costs as a proxy for health needs.<sup>106</sup> This algorithm represents "one of the largest and most typical examples of a class of commercial risk-prediction tools that . . . are applied to roughly 200 million people in the United States each year."<sup>107</sup> The bias underlying this algorithm led to the exclusion of over half the number of Black patients that should have received extra care.<sup>108</sup> Because White patients spent more on healthcare than their equally sick Black counterparts, the algorithm flagged the White patients as sicker and in need of more care and resources.<sup>109</sup> Amy Webb, CEO of the Future Today Institute, observed:

The overwhelming majority of coders are [W]hite 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

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100. *See id.*

101. *Id.*

102. *See* Kristin N. Johnson, *Automating the Risk of Bias*, 87 GEO. WASH. L. REV. 1214, 1221 (2019).

103. Kate Crawford & Ryan Calo, *There Is a Blind Spot in AI Research*, 538 NATURE 311, 312 (2016), <https://www.nature.com/news/there-is-a-blind-spot-in-ai-research-1.20805> [<https://perma.cc/544C-V5DW>].

104. CATHY O'NEIL, WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY 8 (2016).

105. *See, e.g.*, 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/XA4N-DGDZ>] (providing that because "AI algorithms are developed almost entirely in developed regions," they "may not sufficiently reflect the contexts and priorities of developing countries").

106. Ziad Obermeyer, Brian Powers, Christine Vogeli & Sendhil Mullainathan, *Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations*, 366 SCIENCE 447, 447 (2019).

107. *Id.*

108. *Id.*

109. *See id.*; Sujata Gupta, *Bias in a Common Health Care Algorithm Disproportionately Hurts Black Patients*, SCI. NEWS (Oct. 24, 2019, 2:00 PM), <https://www.sciencenews.org/article/bias-common-health-care-algorithm-hurts-black-patients> [<https://perma.cc/SDV4-A7Y9>].

comes, they must choose new hires both for their skills and their worldview.<sup>110</sup>

Equality by design requires diversification of the developer workforce, as AI reflects its creators' values.<sup>111</sup> Without an ethos of diversity among designers, executives, and auditors in the AI industry, the perspectives embedded in the legal system will risk developing a system of intelligent IP law that continues to perpetuate bias.<sup>112</sup> Workplace inclusivity matters. Everyone from developers to company executives needs to promote diversity in their workforce, which is important as a matter of equity. Doing so would empower businesses to develop new products and services that improve user experience and outcomes for the entire consumer population rather than just a sliver.<sup>113</sup> Upstream, this also requires universities that provide the talent pool for developers to recruit diverse students.<sup>114</sup> These efforts will help mitigate algorithms' potential for infection by developer bias.

Algorithms may also harm a protected category by making unforeseeable correlations between data points.<sup>115</sup> This species of algorithmic failure manifests in proxy discrimination, which occurs when AI uses seemingly neutral characteristics as a stand-in for a protected trait, disproportionately impacting protected classes.<sup>116</sup> One reason for proxy discrimination is due to the technology itself.<sup>117</sup> The value of AI often lies precisely in its ability to identify new proxies;<sup>118</sup> it is a feature, not a bug. It may be both impossible and undesirable to block all the biased proxies.<sup>119</sup> For instance, Amazon modified its hiring algorithm "to ignore

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110. LEE RAINIE & JANNA ANDERSON, PEW RSCH. CTR., CODE-DEPENDENT: PROS AND CONS OF THE ALGORITHM AGE 23 (2017), [https://www.pewresearch.org/internet/wp-content/uploads/sites/9/2017/02/PI\\_2017.02.08\\_Algorithms\\_FINAL.pdf](https://www.pewresearch.org/internet/wp-content/uploads/sites/9/2017/02/PI_2017.02.08_Algorithms_FINAL.pdf) [<https://perma.cc/NF9N-VPXA>].

111. See 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 . . .").

112. See Kari Paul, 'Disastrous' Lack of Diversity in AI Industry Perpetuates Bias, *Study Finds*, GUARDIAN (Apr. 16, 2019, 8:47 PM), <https://www.theguardian.com/technology/2019/apr/16/artificial-intelligence-lack-diversity-new-york-university-study> [<https://perma.cc/X6MK-RR3A>].

113. See Felix Chang, *To Build More-Inclusive Technology, Change Your Design Process*, HARV. BUS. REV. (Oct. 19, 2020), <https://hbr.org/2020/10/to-build-more-inclusive-technology-change-your-design-process> [<https://perma.cc/P78M-S635>].

114. See NAT'L SCI. & TECH. COUNCIL, EXEC. OFF. OF THE PRESIDENT, PREPARING FOR THE FUTURE OF ARTIFICIAL INTELLIGENCE 26–27 (2016) [hereinafter WHITE HOUSE AI REPORT], [https://obamawhitehouse.archives.gov/sites/default/files/whitehouse\\_files/microsites/ostp/NSTC/preparing\\_for\\_the\\_future\\_of\\_ai.pdf](https://obamawhitehouse.archives.gov/sites/default/files/whitehouse_files/microsites/ostp/NSTC/preparing_for_the_future_of_ai.pdf) [<https://perma.cc/S5EP-HM2E>].

115. See Cofone, *supra* note 32, at 1413; see also Margaret Hu, *Algorithmic Jim Crow*, 86 FORDHAM L. REV. 633, 658, 661 (2017) (explaining that algorithms can use data—like risk factors—that are not protected categories, but serve as proxies for protected categories).

116. See Slaughter, Kopec & Batal, *supra* note 1, at 20.

117. See Anya E.R. Prince & Daniel Schwarcz, *Proxy Discrimination in the Age of Artificial Intelligence and Big Data*, 105 IOWA L. REV. 1257, 1263 (2020).

118. See *id.* at 1317 n.230.

119. See Cofone, *supra* note 32, at 1413; see also James Grimmelman & Daniel Westreich, *Incomprehensible Discrimination*, 7 CAL. L. REV. ONLINE 164, 171 (2016).

words that denoted gender” after realizing it discriminated on that basis.<sup>120</sup> Nonetheless, the algorithm continued to discriminate based on gender by relying on proxy “words in the resumes that correlated with gender.”<sup>121</sup> In this way, proxy discrimination can perpetuate historical biases.<sup>122</sup> Section IV.A.2 addresses this issue below.

In sum, while algorithms provide a veneer of impartiality, they obscure how they reach their conclusions, thereby camouflaging bias.<sup>123</sup> Developers’ own biases can infect the code, thereby furthering inequalities.<sup>124</sup> With AI’s increasing role in IP law, the lack of diversity in AI could amplify inequality as AI bakes bias and discrimination into the IP system. Proxy discrimination also raises the difficult question regarding how much we can realistically regulate without overburdening the AI process with red tape.<sup>125</sup> Nonetheless, equity audits can still play a useful role; if biases infect training data and the code, audits can reveal such biases, and developers can then debug them.<sup>126</sup> Section IV.B explains how, and it raises the importance of understanding biases that occur in data so we can mitigate their baleful effects.

## 2. Data Bias

AI relies on examples, or training data, to train software models structured loosely on the brain’s neural architecture.<sup>127</sup> Bias occurs when developers select data to benefit consumers like themselves.<sup>128</sup> Profit incentives may also cause developers to prioritize the most commercially relevant segments of the consumer base.<sup>129</sup> In such situations, regulation is especially crucial.

AI applications need broad, diverse data sets or the results will be underrepresentative.<sup>130</sup> Faulty inputs can produce problematic outcomes—

120. *Id.*

121. *Id.*

122. See Prince & Schwarcz, *supra* note 117, at 1296–97; e.g., *Examining the Use of Alternative Data in Underwriting and Credit Scoring to Expand Access to Credit: Hearing Before the Task Force on Fin. Tech. of the H. Comm. on Fin. Servs.*, 116th Cong. 9 (2019) (statement of Kristin N. Johnson, McGlinchey Stafford Professor of Law, Tulane University Law School).

123. See Slaughter, Kopec & Batal, *supra* note 1, at 22–23.

124. See Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 14 (2014).

125. See Cofone, *supra* note 32, at 1391, 1406.

126. See Pauline T. Kim, *Auditing Algorithms for Discrimination*, 166 U. PA. L. REV. ONLINE 189, 190–91 (2017).

127. See Kathleen Walch, *How Neutral Network Training Methods Are Modeled After the Human Brain*, TECHTARGET (Sept. 17, 2021), <https://www.techtargget.com/searchcenter-priseai/feature/How-neutral-network-training-methods-are-modeled-after-the-human-brain> [<https://perma.cc/ZQF4-5VHL>].

128. See RAINIE & ANDERSON, *supra* note 110, at 12.

129. See LEE RAINIE, JANNA ANDERSON & EMILY A. VOGELS, PEW RSCH. CTR., EXPERTS DOUBT ETHICAL AI DESIGN WILL BE BROADLY ADOPTED AS THE NORM WITHIN THE NEXT DECADE 48, 56, 61 (2021), <https://www.pewresearch.org/internet/2021/06/16/experts-doubt-ethical-ai-design-will-be-broadly-adopted-as-the-norm-within-the-next-decade> [<https://perma.cc/QJ6D-MXWR>].

130. See Lee, Resnick & Barton, *supra* note 60.



“garbage in, garbage out.”<sup>131</sup> Biased training data may entrench existing inequities.<sup>132</sup> For instance, facial recognition software has led to mistaken imprisonments based on demographic biases in the software’s development and deployment.<sup>133</sup> On a related note, it is also important that we realize how public consciousness becomes embedded in design values in AI systems. In the legal context, Professor Kara Swanson warned that “there is no such thing as neutral law—that law replicates existing social hierarchies, and we need to look at all bodies of law carefully, to see what power hierarchies they create and what subordination they promote, if we want to promote equality instead.”<sup>134</sup> Training data often consists of case opinions embedded in code to repeat past practices and, in so doing, automate the status quo more efficiently. As a result, data might be skewed because data points are biased, baking in historical prejudice or inequality, and “can create biased algorithms that exacerbate injustice.”<sup>135</sup>

Datasets that exclude or significantly underrepresent marginalized groups reflect societal attitudes against those rarely included in AI’s development.<sup>136</sup> Creating unbiased algorithms requires developers to feed those algorithms with a diverse diet of database sources.<sup>137</sup> Without a rich and diverse body of data, data developers cannot offer algorithms attuned to what equality should look like, even when given a new set of facts.<sup>138</sup> Creating unbiased algorithms also requires an understanding of how inequality in the IP system looks, discussed in Section III.B.<sup>139</sup> Finally, mitigating algorithmic inequality requires improving the training data, which Section IV.A discusses.<sup>140</sup>

### 3. Implementation Flaws

From an implementation standpoint, seceding a degree of legal analysis to algorithms must come with a proportionate assurance that it can do so equitably if AI is going to take root and flourish. As a result, governments will come under increasing pressure to regulate algorithmic dis-

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131. Amanda Levendowski, *How Copyright Law Can Fix Artificial Intelligence’s Implicit Bias Problem*, 93 WASH. L. REV. 579, 585 (2018).

132. See Slaughter, Kopec & Batal, *supra* note 1, at 7–10; W. Keith Robinson, *Artificial Intelligence and Access to the Patent System*, 21 NEV. L.J. 729, 758 (2021).

133. See Slaughter, Kopec & Batal, *supra* note 1, at 10 n.25; Kashmir Hill, *Wrongfully Accused by an Algorithm*, N.Y. TIMES (Aug. 3, 2020), <https://www.nytimes.com/2020/06/24/technology/facial-recognition-arrest.html> [<https://perma.cc/YR7L-E3WJ>].

134. Swanson, *supra* note 10, at 182.

135. Slaughter, Kopec & Batal, *supra* note 1, at 7–8.

136. See Barocas & Selbst, *supra* note 34, at 684–85.

137. See Womble Bond Dickinson, *State Laws Hinder Progress of Non-Bias AI*, JD-SUPRA (June 23, 2021), <https://www.jdsupra.com/legalnews/state-laws-hinder-progress-of-non-bias-7371659> [<https://perma.cc/7BM7-JW4D>].

138. See Re & Solow-Niderman, *supra* note 5, at 259 (“Limited bodies of training data might curtail data scientists’ ability to play with a model and arrive at a working algorithm that sufficiently exhibits equity.”).

139. See *infra* Section III.B.

140. See *infra* Section IV.A.

crimination.<sup>141</sup> Without a conscious effort to mitigate inequality, the progress of algorithmic judging will be fettered by suspicion.<sup>142</sup> Governments will need to explain how algorithm design will flag uncertainty and make decisions with transparency in mind to address this suspicion.<sup>143</sup> The reduction in ambiguity makes it easier for judges to know when they should trust their instincts instead of an automated suggestion.

Without intervening deliberately at a pace that keeps up with AI's rollout, inequity could trap some groups in a mindless conveyor belt that excels at delivering unequal justice. There are signs that this has already taken place. For instance, pursuant to a court order, Uber was required "to reinstate some drivers struck off its ride-hailing app for fraud 'based solely on automated processing, including profiling,'" in breach of the European Union's General Data Protection Regulation.<sup>144</sup> In the same way, we must ensure the adjudicatory algorithms by the private sector—often proprietary systems protected by IP rights—remain accountable.<sup>145</sup> Policymakers should also be aware that inequality may manifest in a two-tiered justice system—with human judges hearing cases from businesses and wealthy individuals while AI judges decide lower-value claims.

Pre-deployment testing, continuous monitoring, and retraining are essential to policing AI for embedded bias.<sup>146</sup> Researchers can uncover the bugs and notice disparate outcomes when they have access to enough data to perform an audit.<sup>147</sup> Developers must simulate and examine algorithmic outputs for anomalous results in order to detect bias.<sup>148</sup> While "no simple test" can "reliably detect and prevent bias, early and ongoing testing of . . . outcomes" can catch flaws sooner.<sup>149</sup>

Even when outcomes are correct, humans are less likely to adopt AI if it cannot explain its reasoning in a way people can comprehend, hence calls for "explainable AI" (XIA).<sup>150</sup> AI correlates data without the goal

141. See, e.g., Sean Hannon Williams, *AI Advice*, 48 FLA. ST. U. L. REV. 761, 794 (2021); Cofone, *supra* note 32, at 1410.

142. See, e.g., Jennifer Cannon, *Report Shows Consumers Don't Trust Artificial Intelligence*, FINTECH NEWS (Dec. 4, 2019), <https://www.fintechnews.org/report-shows-consumers-dont-trust-artificial-intelligence> [<https://perma.cc/6EX9-ALUR>]; cf. Jerry Kaplan, *Why We Find Self-Driving Cars So Scary*, WALL ST. J. (May 31, 2018 12:38 PM), <https://www.wsj.com/articles/why-we-find-self-driving-cars-so-scary-1527784724> [<https://perma.cc/TH8P-P98G>] ("Despite the impression that Jetson-style self-driving cars are just around the corner, public acceptance of their failures may yet prove to be their biggest speed bump.").

143. See Slaughter, Kopec & Batal, *supra* note 1, at 49.

144. Kenny Chee, *Man Versus Machine: Human Beings Losing Out as AI Coldly Fires Under-Performing Workers*, STRAITS TIMES (Feb. 21, 2022, 9:46 PM), <https://www.straitstimes.com/tech/tech-news/man-versus-machine-human-beings-losing-out-as-ai-coldly-fires-under-performing-workers> [<https://perma.cc/4C5U-7UXT>]; Council Regulation 2016/679, art. 22, 2016 O.J. (L 119) 1 (EU).

145. See generally Katyal, *supra* note 9.

146. Slaughter, Kopec & Batal, *supra* note 1, at 16.

147. See *id.* at 17.

148. See Lee, Resnick & Barton, *supra* note 60.

149. Slaughter, Kopec & Batal, *supra* note 1, at 17–18.

150. See Pritam Kanti Paul, *Driving AI Adoption with Explainability at the Core*, FORBES BUS. COUNCIL (Oct. 25, 2021, 9:45 AM), <https://www.forbes.com/sites/forbesbusi->

of providing society with an explanatory or causal model.<sup>151</sup> Nevertheless, the idea of obtaining verdicts from a vending machine, however sophisticated, disrupts traditional legal practices and norms.<sup>152</sup>

Richard M. Re and Alicia Solow-Niederman explain that “equitable justice typically carries an obligation to provide [a] particularized, case-specific explanation that connects legal principles, as applied through a lawful process, to the particular facts at hand.”<sup>153</sup> Society understands judicial opinions when judges explain how they applied their discretion and the law to a given set of facts.<sup>154</sup>

Explainability helps verify that AI is consistent with policy goals and makes stakeholders feel more comfortable relying on AI-generated advice. The fact that algorithms using deep learning techniques can train themselves with new data further obscures accountability in the decision-making process.<sup>155</sup> For all this to be properly programmed into the system, one needs to understand the IP context and limitations of what is possible. Section IV.C addresses how AI can help adjudicate IP issues that raise equitable concerns and its limits.

Professor Frank Pasquale described AI as a black box system “whose workings are mysterious; we can observe its inputs and outputs, but we cannot tell how one becomes the other.”<sup>156</sup> He observed that these “[b]lack boxes embody a paradox of the so-called information age: Data is becoming staggering in its breadth and depth, yet often the information most important to us is out of our reach, available only to insiders.”<sup>157</sup> When algorithms become more accurate, their complexity and opacity increase.<sup>158</sup> These black boxes are impervious even to experts.<sup>159</sup> Moreover, those who own the training algorithms often intentionally keep them secret.<sup>160</sup> Opacity prevents those treated unequally by AI from interrogating its decisions.<sup>161</sup> Part III addresses these issues next in the context of trade secrets, patents, and copyrights.

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nesscouncil/2021/10/25/driving-ai-adoption-with-explainability-at-the-core/?sh=66f9c30d1d4f [https://perma.cc/2X76-FG4H] (“Most AI models today, though sophisticated, are still algorithmic black boxes. The need for XIA becomes critical when AI-powered decisions have legal, financial and ethical implications.”); Re & Solow-Niederman, *supra* note 5, at 260–61 (“But because people accustomed to equitable justice typically expect explanations for legal outcomes, they might demand an AI product that meets that felt need.”).

151. See Re & Solow-Niederman, *supra* note 5, at 246.

152. See *id.* at 244, 246–47, 251.

153. *Id.* at 253.

154. See *id.* at 246.

155. See Davide Castelvecchi, *Can We Open the Black Box of AI?*, 538 NATURE 20, 23 (2016), [https://www.nature.com/polopoly\\_fs/1.20731!/menu/main/topColumns/topLeftColumn/pdf/538020a.pdf](https://www.nature.com/polopoly_fs/1.20731!/menu/main/topColumns/topLeftColumn/pdf/538020a.pdf) [https://perma.cc/KMT8-62Y7].

156. FRANK PASQUALE, *THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION* 3 (2015).

157. *Id.* at 191.

158. Ari Ezra Waldman, *Power, Process, and Automated Decision-Making*, 88 FORDHAM L. REV. 613, 618 (2018).

159. See *id.* at 614, 618.

160. See *id.* at 618–19.

161. See *id.* at 619.

### III. AI INEQUITY IN THE IP SYSTEM

AI, IP, and inequity intersect at the issue of forensic DNA software systems in criminal trials.<sup>162</sup> Information with “independent economic value” that is kept secret enjoys trade secret protection.<sup>163</sup> The most valuable aspects of machine learning lie in the algorithms and underlying data.<sup>164</sup> Trade secrets can shield both from public disclosure, and if the information remains secret, protection can last indefinitely.<sup>165</sup> Section A discusses inequity issues arising from trade secrets. Section B discusses how—unlike family law, voting law, and employment law—IP law does not expressly recognize social bias.<sup>166</sup> As a result, barriers faced by minority groups in accessing the IP system lead to underrepresentation and skewed legal rules, thereby favoring those who can participate.

#### A. TRADE SECRETS

Recommendations by the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS), a risk-assessment tool used to determine defendants’ chance of recidivism, resulted in Eric Loomis’s six-year imprisonment.<sup>167</sup> COMPAS weighs various factors in assessing recidivism risk and generates reports that judges can consult in determining sentences.<sup>168</sup> Loomis argued that trade secrets impeded his ability to challenge the validity of COMPAS’s risk assessment.<sup>169</sup> In response to this argument, COMPAS’s developer, Northpointe, invoked protection under federal trade secret law to bar access to its proprietary algorithm, arguing that giving access would destroy its business model.<sup>170</sup>

Prosecutors regularly introduce reports from similar systems as compelling evidence, but judges often deny requests by accused persons to

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162. See generally Lauren Kirchner, *Where Traditional DNA Testing Fails, Algorithms Take Over*, PROPUBLICA (Nov. 4, 2016, 8:00 AM), <https://www.propublica.org/article/where-traditional-dna-testing-fails-algorithms-take-over> [<https://perma.cc/5HK9-LLTQ>].

163. See Rebecca Wexler, *Life, Liberty, and Trade Secrets: Intellectual Property in the Criminal Justice System*, 70 STAN. L. REV. 1343, 1413–14 (2018).

164. See Jeanne C. Fromer, *Machines as the New Oompa-Loompas: Trade Secrecy, the Cloud, Machine Learning, and Automation*, 94 N.Y.U. L. REV. 706, 722 (2019).

165. See *id.* at 722–23, 726 (2019) (“Both can be kept secret and practically free from independent discovery and reverse engineering . . .”).

166. See Burk, *supra* note 11, at 29 (“The goals and structure of intellectual property law are not generally thought of as being associated with race, gender, or other historically disadvantaged social classifications.”).

167. See Ed Yong, *A Popular Algorithm Is No Better at Predicting Crimes than Random People*, ATLANTIC (Jan. 17, 2018), <https://www.theatlantic.com/technology/archive/2018/01/equivant-compas-algorithm/550646> [<https://perma.cc/AA88-Q77P>]; Mitch Smith, *In Wisconsin, a Backlash Against Using Data to Foretell Defendants’ Futures*, N.Y. TIMES (June 22, 2016), <https://www.nytimes.com/2016/06/23/us/backlash-in-wisconsin-against-using-data-to-foretell-defendants-futures.html> [<https://perma.cc/BPF9-Z7NN>].

168. See *State v. Loomis*, 881 N.W.2d 749, 754 (Wis. 2016).

169. See Brief of Defendant-Appellant at 22–25, *State v. Loomis*, 881 N.W.2d 749 (Wis. 2016) (No. 2015AP157-CR).

170. Rizer & Watney, *supra* note 37, at 213.

access the underlying algorithms and datasets.<sup>171</sup> This is because private developers who own automated technologies like Northpointe view their technologies as trade secrets.<sup>172</sup>

Surveillance technology developers likewise claim trade secret protection to block access to their data.<sup>173</sup> For instance, Palantir Technologies supplied software to the NYPD that allowed the Department to connect crimes with people.<sup>174</sup> When the NYPD switched vendors, Palantir refused to provide the NYPD with a readable version of its data.<sup>175</sup> The issue goes beyond the criminal justice system to affect our daily lives. For example, Rashmi Dyal-Chand's work explores how an "Anglo bias" crept into word processing autocorrect functions, warning that "the trade secret protection of core aspects of autocorrect makes it very difficult to know how Anglo bias crept into this technology."<sup>176</sup>

A Center for Democracy and Technology report confirmed that "developers continue to ward off attempts to unearth details about how their tools function by asserting that the information is protected by trade secret law."<sup>177</sup> Moreover, mounting evidence suggests developers fail to share changes in their methodology with oversight bodies.<sup>178</sup> While trade secrets enable companies to commercialize AI, they can "perpetuate and exacerbate existing discriminatory social structures when these systems go unchecked and unregulated."<sup>179</sup> Seeking access also assumes that those who want to know know whom to ask. Unfortunately, many may not even know that an algorithm has discriminated against them—this outcome is inequitable.

Trade secret law may infringe upon our lives without transparency or accountability.<sup>180</sup> Faulty AI that predicts recidivism exacerbates societal inequalities while trade secret law shields developers from scrutiny.<sup>181</sup> Copyright law has the fair use doctrine, an "equitable rule of reason" that

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171. See Katyal, *supra* note 9, at 117–18 ("In countless cases, both inside and outside of the criminal justice system, aggrieved parties have been denied access to the source code that governs them.").

172. Rebecca Wexler, Opinion, *When a Computer Program Keeps You in Jail*, N.Y. TIMES (June 13, 2017), <https://www.nytimes.com/2017/06/13/opinion/how-computers-are-harming-criminal-justice.html> [<https://perma.cc/ZP56-R8YN>].

173. See Elizabeth E. Joh, *The Undue Influence of Surveillance Technology Companies on Policing*, 92 N.Y.U. L. REV. ONLINE 19, 36–37 (2017).

174. *Id.* at 37.

175. *Id.*; Katyal, *supra* note 9, at 118.

176. Rashmi Dyal-Chand, *Autocorrecting for Whiteness*, 101 B.U. L. REV. 191, 197–210, 249 (2021).

177. TAYLOR R. MOORE, CTR. FOR DEMOCRACY & TECH., TRADE SECRETS AND ALGORITHMS AS BARRIERS TO SOCIAL JUSTICE (2017), <https://cdt.org/wp-content/uploads/2017/08/2017-07-31-Trade-Secret-Algorithms-as-Barriers-to-Social-Justice.pdf> [<https://perma.cc/77QK-CGFQ>].

178. Jeanna Matthews et al., *The Right to Confront Your Accusers: Opening the Black Box of Forensic DNA Software*, PROC. 2019 AAAI/ACM CONF. ON AI, ETHICS & SOC'Y 321 (Jan. 2019).

179. MOORE, *supra* note 177.

180. See Charles Tait Graves & Sonia K. Katyal, *From Trade Secrecy to Seclusion*, 109 GEO. L.J. 1337, 1369–70, 1370 n.148 (2021).

181. See MOORE, *supra* note 177.

“permits courts to avoid rigid application of the copyright statute when, on occasion, it would stifle the very creativity which that law is designed to foster.”<sup>182</sup> So does trademark law, in which the fair use doctrine balances trademark enforcement objectives against free speech principles under the First Amendment.<sup>183</sup> Patent law similarly contains the doctrine of patent misuse, which provides a check on patentees who impermissibly broaden the scope of their patent grant with anticompetitive effect.<sup>184</sup>

In contrast, while trade secret law does have two key limitations to balance public interests against controlling access to proprietary information, neither independent discovery nor reverse engineering will avail those seeking access to algorithms and data.<sup>185</sup> Unlike copyrights and patents, there is no formal examination to obtain the designation.<sup>186</sup> The lack of checks puts trade secret law in tension with policies designed to reduce overreaching.<sup>187</sup>

Doctrinally, trade secrets are versatile and attractive to AI developers. Professor Charlotte Tschider notes that “AI is a natural fit for trade secret protection due to the unavailability of alternatives like patent law and the natural opacity of its processes and algorithms.”<sup>188</sup> Trade secret-protection not only covers the subject matter protected by copyright and patent law but also protects certain information that may not be patentable or copyrightable.<sup>189</sup>

The prevalence of cloud computing has also added barriers to accessing code and data.<sup>190</sup> Professor Jeanne Fromer warns, “With the growth of cloud computing, businesses now have a technological path—not only a contractual path—toward robust secrecy of their software.”<sup>191</sup> Compa-

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182. *Google LLC v. Oracle Am., Inc.*, 141 S. Ct. 1183, 1196 (2021) (quoting *Stewart v. Abend*, 495 U.S. 207, 236 (1990)); see also Daryl Lim, *Substantial Similarity’s Silent Death*, 48 PEPP. L. REV. 713, 763–67 (2021) (discussing fair use in copyright law).

183. See Deborah R. Gerhardt, *A Masterclass in Trademark’s Descriptive Fair Use Defense*, 52 AKRON L. REV. 787, 787–88 (2019); see also Lim, *supra* note 27 (discussing fair use in trademark law).

184. See Daryl Lim, *Patent Misuse and Antitrust: Rebirth or False Dawn?*, 20 MICH. TELECOMMS. & TECH. L. REV. 299, 323, 377–78 (2014).

185. See Fromer, *supra* note 164, at 722–23; *Kewanee Oil Co. v. Bicron Corp.*, 416 U.S. 470, 476 (1974); Audrey Millemann & Weintraub Tobin, *Trade Secret or Patent?*, JDSUPRA (Jan. 13, 2022), <https://www.jdsupra.com/legalnews/trade-secret-or-patent-3068606> [<https://perma.cc/DE92-CM8V>].

186. See Dyal-Chand, *supra* note 176, at 231 (“By contrast, trade secret law does not oblige owners either to disclose their inventions or to provide other forms of access.”).

187. See Robin Feldman & Charles Tait Graves, *Naked Price and Pharmaceutical Trade Secret Overreach*, 22 YALE J.L. & TECH. 61, 81–83 (2020); see also Re & Solow-Niederman, *supra* note 5, at 260 (“Without access to these proprietary data sets, the universe of available information on which to train an equitable AI adjudicator is even more limited.”).

188. Charlotte A. Tschider, *Legal Opacity: Artificial Intelligence’s Sticky Wicket*, 106 IOWA L. REV. ONLINE 126, 132 (2021).

189. See *What’s the Difference Between a Trade Secret and a Patent?*, AJ PARK (Apr. 23, 2018), <https://www.ajpark.com/insights/whats-the-difference-between-a-trade-secret-and-a-patent> [<https://perma.cc/24B4-5FZJ>]; *Trade Secrets vs Patents vs Copyrights vs Trademarks*, NONDISCLOSUREAGREEMENT.COM, <https://nondisclosureagreement.com/trade-secrets-vs-patents-vs-copyrights.html> [<https://perma.cc/RPG5-YKCV>].

190. See Fromer, *supra* note 164, at 724.

191. *Id.* at 719.

nies offer software as a service via the cloud, rendering the code underneath the software inaccessible to users.<sup>192</sup> Machine learning software does not need to store data in the predictive algorithm it generates, allowing the data to be kept internally.<sup>193</sup> Most of the action takes place on the provider's secure computers.<sup>194</sup> Rather than releasing their software, developers can safeguard their code from reverse engineering.<sup>195</sup> This complements trade secret law's bent toward discouraging proprietary information disclosure. If judges make decisions based on AI's recommendations that defendants cannot examine or dispute, that adjudicatory process conflicts with defendants' due process rights and risks undermining the judicial system's integrity.<sup>196</sup>

Inventors traditionally used trade secrecy to protect against misappropriation, but they now use it as a barrier to scrutinizing algorithmic bias.<sup>197</sup> Early trade secret cases involved rivals or departing employees.<sup>198</sup> Professor Sonia Katyal observes that cases like the one in which COMPAS was at issue “do not involve misappropriation for the purposes of unfair competition, but they implicate core concerns about fairness and accountability to the public. These interests would only escalate the plaintiff's impetus to avoid discovery and identification.”<sup>199</sup> Moreover, she blames “the failure of our system of intellectual property law to definitively address the boundaries of software protection and its implications for source code secrecy.”<sup>200</sup>

Supreme Court decisions have essentially made patent protection for software like COMPAS nonviable.<sup>201</sup> As Professor Katyal notes, “[d]isclosing a way of assessing recidivism with a computer to the [USPTO] would unlikely be worth Northpointe's time and trouble, given the dubious protection that software patents now receive.”<sup>202</sup>

Trade secrecy and the absence of accountability created by AI create a

192. *Id.*

193. *Id.* at 723.

194. *See id.* at 719.

195. *See id.* at 719–20; *see also id.* at 719 (“With its object code kept hidden, no longer is this software at the mercy of those consumers who have sufficient expertise and devotion to reverse engineer it from object code.”).

196. Rizer & Watney, *supra* note 37, at 213.

197. *See* Mark A. Lemley, *The Surprising Virtues of Treating Trade Secrets as IP Rights*, 61 *STAN. L. REV.* 311, 315 (2008); Deborah Won, Note, *The Missing Algorithm: Safeguarding Brady Against the Rise of Trade Secrecy in Policing*, 120 *MICH. L. REV.* 157, 167, 169 (2021).

198. *See* Lemley, *supra* note 197, at 315; *e.g.*, Peabody v. Norfolk, 98 *Mass.* 452, 458–61 (1868).

199. Sonia K. Katyal, *The Paradox of Source Code Secrecy*, 104 *CORNELL L. REV.* 1183, 1248 (2019).

200. *Id.* at 1187 (noting that the “uncertain and porous boundaries [of copyright and patent protection], subject to inconsistency, variation, and indeterminacy, have basically ushered in a system where the most risk-averse option, rationally, is to rely on trade secrecy to protect source code and to limit disclosure to the public as a result”).

201. *E.g.*, *Alice Corp. v. CLS Bank Int'l*, 573 *U.S.* 208 (2014); *see also* Daryl Lim, Response, *The Influence of Alice*, 105 *MINN. L. REV. HEADNOTES* 345, 349–52 (2021).

202. Katyal, *supra* note 9, at 124.

civil rights issue.<sup>203</sup> As private companies infiltrate government decision-making, trade secret law obscures public accountability.<sup>204</sup> The veil of trade secrets sweeps ever wider, with the private sector providing public services ranging from telecommunications to voting systems.<sup>205</sup> One potential solution is to expose bias with more transparency.<sup>206</sup>

Indeed, a key advantage of algorithmic-based risk assessment is the ability to audit errors and improve the accuracy of predictions.<sup>207</sup> Professor Ignacio Cofone argues that “[t]he fact that algorithms are coded makes it easier to regulate algorithmic decision-makers than human ones, absent trade secrets.”<sup>208</sup> For example, defendants could dispute an analysis with access to the underlying code and data sets. Allowing trade secrets to prevent defendants and courts from scrutinizing bias in the code stymies the audit process.<sup>209</sup>

Some argue for a social justice exemption to trade secret law analogous to the copyright’s fair use defense to ensure IP rights remain socially beneficial.<sup>210</sup> Is there a legal precedent for this? Federal statutes already allow government agencies to disclose trade secrets for the public good.<sup>211</sup> For instance, the Securities and Exchange Commission (SEC) has a public interest mandate to disclose trade secrets.<sup>212</sup> One trigger for the exemption could be preserving a defendant’s due process rights.<sup>213</sup> Another could be verifying whether the algorithm has inbuilt bias checks, encouraging developers to undertake audits or internal ethics reviews before deployment, and avoiding lawsuits.<sup>214</sup>

At the same time, in civil cases, courts generally allow discovery requests coupled with protective orders.<sup>215</sup> Counsel and expert consultants can get source code information subject to password protection and other security measures.<sup>216</sup> Developers can turn over the source code and still retain protection of their proprietary information.<sup>217</sup>

Assuming access becomes possible, where should defendants focus their attention? The problem is that machine-learning processes are

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203. *See id.* at 60, 118–20.

204. *See* David S. Levine, *Secrecy and Unaccountability: Trade Secrets in Our Public Infrastructure*, 59 FLA. L. REV. 135, 137–40 (2007).

205. *See id.* at 137.

206. *See* Katyal, *supra* note 9, at 119–20.

207. Rizer & Watney, *supra* note 37, at 214.

208. Cofone, *supra* note 32, at 1411.

209. *See* Pauline T. Kim, *Big Data and Artificial Intelligence: New Challenges for Workplace Equality*, 57 U. LOUISVILLE L. REV. 313, 327 (2019).

210. *See* MOORE, *supra* note 177; Deepa Varadarajan, *Trade Secret Fair Use*, 83 FORDHAM L. REV. 1401, 1403–06 (2014).

211. *See* Stephen R. Wilson, *Public Disclosure Policies: Can a Company Still Protect Its Trade Secrets?*, 38 NEW ENG. L. REV. 265, 278 (2004).

212. *See id.* at 279.

213. *See* MOORE, *supra* note 177.

214. *See id.*

215. *See* Wexler, *supra* note 163, at 1401.

216. *See* Katyal, *supra* note 199, at 1277.

217. *See id.* at 1277–78.



evolving and will limit the practical value of access.<sup>218</sup> The causal relationships between data points and variables may be incomprehensible without access to training data.<sup>219</sup> For this reason, defendants should focus more on access to the data than the code. As Kartik Hosanagar and Vivian Jair observed,

machine 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.<sup>220</sup>

Moreover, few developers have the vast resources needed to create or replicate the data independently.<sup>221</sup> While reverse engineering is legally permissible, neither the data nor the algorithms are accessible, and the models are likely too complex to distill the underlying data.<sup>222</sup>

Trade secrets raise important equity considerations and limitations—beyond access to the algorithm and data—that policymakers must know. Even if the law mandates access to both the algorithm and the underlying data, those with the means to understand the algorithm can then manipulate its outcomes, benefitting more than those who lack such means and placing the latter group at a disadvantage.<sup>223</sup> Additional transparency may encourage actors to game the system.<sup>224</sup> Moreover, neither legal teams nor judges would likely have the statistical or algorithmic expertise required to meaningfully analyze algorithms or data for bias errors.<sup>225</sup> They would need expert witnesses, raising the price of bringing such a claim and the gap between those who can afford it and those who cannot, making the challenge a rich person's defense.<sup>226</sup> Moreover, carving out a social justice exemption to expose algorithmic inequalities may have unintended consequences. Trade secret law governs a myriad of industries and has a carefully designed system of exceptions and limitations. Policymakers will need to carefully consider the carveout's spillover effects, including the potential for future carveouts to whittle trade secret

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218. *See id.* at 1250–51.

219. Rizer & Watney, *supra* note 37, at 215.

220. Kartik Hosanagar & Vivian Jair, *We Need Transparency in Algorithms, But Too Much Can Backfire*, HARV. BUS. REV. (July 25, 2018), <https://hbr.org/2018/07/we-need-transparency-in-algorithms-but-too-much-can-backfire> [<https://perma.cc/PDA7-KXUS>].

221. Fromer, *supra* note 164, at 723; *see also* Levendowski, *supra* note 131, at 609 (“Without the resources to get the vast amounts [of] data easily acquired by major AI players, meaningful competition becomes all but nonexistent.”).

222. *See* Fromer, *supra* note 164, at 710–11, 723.

223. *See* Re & Solow-Niederman, *supra* note 5, at 266–67 (“[E]fforts to render AI adjudication comprehensible, whether through interpretability or another form of transparency, could asymmetrically allow sophisticated actors to adjust their conduct or litigation strategies in ways that would predictably achieve desired results.”).

224. *See id.* at 266, n.82; Hosanagar & Jair, *supra* note 220.

225. *See* Rizer & Watney, *supra* note 37, at 220.

226. *See id.*

protection into a block of Swiss cheese.<sup>227</sup>

In designing a response, Professor Steven Jamar recommended that “IP regulation for AI programs should be done at the federal level and should be *sui generis*.”<sup>228</sup> Moreover, Professor Jamar also argued the following:

The acquisition, accumulation, or use of user data by the AI programs in such settings should not be afforded IP protection unless they are XIA compliant such that users and regulators can effectively understand and make judgments about which sorts of intrusions should be allowed or which should be limited.<sup>229</sup>

With commercial AI systems acting as arbiters of justice, targeted safeguards to trade secrets reconcile the need for secrecy with audits, and the openness required in criminal and civil procedure with the United States’ strong legal culture of protecting intellectual property rights.<sup>230</sup>

A preemptory rule in trade secret law would be consistent with patent, copyright, and trademark law. It would also need to be consistent with the Defend Trade Secret Act’s (DTSA)<sup>231</sup> intent to harmonize nationwide trade secret protection.<sup>232</sup> Due process rights and equal protection interests could function as targeted safeguards to limit the exception to a narrow group of circumstances impacted by the risk-assessment tool.<sup>233</sup> The law must succeed in establishing a path forward where the courts can respect trade secret rights without disrespecting the rights of the accused, bringing all of us to an equitable world where algorithms do not operate without access or accountability when it matters.

## B. BIASES IN PATENT AND COPYRIGHT LAW

Patent law is the quintessential technocratic regime. Judges fill court decisions with arcane claim terms, diagrams, and scientific concepts.<sup>234</sup> However, Professor Dan Burk observes that patent criteria were drawn from an environment infected with racial biases and sexism under the surface.<sup>235</sup> He points to how patent law stereotypes the invention process

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227. *See id.* (“Changing the law to accommodate this specific need could inadvertently lead to the creation of other exemptions and increase the complexity of trade-secret laws in other sectors of the economy.”).

228. Jamar, *supra* note 16, at 23.

229. *Id.* at 23–24.

230. *See Intellectual Property Enforcement*, U.S. DEP’T OF STATE, <https://www.state.gov/intellectual-property-enforcement> [<https://perma.cc/A9ZV-CNE8>].

231. Defend Trade Secrets Act of 2016, Pub. L. 114-135, 130 Stat. 376 (2016).

232. *See* Rodney A. Satterwhite, David L. Greenspan & John G. McDonald, *House of Representatives Passes the “Defend Trade Secrets Act,”* MCGUIREWOODS (May 3, 2016), <https://www.mcguirewoods.com/client-resources/Alerts/2016/5/House-Representatives-Passes-Defend-Trade-Secrets-Act> [<https://perma.cc/5QXE-C3QV>].

233. *See* Rizer & Watney, *supra* note 37, at 202–04.

234. *See generally* CAITLAIN DEVEREAUX LEWIS & KATHRYN B. ARMSTRONG, CONG. RSCH. SERV., R44962, PATENT LAW: A PRIMER AND OVERVIEW OF EMERGING ISSUES (2017), <https://sgp.fas.org/crs/misc/R44962.pdf> [<https://perma.cc/PM8C-NBW2>].

235. *See* Burk, *supra* note 11, at 30–31; *see also* Kahn, *supra* note 11, at 402–06 (examining racist assumptions in patent non-obviousness doctrine).

according to the way men typically solve problems.<sup>236</sup> For instance, “rational” and “analytical” male approaches to problem-solving, as opposed to “emotive” or “intuitive” female problem-solving methods, “are more amenable to satisfaction of the teaching and disclosure requirements of patent law as currently formulated.”<sup>237</sup> Professor Burk argues that feminine approaches can produce useful and valuable innovations, “and both likely play a role in technical creativity.”<sup>238</sup>

Similarly, Professor Shlomit Yanisky-Ravid’s work examines the way patentable subject matter doctrine conceptualizes “invention,” “technology,” and “industrial application” in ways that do not reflect nonmechanical inventions that women typically create.<sup>239</sup> Because female-centric inventions are inadequately protected, potential innovations serving women’s needs could be lost.<sup>240</sup> If Professors Burk and Yanisky-Ravid are correct, the foundation of IP law itself may need reimagining. Otherwise, legal concepts shaped by bias that is currently embedded in the standards for obtaining a patent right, infringement, defenses, or remedies could become further entrenched to create a system of algorithmic injustice.

Recall that target variables and class labels may inadvertently penalize protected classes.<sup>241</sup> For instance, a target variable reflecting a characteristic that is systematically present or absent in a particular group may skew the algorithm.<sup>242</sup> Patent law’s “non-obviousness” doctrine and copyright law’s “creativity” standards have largely tracked European male sensibilities in a manner tone-deaf to the way women and racial minorities create and invent.<sup>243</sup> For instance, copyright law excludes fine arts and other expressive “crafts” that Western culture typically associates with females.<sup>244</sup> Patent eligibility also assumes analytical and rational processes, neglecting “feminine” ways of thinking and knowing.<sup>245</sup> As noted above, women tend to approach problem-solving differently than men. These differences involve different cognitive parameters and interpersonal skills.<sup>246</sup>

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236. See Burk, *supra* note 11, at 31; see also Allie Porter, *Where Are the Women? The Gender Gap Within Intellectual Property*, 28 TEX. INTELL. PROP. L.J. 511, 519 (2020) (“[W]omen are often socialized to approach problem-solving differently from their male counterparts.”).

237. Burk, *supra* note 11, at 31.

238. See *id.* at 31.

239. See Shlomit Yanisky-Ravid, *Eligible Patent Matter—Gender Analysis of Patent Law: International and Comparative Perspectives*, 19 AM. U. J. GENDER SOC. POL’Y & L. 851 (2011).

240. See Sara Reardon, *Gender Gap in US Patents Leads to Few Inventions that Help Women*, NATURE (Aug. 20, 2021), <https://www.nature.com/articles/d41586-021-02298-9> [<https://perma.cc/HB34-L2Z6>].

241. See Barocas & Selbst, *supra* note 34, at 680; *supra* notes 98–101 and accompanying text.

242. Barocas & Selbst, *supra* note 34, at 680–82.

243. See Shelley Wright, *A Feminist Exploration of the Legal Protection of Art*, 7 CANADIAN J. WOMEN & L. 59, 67 (1994); e.g., Rosenblatt, *supra* note 13, at 598; Burk, *supra* note 77, at 903–04.

244. See Wright, *supra* note 243, at 86–94.

245. See Burk, *supra* note 77, at 904–05, 908.

246. See Burk, *supra* note 11, at 31.

In this way, the lack of diversity in the IP system feeds skewed IP doctrine. Minorities have historically suffered from unequal access to the IP system.<sup>247</sup> In his work on minority access to the patent system, Professor Keith Robinson thus warned that “AI enthusiasm threatens to make the patent system less accessible for underrepresented innovators.”<sup>248</sup> Moreover, he provided that while “women and minorities have [historically] had difficulty accessing the patent system[,]” such difficulty “is only getting worse.”<sup>249</sup>

Barriers to access could be geographic, with research revealing a link between innovation and patenting on the one hand. On the other, geographic location, race, poverty, and housing metrics may also serve as entry barriers.<sup>250</sup> For instance, Black inventors’ patent applications are more likely to be denied by the USPTO.<sup>251</sup> While not racially motivated, minority inventors’ circumstances place them at a disadvantage in meeting the patentability requirements.<sup>252</sup> Moreover, one study concluded that Whites were over three times more likely to receive patents than Blacks and eight times more likely than Hispanics.<sup>253</sup>

Similarly, men far outnumber women as patent attorneys and patent agents.<sup>254</sup> Despite making up more than half the population, women only make up a tenth of inventors in the United States.<sup>255</sup> Female patent applicants are few and far between, “even when counted as co-inventors.”<sup>256</sup> In addition, women “face biases in the examination process,” with their applications more likely to be rejected or narrowed than those of White male applicants.<sup>257</sup> A recent study reported that female applicants appeal less frequently against rejections of their applications than male applicants.<sup>258</sup> These factors, in turn, result in a larger gender gap in patent grants.

Another less discussed metric is income level. A recent study corroborates the sobering picture of IP participation among the poor.<sup>259</sup> The

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247. See Robinson, *supra* note 132, at 739; see also Burk, *supra* note 14, at 276 (“The historical disadvantage experienced by minority creators remains unremedied, as demonstrated by current metrics of participation in IP systems.”).

248. Robinson, *supra* note 132, at 736.

249. *Id.* at 739.

250. See Burk, *supra* note 14, at 276–77; Bell et al., *supra* note 89, at 647.

251. Burk, *supra* note 14, at 277.

252. See *id.* at 277; see also W. Michael Schuster, R. Evan Davis, Kourtenay Schley & Julie Ravenscraft, *An Empirical Study of Patent Grant Rates as a Function of Race and Gender*, 57 AM. BUS. L.J. 281, 282–83 (2020) (reporting that minority patent applicants with racially associated names are as likely to obtain a patent as applicants with non-racially associated names).

253. See Bell et al., *supra* note 89, at 666–67.

254. Burk, *supra* note 11, at 31.

255. Kyle Jensen, Balázs Kovács & Olav Sorenson, *Gender Differences in Obtaining and Maintaining Patent Rights*, 36 NATURE BIOTECHNOLOGY 307, 307 (2018).

256. See Burk, *supra* note 11, at 31.

257. See Jensen, Kovács & Sorenson, *supra* note 255, at 307; Miriam Marcowitz-Bitton & Emily Michiko Morris, *Unregistered Patents*, 95 WASH. L. REV. 1835, 1838–39 (2020).

258. Jensen, Kovács & Sorenson, *supra* note 255, at 307–08.

259. See Bell et al., *supra* note 89, at 647–49 (finding that high socio-economic status at birth predicts later probability of obtaining a patent, such that “there are many ‘lost Ein-

study found that children from families in the top 1% by income are ten times more likely than those from below-median-income families to receive patents.<sup>260</sup> The study also found that only “18% of inventors born in 1980 are women.”<sup>261</sup> Racial demographics are even more sobering, with Hispanics making up 3.3% of inventors and Blacks comprising 0.4% of inventors.<sup>262</sup> One critical reason for these disparities is that female and minority inventors are disadvantaged in accessing the funding, networks, and support structures needed to navigate the patenting process.<sup>263</sup>

To address barriers to access, Professor Robinson argues for proactively aiding small businesses, women, and underrepresented minorities and, in doing so, improving upward mobility, innovation responsive to the distinctive needs of these groups, and overall innovation in the United States.<sup>264</sup> Another possibility for increasing IP system access involves foregoing the patent and trademark application and examination process, say Miriam Marcowitz-Bitton and Emily Michiko Morris, arguing that “if patent protections were automatic and did not require registration,” inventors could thereby “avoid the costs and biases of patent registration, and the gender and racial disparities in patenting would be significantly narrowed.”<sup>265</sup>

It is important to underscore that inequitable underrepresentation is prevalent in every artery of the IP ecosystem—trademarks, patents, copyright, and trade secrets.<sup>266</sup> For instance, registrations by Black and Latino trademark owners lag compared to the general population.<sup>267</sup> Similarly, with respect to the copyright system, “registration is required to enforce a copyright,” so racial minorities’ underrepresentation in copyright registrations suggests that they do not derive “the full benefit of the copyright system.”<sup>268</sup>

There is a rich vein of scholarship on disparate impact in various realms in copyright.<sup>269</sup> For example, Professors Robert Brauneis and Dotan

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steins’—individuals who would have had highly impactful inventions had they been exposed to innovation in childhood—especially among women, minorities, and children from low-income families”).

260. *Id.* at 649.

261. *Id.* at 668.

262. Robinson, *supra* note 132, at 743.

263. See Marcowitz-Bitton & Morris, *supra* note 257, at 1837–38.

264. See Robinson, *supra* note 132, at 736–38.

265. See Marcowitz-Bitton & Morris, *supra* note 257, at 1839.

266. See *id.* at 1837–38; Holly Fechner & Matthew S. Shpanka, *Closing Diversity Gaps in Innovation: Gender, Race, and Income Disparities in Patenting and Commercialization of Innovations*, 19 *TECH. & INNOVATION* 727, 728–29 (2018); W. Michael Schuster, Miriam Marcowitz-Bitton & Deborah R. Gerhardt, *An Empirical Study of Gender and Race in Trademark Prosecution*, 94 *S. CAL. L. REV.* 1407, 1416–29 (2021); Robert Brauneis & Dotan Oliar, *An Empirical Study of the Race, Ethnicity, Gender, and Age of Copyright Registrants*, 86 *GEO. WASH. L. REV.* 46 (2018).

267. See Burk, *supra* note 14, at 277–78 (“This underrepresentation of USPTO registrations likely places [Black and Latinos] at a disadvantage in accruing the benefits of the trademark system.”).

268. See *id.*

269. See Rosenblatt, *supra* note 13, at 609 & n.71.

Oliar's work illustrates how underrepresentation extends to the copyright system.<sup>270</sup> They note that Hispanics, Asian and Pacific Islanders, American Indians, and individuals of multiple races are underrepresented in copyright registrations while White copyright holders are overrepresented.<sup>271</sup> Moreover, in the study that Brauneis and Oliar conducted, two-thirds of the copyright owners were men.<sup>272</sup>

Suppose we use copyright case law developed in an "environment marred by [inequality]" in order to "train AIs to assess future metrics."<sup>273</sup> In that case, AI's processes and outputs will naturally incorporate and perpetuate the same inequality.<sup>274</sup> Professor Elizabeth Rosenblatt's work on implicit hierarchies in copyright law indicates that courts have systematically devalued creative meaning-making's "dialogic and incremental nature."<sup>275</sup> In particular, copyright's requirement that a work be "fixed in a tangible medium of expression" is often absent in the way Blacks and others create music, resulting in a model that negatively classifies those groups.<sup>276</sup> For instance, Biz Markie's and N.W.A.'s uses of sampled sound recordings in their hip-hop and rap music constituted copyright infringement.<sup>277</sup> Professor Rosenblatt argues that the law treats the creative output of people of color as "unoriginal," and courts deny such individuals legal protection even though some cultures produce cumulative creativity.<sup>278</sup> In these cultures, groups creating such works do not expect market exclusivity and anticipate the reuse or remixing of their works.<sup>279</sup>

Moreover, courts have held that artists cannot copyright stylistic contributions, effectively allowing White artists to copy Black performers or arrangers' arrangements without compensation.<sup>280</sup> In this way, Professor Rosenblatt argues that fixation "devalues improvisatory and performance-based art forms often associated with racialized cultures, such as DJ-ing and record scratching; break dancing, folk dancing, and voguing; and

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270. See Brauneis & Oliar, *supra* note 266.

271. *Id.* at 59–61 (reporting an underrepresentation of Hispanics by 45%, Asian and Pacific Islanders by 83%, American Indians and Alaska natives by 77%, and people of multiple races by 62%); see also *id.* (reporting that Whites produced 116% of the copyrighted works as a share of the general population). Interestingly, in contrast to patents, Black owners were found to be overrepresented in the copyright system, producing 120% of the copyrighted works as a share of the general population. *Id.* at 61–62.

272. *Id.* at 73.

273. See Burk, *supra* note 14, at 282.

274. See *id.* at 282–84 ("[T]he corpus of past creative works from which we might train AIs to generate future works were developed in an environment marred by prejudice and will similarly carry the marks of their origins.").

275. Rosenblatt, *supra* note 13, at 591.

276. See *id.* at 618–24.

277. See *id.* at 629–30; *Grand Upright Music Ltd. v. Warner Bros. Records, Inc.*, 780 F. Supp. 182, 183 (S.D.N.Y. 1991); *Bridgeport Music, Inc. v. Dimension Films*, 410 F.3d 792 (6th Cir. 2005).

278. See Rosenblatt, *supra* note 13, at 595, 610, 627.

279. See *id.* at 616.

280. See *id.* at 620 ("White artists became famous for their recreations of African American music, and record companies became rich by mining African American sources.").

storytelling.”<sup>281</sup> She notes that “in addition to devaluing oral- and performance-tradition creators and works, the fixation requirement also contributes to a process of ‘sacralization’ that elevates the fixed versions of works over their unfixed versions.”<sup>282</sup>

Similarly, Professors Anjali Vats and Deidré Keller suggest that copyright concepts like originality bake in racial bias:

[W]hites have historically constructed information regimes in ways which devalue the knowledge and practices of non-[W]hites; [W]hites have historically held the power and authority to determine the legal structures which govern intellectual property rights; [W]hites have historically crafted legal doctrines which favor the protection of Western understandings of creativity; and [W]hites largely continue to manage domestic and international intellectual property rights regimes.<sup>283</sup>

At the same time, Professor Rosenblatt cautions against overreacting, warning that “it would be foolish to abandon copyright in principle simply because its current formulation incorporates potentially discriminatory discourse.”<sup>284</sup> She points to copyright law’s “many practical benefits, including allowing creators to professionalize without depending on direct patronage.”<sup>285</sup> Significantly, “cases in which copyright owners of color (or their estates) . . . successfully sued or settled with popular music stars” illustrate copyright’s role in furthering social justice.<sup>286</sup> Nonetheless, the fact remains that music “publishers are more likely to own copyrights and pursue and prevail in legal claims than individual creators are, and the benefit to individual innovators of color is indirect (at best).”<sup>287</sup>

Finally, Professor Rosenblatt highlights the baked-in systematic bias—because “judicial aesthetic biases make majority copyright owners more likely to pursue and prevail in legal claims than minority copyright owners, the tools of copyright law are more likely to harm minority creators than help them.”<sup>288</sup> Penalizing cumulative creativity sends the message “that there is something shameful about building upon preexisting works” and “undermines the inherently dialogic nature of creation and the equality-promoting benefits of shared vocabulary.”<sup>289</sup> This result, too, is inequitable.

Preexisting biases in case law can infect training data and labeling examples when training machine learning algorithms.<sup>290</sup> Even when they

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281. *Id.* at 620–21.

282. *Id.* at 622.

283. Anjali Vats & Deidré A. Keller, *Critical Race IP*, 36 *CARDOZO ARTS & ENT. L.J.* 735, 758–59 (2018).

284. *See* Rosenblatt, *supra* note 13, at 650.

285. *Id.*

286. *Id.* at 650 & n.258.

287. *See id.* at 651.

288. *Id.*

289. *Id.* at 651–52.

290. *See* Levendowski, *supra* note 131, at 591–92 (explaining how bias can skew the results of machine learning algorithms); Barocas & Selbst, *supra* note 34, at 680–82.

are correct, a model that teaches an algorithm from examples of past cases may become problematic when the assumptions underlying the case law change.<sup>291</sup> As discussed in Part II, intervening in a concerted and urgent way requires us to understand structural barriers to the IP system and how judges deciding IP cases are complicit by baking inequality into their decisions. Part III has explained how this happened. Intervention requires a bold vision of equity by design that deals with the issues of data regulation, equity audits, and how equitable justice in AI should look.

#### IV. EQUITY BY DESIGN

Opportunities exist for concurrently improving fairness in algorithmic outcomes. Section A addresses the issue of data regulation and asks if the answer is to feed the algorithm with less data, more data, or better data. Section B deals with the issue of equity audits, emphasizing that black box audits can make AI more transparent, interpretable, and accountable.<sup>292</sup> Section C then concludes by focusing on the promise and limitations of equitable algorithmic justice.

##### A. DATA

Algorithms rely on training data to learn how courts decided earlier cases and translate those decisions into logic-based rules that can apply to new cases in order to predict outcomes.<sup>293</sup> Many of the voices joining in the discourse on AI call for improvements in the data used to develop the systems: the Obama White House noted the importance of data “for a future in which [AI] plays a growing role,”<sup>294</sup> and Professor Woodrow Hartog argues that “[i]n the world of big data, more is always better.”<sup>295</sup> All of this suggests that, in order to address inequality, more data is better.<sup>296</sup> Making more data and better data available to developers certainly sounds right, but is it necessarily true?

##### 1. More Data

Machine learning algorithms learn from examples unearthed through data mining.<sup>297</sup> Algorithms use these examples to develop models to guide decisions.<sup>298</sup> The problem is that training data is not representative

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291. See Barocas & Selbst, *supra* note 34, at 682.

292. See Rizer & Watney, *supra* note 37, at 215.

293. See Harry Surden, *Machine Learning and Law*, 89 WASH. L. REV. 87, 103–05, 109 (2014).

294. WHITE HOUSE AI REPORT, *supra* note 114, at 30.

295. WOODROW HARTOG, *PRIVACY'S BLUEPRINT: THE BATTLE TO CONTROL THE DESIGN OF NEW TECHNOLOGIES* 51 (2018).

296. See Peter K. Yu, *Beyond Transparency and Accountability: Three Additional Features Algorithm Designers Should Build into Intelligent Platforms*, 13 NE. U. L. REV. 263, 290 (2020).

297. See Barocas & Selbst, *supra* note 34, at 677–78, 680.

298. See *id.* at 677.



of the stakeholder population.<sup>299</sup> Likewise, one group's overrepresentation in a dataset will inflate its attributes.<sup>300</sup> Diluting biased data with representative training data could help.

However, the problem is getting access to representative data. As Professors Mark Lemley and Brian Casey put it,

There is at least one obstacle standing in the way of ML's seemingly inexorable learning curve. Virtually all the data used to compile training sets is protected by copyright. And just as was true of TDM readers in the '90s, '00s, and '10s, this new breed of robotic readers appears destined to give rise to a host of doctrinal and policy challenges in the years ahead. Indeed, it already has.<sup>301</sup>

They warn that small “datasets—particularly those with large and non-random gaps due to failures of copyright licensing—will lead to” inferior decisions with real-world consequences for minorities when they interface with AI.<sup>302</sup>

Copyright owners have historically maintained an uneasy relationship with technology—from the age of piano rolls to peer-to-peer file sharing to scanning entire volumes of books to create a searchable database.<sup>303</sup> Copyright law, by its nature, also threatens to impede access to copyrighted data, which may lead to the creation or promotion of biased AI systems.<sup>304</sup> Professor Amanda Levendowski explains, “Copyright law causes friction that limits access to training data and restricts who can use certain data,” and “[t]his friction is a significant contributor to biased AI.”<sup>305</sup> The issue is a live and fraught one that developers who wish to access copyrighted data must contend with.<sup>306</sup>

Copyright protection can extend to compilations of uncopyrightable facts; if there is originality in the selection or arrangement of those facts, they can receive protection.<sup>307</sup> Copyright infringement remedies are misaligned with the harms that authors suffer from data access.<sup>308</sup> Statutory

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299. *See id.* at 684 (noting that “[e]ven a dataset . . . of consistently high quality can suffer from statistical biases that fail to represent different groups in accurate proportions”).

300. *See id.* at 686–87.

301. Mark A. Lemley & Bryan Casey, *Fair Learning*, 99 *TEX. L. REV.* 743, 754 (2021).

302. *See id.* at 770–71 (“Facial recognition software performs worse at distinguishing individuals in small racial groups because since those groups are small, it has fewer unique data points allowing it to draw fine distinctions between faces in those groups.”).

303. *See Levendowski, supra* note 131, at 594; *White-Smith Music Publ'g Co. v. Apollo Co.*, 209 U.S. 1 (1908) (copyright infringement action involving piano rolls); *Metro-Goldwyn-Mayer Studios, Inc. v. Grokster, Ltd.*, 259 F. Supp. 2d 1029 (C.D. Cal. 2003) (copyright infringement claim involving peer-to-peer file sharing); *Authors Guild v. Google, Inc.*, 804 F.3d 202 (2d Cir. 2015) (copyright infringement claim involving mass book-digitization projects).

304. *See Levendowski, supra* note 131, at 589.

305. *Id.* (“The friction caused by copyright law encourages AI creators to use biased, low-friction data (BLFD) for training AI systems, . . . despite those demonstrable biases.”).

306. *See id.* at 595 (“To date, no court has yet determined whether a copy made to train AI is a ‘copy’ under the Copyright Act of 1976, let alone whether such a copy is infringement.”).

307. *See Feist Publ'ns, Inc. v. Rural Tel. Serv. Co.*, 499 U.S. 340, 350–51 (1991).

308. *See* 17 U.S.C. § 504(c).

damages are not calibrated based on the owner's actual loss or the developer's gain.<sup>309</sup> Rather, the statutory damages regime "systematically overcompensate[s] plaintiffs with small-value works" by awarding them statutory damages up to \$150,000 per work.<sup>310</sup>

Moreover, copyright infringement "is a strict liability offense."<sup>311</sup> Uncertainty about access to copyrighted content for training AI chills those who wish to audit it for bias.<sup>312</sup> The risk of suit is real, as scholars have noted.

[W]hile [current fair use] precedent . . . may look promising for those who collect and use datasets, there is no guarantee that courts will extend this precedent to similar technologies or legal contexts. . . . [B]oth the courts and the court of public opinion have begun to depart from the precedents established by the Google Books cases. And these departures could have lasting ramifications for the use of copyrighted data to train [machine learning] systems.<sup>313</sup>

The datasets necessary to audit AI likely containing millions of copyrighted works, so statutory damages could cripple developers.<sup>314</sup>

Professors Mark Lemley and Bryan Casey argue that fair use can open a path to access the copyrighted works required to better train algorithms.<sup>315</sup> They suggest that while fair use should not excuse expressive, commercial machine learning, it can and should allow social justice-related uses of copyrighted words.<sup>316</sup> Biased data may stem from individual data—such as that pertaining to the risk of recidivism, credit risk scores, or identity matches—that copyright does not protect.<sup>317</sup> However, the alternative is market failure. As Lemley and Casey put it, "because training sets are likely to contain millions of different works with thousands of different owners, there is no plausible option simply to license all of the underlying photographs, videos, audio files, or texts for the new use."<sup>318</sup>

Work by Professor Matthew Sag develops this idea. On doctrinal grounds, he argues that "[a]llowing text mining and other similar non-expressive uses of copyrighted works without authorization is entirely consistent with the fundamental structure of copyright law because, at its heart, copyright law is concerned with the communication of an author's

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309. See Lemley & Casey, *supra* note 301, at 759; 17 U.S.C. § 504(c)(2).

310. Lemley & Casey, *supra* note 301, at 769 ("[A machine learning] that copies millions of works could potentially face hundreds of billions of dollars in statutory damages.").

311. *Id.* at 758.

312. See Levendowski, *supra* note 131, at 596–97, 603–04.

313. Lemley & Casey, *supra* note 301, at 763.

314. See *id.* at 748, 769.

315. See *id.* at 770–73.

316. See *id.* at 760, 765, 783; see also *id.* at 748 n.31 ("'Fair' from both a commercial perspective and 'fair' as the term is understood in the context of social justice and equity.").

317. See *id.* at 756–58.

318. *Id.* at 748.

original expression to the public.”<sup>319</sup> He explains, “Non-expressive uses generate information *about* a work, that information may be useful, it may be valuable, it may even affect the demand for the underlying work, but metadata about a work does not in any way fulfill the public’s demand for the author’s original expression.”<sup>320</sup> Moreover, “[b]y definition, a non-expressive use does not usurp the copyright owner’s communication of her original expression to the public because the expression is not communicated.”<sup>321</sup> The law has thus authorized full-text searches that involve wholesale copying of copyrighted works.<sup>322</sup>

Arguments like these carry logical force. Copyrighted works contain more information than their authors conceived, some of which is accessible only by AI.<sup>323</sup> Copying text, images, and audiovisual work for data mining should not be a fraught issue.<sup>324</sup> As Professor Levendowski put it, a permissive interpretation of fair use is fittingly necessary to promote fairer AI. Critically, she notes that “[t]he normative values embedded in the tradition of fair use align ultimately with the goal of mitigating bias. Fair use can, quite literally, promote the creation of fairer AI systems.”<sup>325</sup>

Several courts rejected fair use arguments in somewhat analogous contexts.<sup>326</sup> Since training data lacks an independent creative purpose, the argument is that commercial entities misappropriate others’ works and need to pay for what they take.<sup>327</sup> These developers should obtain bulk licenses, perhaps in mechanical licenses for sound recordings.<sup>328</sup> The alternative is to traverse a minefield of copyrighted works, with the attendant risk that a court might find their use unfair.<sup>329</sup>

In judging the issue, courts lean on industry custom to determine if using that content is permissible.<sup>330</sup> A trend toward licensing content for training data could limit access to the necessary content for developers who want to make AI processes equitable.<sup>331</sup> If this trend continues, cop-

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319. Matthew Sag, *The New Legal Landscape for Text Mining and Machine Learning*, 66 J. COPYRIGHT SOC’Y U.S.A. 291, 302 (2019).

320. *Id.* at 320.

321. *Id.*

322. *See* Authors Guild, Inc. v. HathiTrust, 755 F.3d 87, 97–98, 101 (2d Cir. 2014); *see also* Authors Guild v. Google, Inc., 804 F.3d 202, 221 (2d Cir. 2015) (“[N]ot only is the copying of the totality of the original reasonably appropriate to Google’s transformative purpose, it is literally necessary to achieve that purpose. If Google copied less than the totality of the originals, its search function could not advise searchers reliably whether their searched term appears in a book (or how many times).”).

323. *See* Sag, *supra* note 319, at 292.

324. *But see id.*

325. *Id.* at 630.

326. *See, e.g.,* Associated Press v. Meltwater U.S. Holdings, Inc., 931 F. Supp. 2d 537, 541 (S.D.N.Y. 2013); Fox News Network, LLC v. Tveyes, Inc., 883 F.3d 169, 173–74, 182 (2d Cir. 2018).

327. *See* Lemley & Casey, *supra* note 301, at 765.

328. *See id.*

329. *See id.* at 759; *see also id.* at 769 (“And with thousands or even hundreds of thousands of different copyright owners, the risk of multiple opportunistic suits is high.”).

330. *See* Jennifer E. Rothman, *The Questionable Use of Custom in Intellectual Property*, 93 VA. L. REV. 1899, 1902–05 (2007).

331. *See* Levendowski, *supra* note 131, at 629.

right law will be complicit in perpetuating biases.<sup>332</sup> While there is, in theory, a “market for licensing works for use as AI training data,”<sup>333</sup> “courts consider only the loss [of] potential licensing revenues from ‘traditional, reasonable, or likely to be developed markets.’”<sup>334</sup> Substitutability defines the boundaries of what is traditional, reasonable, or likely, and “[u]sing copyrighted works as training data for AI systems is not a substitute for the original expressive use of the works.”<sup>335</sup> Further, transformative works are not substitutions for the originals.<sup>336</sup> Providing developers “[b]road access to training sets” will both advance policy objectives and make AI systems “better, safer, and fairer.”<sup>337</sup> So in this sense, an algorithm’s use of training data is highly transformative.<sup>338</sup>

Professor Sag argues that the market for data mining cannot be a protectable market under fair use, providing that while “every use by a defendant represents something that could be licensed to the defendant,” courts recognize the copyrighted material’s potential effect on the market only when it implicates a “cognizable copyright interest.”<sup>339</sup> That position is correct, at least according to the Second Circuit, which rejected the argument that it was a cognizable harm not to be paid for text mining, noting, “Lost licensing revenue counts . . . only when the use serves as a substitute for the original and the full-text-search use does not.”<sup>340</sup>

According to Professor Levendowski, the cost of giving copyright owners control is that competition and access needs will pay the price.<sup>341</sup> Copyright law impedes bias mitigation and hobbles rivals from offering less biased AI systems.<sup>342</sup> And with respect to access, copyright law encourages developers to rely on low-risk sources for training data, even if demonstrably biased.<sup>343</sup> She concludes, “If we hope to create less biased commercial AI systems, using copyright-protected works as AI training data will be key.”<sup>344</sup>

One potential response could exempt reverse engineering black-box al-

332. See Rothman, *supra* note 330, at 1955.

333. Levendowski, *supra* note 131, at 629.

334. *Associated Press v. Meltwater U.S. Holdings, Inc.*, 931 F. Supp. 2d 537, 560 (S.D.N.Y. 2013) (quoting *Am. Geophysical Union v. Texaco, Inc.*, 60 F.3d 913, 930 (2d Cir. 1994)).

335. See Levendowski, *supra* note 131, at 629.

336. *Id.* (“Courts have consistently rejected allegations that a transformative work can serve as a substitute for the original.”) (citing *Authors Guild, Inc. v. HathiTrust*, 755 F.3d 87, 96 (2d Cir. 2014)).

337. Lemley & Casey, *supra* note 301, at 748 & n.31.

338. See *id.* (“Professor Matthew Sag has examined how using copyrighted works as ‘grist for the mill’ serves a fundamentally different purpose than the one reflected in valuing works for their original expression.” (quoting Matthew Sag, *Copyright and Copy-Reliant Technology*, 103 Nw. U. L. REV. 1607, 1608 (2009)).

339. Sag, *supra* note 319, at 328.

340. *HathiTrust*, 755 F.3d at 98–100; Sag, *supra* note 319, at 328.

341. See Levendowski, *supra* note 131, at 597.

342. See *id.* at 597 (“[T]he rules of copyright law massively favor incumbents by causing friction for others to implement bias mitigation techniques or compete to converting customers.”).

343. *Id.* at 597.

344. *Id.* at 621.

gorithms to make data accessible to developers and auditors.<sup>345</sup> The algorithm copies and reads the works “by applying mathematical functions to . . . generate abstract statistics.”<sup>346</sup> Singapore has recently allowed “commercial and non-commercial” uses of copyrighted data, and “there is no limitation as to the purposes for which” the data can be used.<sup>347</sup> However, the legislative exception only covers users with “‘lawful access’ to the copy of the work,” and if the first copy is infringing, the user must have had no knowledge of it.<sup>348</sup> The exception prohibits contractual override prospectively and retroactively.<sup>349</sup> It also has extraterritorial effect, applying both to contracts governed by Singaporean law and contracts governed by foreign law “where the choice of foreign law is wholly or mainly to evade any copyright exception.”<sup>350</sup>

Another response could create a civil rights exception to text and data mining. For example, Professor Mary Fan proposed establishing “a right of access to pooled personal data for public purposes” while safeguarding sensitive information by using “a controlled-access procedure akin to that used by institutional review boards in medical research today.”<sup>351</sup> In addition, “regulatory sandboxes and safe harbors” would help “encourage companies to voluntarily share data for public interest purposes.”<sup>352</sup> In order to balance out blind spots and offer more equitable options, AI system creators can carve out exemptions for auditing AI for bias and supplement datasets with additional datasets of copyrighted and non-copyrighted works.<sup>353</sup>

Safe harbors in IP law create a bright-line rule to protect behaviors that may otherwise be permitted only circumstantially and therefore risky to those undertaking them. For example, Internet Service Providers (ISPs) enjoy immunity from damages under the Digital Millennium Copyright Act (DMCA) for providing several key services.<sup>354</sup> The Patent Act also provides a safe harbor for making, using, offering to sell, selling, or importing patented inventions made primarily “using recombinant DNA, recombinant RNA, hybridoma technology, or other processes involving site specific genetic manipulation techniques.”<sup>355</sup> Safe harbors exist only

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345. See Rizer & Watney, *supra* note 37, at 219 (citing Levendowski, *supra* note 131, at 604, 621–22).

346. See Sag, *supra* note 319, at 300.

347. Alban Kang & Pin-Ping Oh, *Coming Up in Singapore: New Copyright Exception for Text and Data Mining*, BIRD & BIRD INSIGHTS (Sept. 19, 2021), <https://www.twobirds.com/en/insights/2021/singapore/coming-up-in-singapore-new-copyright-exception-for-text-and-data-mining> [<https://perma.cc/3UP3-TVXZ>].

348. *Id.*

349. *See id.*

350. *Id.*

351. Mary D. Fan, *The Right to Benefit from Big Data as a Public Resource*, 96 N.Y.U. L. REV. 1438, 1438 (2021).

352. *Id.*

353. See Levendowski, *supra* note 131, at 621.

354. See Fan, *supra* note 351, at 1488; Digital Millennium Copyright Act, 17 U.S.C. § 512(a)–(e).

355. See 35 U.S.C. § 271(e)(1).

to protect defendants.<sup>356</sup> But, as Professor Fan observed, “[t]he point is that safe harbors can be useful in encouraging socially beneficial innovation and behaviors.”<sup>357</sup>

Another reason companies cite for their resistance to share algorithms, training data, or other proprietary information is privacy.<sup>358</sup> How would we protect privacy rights? Anonymizing samples can address privacy concerns.<sup>359</sup> Terms and conditions of service allow users to decide whether to license their profile pictures and other personal information in exchange for access to friends’ and followers’ status updates and selfies.<sup>360</sup> Allowing developers to access that information under a “civil rights” exception would enrich the dataset. Accessing that data hinges on consent or legislation, not compensation.<sup>361</sup>

Fostering equality will require efforts to promote diversity in training data. Addressing algorithmic discrimination requires the law to foster diversity in algorithm design and algorithmic data.<sup>362</sup> Without this diversity, the rise of algorithms will simply perpetuate and amplify the many historical inequalities in the offline world—algorithms could get stuck in a feedback loop in which outcomes are used as training and feedback data.<sup>363</sup> The case for access must also be one for continued access. Neural networks require a continuous flow of more current data to make better predictions.<sup>364</sup> The alternative would be a market failure for fair use, where uses that serve the public interest are not allowed despite not substantially impairing copyright owners.<sup>365</sup> If more data is good, is less data bad? As it turns out, maybe not.

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356. See *What Is a Safe Harbor?*, WINSTON & STRAWN LLP, <https://www.winston.com/en/legal-glossary/safe-harbor.html> [<https://perma.cc/EMW6-GYK9>].

357. Fan, *supra* note 351, at 1488.

358. See Yu, *supra* note 296, at 268, 291; see also Kim, *supra* note 126, at 191–92 (“[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.”).

359. See Peter K. Yu, *The Algorithmic Divide and Equality in the Age of Artificial Intelligence*, 72 FLA. L. REV. 331, 375 (2020) (“[T]echnology 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.”).

360. See Cadie Thompson, *What You Really Sign Up for When You Use Social Media*, CNBC (May 27, 2015, 12:18 PM), <https://www.cnn.com/2015/05/20/what-you-really-sign-up-for-when-you-use-social-media.html> [<https://perma.cc/8G5P-VC72>].

361. See *What Does User Consent Mean and Why Does It Matter?*, SECURITY (May 13, 2022), <https://securiti.ai/blog/user-consent> [<https://perma.cc/UA6H-VC92>].

362. See Yu, *supra* note 359, at 367.

363. See *id.* at 367–68.

364. See *How to Apply Continual Learning to Your Machine Learning Models*, TOWARDS DATA SCI. (July 11, 2019), <https://towardsdatascience.com/how-to-apply-continual-learning-to-your-machine-learning-models-4754adcd7f7f> [<https://perma.cc/68ZK-WYSU>].

365. See Wendy J. Gordon, *Fair Use as Market Failure: A Structural and Economic Analysis of the Betamax Case and Its Predecessors*, 30 J. COPYRIGHT SOC’Y U.S.A. 253, 254–55, 271–76 (1983).

## 2. *Less Data*

Concerns over socio-economic and demographic factors improperly creeping into decision-making predate AI.<sup>366</sup> The difference is that algorithms now allow developers to better limit protected classifications; input variables are defined and can be chosen so as to shift focus to other variables that may equally or better predict the risk of infringement or some other outcome that IP policy may be interested in.<sup>367</sup> So how can we filter the data for bias without sacrificing its efficacy?

The problem with shutting out discriminatory data is that it loses the potential to help detect inequity.<sup>368</sup> Blocking information can reduce accuracy and hobble the ability to detect bias in the first place.<sup>369</sup> A better approach allows not less but more data and identifies which data fragments are proxies for variables of interest.<sup>370</sup> Developers can then debug bias by having the algorithm compare “potential decision[s] with information and . . . counterfactual decisions[s] without information.”<sup>371</sup> Developers can then encrypt sensitive attributes.<sup>372</sup> They send the encrypted data to the service provider that deploys it, disaggregating the data so no one can see all of the sensitive information.<sup>373</sup> Differential privacy can add noise to the data, so a company that collects the aggregated data for analysis does not know the identity of its users.<sup>374</sup>

Yet other options exist. Laws can block human decision-makers from accessing data that might prejudice their decisions.<sup>375</sup> Developers can also use an intermediate proxy to preserve data about an individual’s attributes while obfuscating and removing information about membership concerning the protected subgroup.<sup>376</sup> This technique “preserves the information that the algorithm needs while encoding sensitive attributes.”<sup>377</sup> The new dataset scrubs data on individuals regarding a “protected category, while keeping group information about the protected category and satisfying statistical parity.”<sup>378</sup>

Proxy discrimination is a harder issue to address. A multitude of “fea-

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366. See Rizer & Watney, *supra* note 37, at 216.

367. *See id.*

368. See Cofone, *supra* note 32, at 1426.

369. *Id.* at 1415; see also Kim, *supra* note 126, at 918. But see Ignacio N. Cofone, *Antidiscriminatory Privacy*, 72 SMU L. REV. 139, 140–141 (2019) (suggesting that blocking access to some data can safeguard protected classes by “prevent[ing] the decisionmaker from acquiring the information about an individual’s protected class in the first place, which prevents her from taking an action that antidiscrimination law would deem unlawful”).

370. See Cofone, *supra* note 32, at 1413, 1415.

371. *See id.* at 1411.

372. *See id.* at 1425.

373. *See id.*

374. *See id.* at 1425–26.

375. *See id.* at 1425; Cofone, *supra* note 369, at 140–141.

376. See Cofone, *supra* note 32, at 1426.

377. *Id.*

378. *Id.*

tures could correlate with the protected category only slightly.”<sup>379</sup> No one feature may alter the outcome significantly on its own, but all of them together or in some combination might.<sup>380</sup> Proxies “can [also] change their meaning over time.”<sup>381</sup> For example, a data point not previously a proxy for race or another attribute could become one in the future.<sup>382</sup> In such an instance, Professor Cofone observes that “one would never cease to find more information points that, to some degree, are predictive of each other and would need to be blocked.”<sup>383</sup>

For this reason, developers need to continually “collect and control information” to study the impact on race and other characteristics while preventing information on those characteristics from perpetuating inequality.<sup>384</sup> They can then design the AI system so as not to ignore data because it appears abnormal based on the small number of data points.<sup>385</sup> The key is to find targeted ways to reduce disparities between groups without sacrificing the model’s performance, not to turn off the spigot of information. We must collect better data and then decide how to use it.

### 3. Better Data

In its report on AI, the Obama White House noted that “AI needs good data. If the data is incomplete or biased, AI can exacerbate problems of bias.”<sup>386</sup> Training data may become outdated, ossifying rules that should be discarded.<sup>387</sup> The values of both AI creators and users shift over time, leaving humans to continually “arbitrate conflicts between outcomes and stated goals.”<sup>388</sup>

IP scholars have explored specific areas to build legal models of equity by design, such as fair use.<sup>389</sup> Fair use determinations are fact-specific, leading “policymakers, commentators, and industry representatives” to criticize them “for being unclear and unpredictable.”<sup>390</sup>

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379. *Id.* at 1413 (“The proxies that algorithmic processes might identify, or even the fact of whether an algorithm will identify a proxy at all, is difficult—and sometimes impossible—to predict.”).

380. *See id.*

381. *Id.* at 1414.

382. *Id.* (“[T]he proxies involved could be emergent: they may not be proxies before, but appear later in the process.”).

383. *Id.*

384. *See id.* at 1426.

385. *See id.* at 1411.

386. WHITE HOUSE AI REPORT, *supra* note 114, at 30.

387. *See* Re & Solow-Niderman, *supra* note 5, at 268–69 (“AI adjudicators could be fundamentally unchanging, despite substantial exogenous events to which a human judge (or, at longer intervals, a population of such judges) would react.”).

388. Lee, Resnick & Barton, *supra* note 60.

389. *See* Niva Elkin-Koren, *Fair Use by Design*, 64 UCLA L. REV. 1082, 1085 (2017). “Fair use by design has become a necessity in an era of algorithmic governance. The need to develop such tools is necessary in order to tilt the copyright balance back to its origin in our robo notice environment.” *Id.* at 1100; *see also* Burk, *supra* note 41, at 284–85 (2019) (“[I]t may seem desirable to incorporate context-specific fair use metrics into copyright-policing algorithms, both to protect against automated overdeterrence and to inform users of their compliance with copyright law.”).

390. Yu, *supra* note 42, at 352.



Like the motorists in Singapore, copyright users can turn to AI to predict their likelihood of success.<sup>391</sup> We should not devalue probabilistic assessments. Probability, not precision, drives legal assessments both in and out of court, including settlements.<sup>392</sup> Seen in this light, automating adjudication simply makes what we are doing better. As Professor Yu observes,

algorithms are incapable of making precise determinations of what the law would or would not permit, unless the use in question is identical, or virtually identical, to the use in a previously adjudicated case. Notwithstanding this shortcoming, algorithms may be able to determine, with high probability, whether the law would permit such a use.<sup>393</sup>

He is optimistic that “[s]uch a determination will become even more accurate as automated fair use systems take better advantage of big data analysis and machine learning capabilities.”<sup>394</sup>

Better data will also help avoid technical bias that leads to social inequality. Consider the “Next Rembrandt,” where Rembrandt’s digitized paintings trained an AI, but the AI generated a work that failed to capture Rembrandt’s progressive treatment of women.<sup>395</sup> That failure stemmed in part from the project developers’ biases in the selection process.<sup>396</sup> Incorporating digitized training data from women and persons of color would have helped.<sup>397</sup>

An AI system that presents choices with pros and cons rather than simply deciding on a route will improve accountability without sacrificing efficiency.<sup>398</sup> The algorithm presents the alternatives it considered, together with a score indicating how confident it is in being correct.<sup>399</sup> These options provide judges with information to make informed decisions without “blindly handing over control.”<sup>400</sup>

However, there is a limit to what more, less, or even better data can do. Facial recognition technology, for example, may fail to recognize a Black face.<sup>401</sup> Moreover, facial features may be an unreliable measure for authenticating identity.<sup>402</sup> Although developers can debug technical biases like these, “this correction still assumes that facial recognition is a feasible and desirable method of identifying any individual, and that is a social assumption that, if incorrect or problematic, cannot be corrected with

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391. *See id.* at 352–53; Yu, *supra* note 50.

392. *See* Yu, *supra* note 42, at 353.

393. *Id.*

394. *Id.*

395. *See* Burk, *supra* note 14, at 283 (citing Tsila Hassine & Ziv Neeman, *The Zombification of Art History: How AI Resurrects Dead Masters, and Perpetuates Historical Biases*, 11 J. SCI. & TECH. ARTS 28, 31 (2019)).

396. *See* Burk, *supra* note 14, at 283–84.

397. *See id.* at 284.

398. *See* K.N.C., *supra* note 17.

399. *See id.*

400. *See* Re & Solow-Niederman, *supra* note 5, at 282–83.

401. *See* Burk, *supra* note 14, at 281.

402. *See id.* at 281, 284.

better data.”<sup>403</sup> That is why we need equity audits.

## B. EQUITY AUDITS

Equity audits help reveal the reasons for bias in a model.<sup>404</sup> For example, data may underrepresent certain groups or a metric might correlate outcome with a defendant’s protected characteristic that might reveal a pattern of bias.<sup>405</sup> In this case, additional training data can improve accuracy and minimize unfair results.<sup>406</sup>

The problem is that AI systems are generally not designed “with oversight and accountability in mind.”<sup>407</sup> It is not enough for the system to be transparent if it is not interpretable.<sup>408</sup> For example, as discussed above, neural networks are often labeled “black boxes” due to the many variables they compute.<sup>409</sup> However, calling these networks black boxes is not completely accurate. Auditors can precisely track each neuron and layer in the computation process.<sup>410</sup> It is the sum of a myriad of intermediate decisions by each neuron, making its analysis inexplicable.<sup>411</sup>

How might such audits work in practice? System auditors conduct impact assessments to check if the algorithm detects biases.<sup>412</sup> This allows developers to build compliance in with equality at the design stage and may include monitoring mechanisms.<sup>413</sup> In terms of scope, audits must cover the algorithms, training data, and algorithmic outcomes.<sup>414</sup> If concerns cannot be addressed, developers can also halt production of the algorithm early.<sup>415</sup>

Equity audits must distinguish between traceability and explainability. Most algorithms have high traceability, such that auditors can run algo-

403. *See id.* at 284.

404. *See* Kim, *supra* note 126, at 190–91.

405. *See id.* at 190.

406. *See* Lee, Resnick & Barton, *supra* note 60.

407. *See* Joshua A. Kroll, Joanna Huey, Solon Barocas, Edward W. Felten, Joel R. Reidenberg, David G. Robinson & Harlan Yu, *Accountable Algorithms*, 165 U. PA. L. REV. 633, 640 (2017).

408. *See* Andrew D. Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085, 1103 (2018).

409. *See supra* notes 156–61 and accompanying text; Froomkin, Kerr & Pineau, *supra* note 30, at 47.

410. Froomkin, Kerr & Pineau, *supra* note 30, at 47–48; *see also* Dave Gershgorn, *MIT Researchers Can Now Track AI’s Decisions Back to Single Neurons*, QUARTZ (July 20, 2022), <https://qz.com/1022156/mit-researchers-can-now-track-artificial-intelligences-decisions-back-to-single-neurons> [<https://perma.cc/G4VA-GSQU>].

411. *See* Froomkin, Kerr & Pineau, *supra* note 30, at 48.

412. *See* Lorna McGregor, Daragh Murray & Vivian Ng, *International Human Rights Law as a Framework for Algorithmic Accountability*, 68 INT’L & COMPAR. L.Q. 309, 330 (2019).

413. *See id.*

414. *See* Peter K. Yu, *Artificial Intelligence, the Law-Machine Interface, and Fair Use Automation*, 72 ALA. L. REV. 187, 208 (2020); *see also* Anupam Chander, *The Racist Algorithm?*, 115 MICH. L. REV. 1023, 1024–25 (“What we need . . . is a *transparency of inputs and results*, which allows us to see that the algorithm is generating discriminatory impact.”).

415. *See* McGregor, Murray & Ng, *supra* note 412, at 330.

rithms repeatedly to generate the same results.<sup>416</sup> However, algorithms have low explainability since the logic behind their reasoning is often obscure.<sup>417</sup> For this reason, equity audits must interrogate why developers selected certain types of training data. There must also be a process for auditing technical diligence, fairness, and equity from design to execution.<sup>418</sup>

Requiring accountability in the context of bidding for government contracts complements audits.<sup>419</sup> Such requirements could expressly compel AI developers to show evidence of equity by design in their AI architecture. AI systems that pass the audit could receive a certification of quality assurance.<sup>420</sup> This certification process encourages competition to maintain algorithmic quality.<sup>421</sup> In addition, once developed, periodic audits can help ensure that the systems remain neutral.<sup>422</sup>

Whistleblower protections can also complement this system of equity audits.<sup>423</sup> They allow employees to raise the alarm externally if internal reporting fails to lead to action.<sup>424</sup> To encourage whistleblowing, these employees will need the protection of an immunity regime, which, unfortunately, does not yet exist.<sup>425</sup>

Here, an unlikely antagonist from Section III.A may provide the solution. The DTSA protects whistleblowers who misappropriate trade secrets.<sup>426</sup> The whistleblower immunity provision ensures that employers and others cannot use lawsuits to intimidate whistleblowers.<sup>427</sup> In the AI context, the DTSA could immunize those most likely to know of the discriminatory impact of an algorithm.<sup>428</sup> The whistleblower process could

416. See Froomkin, Kerr & Pineau, *supra* note 30, at 48.

417. See *id.*; McGregor, Murray & Ng, *supra* note 412, at 319.

418. See Yu, *supra* note 296, at 275.

419. See Cary Coglianese & Erik Lampmann, *Contracting for Algorithmic Accountability*, 6 ADMIN. L. REV. ACCORD 175, 180–81, 192–94 (2021).

420. See Yu, *supra* note 42, at 358 (discussing quality assurance process to certify different algorithms capable of making high-quality decisions).

421. See *id.*

422. *Id.* at 359; see also *Statement On Algorithmic Transparency and Accountability*, U.S. ASS'N FOR COMPUTING MACH. 1–2 (Jan. 12, 2017), [https://www.acm.org/binaries/content/assets/public-policy/2017\\_usacm\\_statement\\_algorithms.pdf](https://www.acm.org/binaries/content/assets/public-policy/2017_usacm_statement_algorithms.pdf) [<https://perma.cc/MDU5-P7R5>] (“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.”).

423. See Katyal, *supra* note 9, at 126–29; Orly Lobel, *Lawyering Loyalties: Speech Rights and Duties Within Twenty-First-Century New Governance*, 77 FORDHAM L. REV. 1245, 1249 (2009).

424. See Lobel, *supra* note 423, at 1250.

425. See Levendowski, *supra* note 131, at 605.

426. See Katyal, *supra* note 9, at 130–31.

427. See Peter S. Menell, *The Defend Trade Secrets Act Whistleblower Immunity Provision: A Legislative History*, 1 BUS. ENTREPRENEURSHIP & TAX. L. REV. 398, 401, 423 (2017); see also 162 CONG. REC. S1636 (daily ed. Apr. 4, 2016) (per Senator Leahy, “The provision protects disclosures made in confidence to law enforcement or an attorney for the purpose of reporting a suspected violation of law and disclosures made in the course of a lawsuit, provided that the disclosure is made under seal”).

428. See Katyal, *supra* note 9, at 133.

shield the investigative process from public disclosure.<sup>429</sup> The problem is that employees seeking to expose biased training data or algorithms must copy the data to share it.<sup>430</sup> The fair use framework set out in Section III.A could help excuse acts that would otherwise be infringing.

Finally, algorithm designs must include ethical standards. For instance, Allegheny County's Family Screening Tool is "a predictive risk modeling tool designed to improve child welfare call screening decisions."<sup>431</sup> Prior to adopting the tool, the County consulted with ethicists and made its decision-making process available to the public.<sup>432</sup> Equity audits, accountability requirements, and incentives can proactively encourage organizations to address algorithmic bias.<sup>433</sup> Testing and reviewing algorithms helps to "identify" and "mitigate discriminatory outcomes."<sup>434</sup>

The question at the heart of whether we can delegate judicial discretion to an algorithm is how it would adjudicate issues equitably. In IP litigation, AI will impact areas of IP law where "equitable justice," or "discretionary moral judgment," come into play the most.<sup>435</sup> The next Section considers this issue.

### C. EQUITABLE JUSTICE

Equitable justice reflects ethical or regulatory norms baked into the law by applying them to the facts.<sup>436</sup> In circumstances that warrant vindicating a party that might otherwise lose under the letter of the law, equitable justice bends rote, rule-based results. These include inequitable conduct,<sup>437</sup> patent misuse,<sup>438</sup> fair use,<sup>439</sup> and cases involving attorney

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429. *See id.* at 132–33 ("The advantage of this process ostensibly ensures that potential allegations are carefully explored before any legal action is taken, and that algorithms are always behind the protected veil of secrecy or under seal in court.").

430. *See* Levendowski, *supra* note 131, at 605.

431. Re & Solow-Niederman, *supra* note 5, at 286 (quoting *Developing Predictive Risk Models to Support Child Maltreatment Hotline Screening Decisions*, ALLEGHENY CNTY. ANALYTICS (Mar. 2017), <https://www.alleghenycountyanalytics.us/wp-content/uploads/2017/04/Developing-Predictive-Risk-Models-package-with-cover-1-to-post-1.pdf> [https://perma.cc/79ZS-BZ5Y]).

432. *Id.* at 286–87.

433. *See* Lee, Resnick & Barton, *supra* note 60.

434. *Id.*

435. *See* Re & Solow-Niederman, *supra* note 5, at 246.

436. *See id.* at 252 ("Equitable justice is most visible in discrete judicial rulings that are governed by standards and applied to facts ascertained through individualized proceedings.").

437. *See* Therasense, Inc. v. Becton, Dickinson & Co., 649 F.3d 1276, 1288 (Fed. Cir. 2011) ("[I]nequitable conduct charges cast a dark cloud over the patent's validity and paint the patentee as a bad actor.").

438. *See* C.R. Bard, Inc. v. M3 Sys., Inc., 157 F.3d 1340, 1372 (Fed. Cir. 1998) ("The defense of patent misuse arises from the equitable doctrine of unclean hands, and relates generally to the use of patent rights to obtain or to coerce an unfair commercial advantage.").

439. *See* NXIVM Corp. v. Ross Inst., 364 F.3d 471, 479 (2d Cir. 2004) (observing that "the subfactor pertaining to defendants' good or bad faith must be weighed").

fees<sup>440</sup> and enhanced damages.<sup>441</sup>

AI can trawl through large data sets to identify cancer cells or predict how proteins fold by pinpointing data signatures in natural phenomena.<sup>442</sup> However, legal concepts like inequitable conduct are as much social constructs as currency or national borders, a “product of social agreement and convention.”<sup>443</sup> Legal nuance may become lost when transposing written law into code if it is nonquantifiable.<sup>444</sup> Moreover, there is a limit to how much one can code since, as Professor Yu put it, courts “allow users to test the law’s limits.”<sup>445</sup>

Without an independent baseline, getting it “right” requires more than technical accuracy.<sup>446</sup> Instead, algorithms will need to distill the salience of courts’ constructions of social facts while being sensitive to updating their relevance over time.<sup>447</sup> Algorithms require preprogrammed input and outcome rules but “will have considerable difficulty determining *ex ante* how judges will rule in new situations. Inevitably, such translation will also bring up complicated questions concerning the computer programmers’ understanding and interpretation of the law.”<sup>448</sup> It is difficult for standards to fit into objective, observable factors without accounting for context.

Moreover, if social barriers impede marginalized groups from contributing to copyright and patent law’s constitutional mandate to “promote the Progress of Science and useful Arts”<sup>449</sup>—such as through its construction that systematically disadvantages certain groups based on their geography, socio-economic conditions, or manner of innovating or creating—then the AI system, no matter how accurate, will nonetheless abet inequality and undermine diversity, equity, and inclusion.<sup>450</sup> This drawback

440. *See* *Matthew Bender & Co. v. W. Publ’g Co.*, 240 F.3d 116, 125 (2d Cir. 2001) (“[B]ad faith in the conduct of the litigation is a valid ground for an award of fees.”).

441. *See* *Aro Mfg. Co. v. Convertible Top Replacement Co.*, 377 U.S. 476, 508 (1964) (noting that enhanced damages were available for willful or bad faith infringement).

442. *See* *AI Identifies Cancer Cells*, MAX DELBRÜCK CTR. FOR MOLECULAR MED. (June 10, 2022), <https://www.mdc-berlin.de/news/press/ai-identifies-cancer-cells> [<https://perma.cc/MJM4-QD86>]; Ewen Callaway, *DeepMind’s AI Predicts Structures for a Vast Trove of Proteins*, 595 NATURE 635 (2021), <https://www.nature.com/articles/d41586-021-02025-4> [<https://perma.cc/9YQE-SDHJ>].

443. *See* Burk, *supra* note 14, at 285–87 (“[U]nlike Plank’s constant or terminal velocity, such social facts have no independent valence; they are entirely malleable, change over time, and need not be the same in the future as they have in the past.”).

444. *See* Maayan Perel & Niva Elkin-Koren, *Accountability in Algorithmic Copyright Enforcement*, 19 STAN. TECH. L. REV. 473, 486–87 (2016); *see also* Bert-Jaap Koops, *Criteria for Normative Technology: The Acceptability of ‘Code as Law’ in Light of Democratic and Constitutional Values*, in *REGULATING TECHNOLOGIES: LEGAL FUTURES, REGULATORY FRAMES AND TECHNOLOGICAL FIXES* 160–62 (Roger Brownsword & Karen Yeung eds., 2008) (discussing the translation between “law in the books” and “law in technology”).

445. *See* Yu, *supra* note 42, at 332; Burk, *supra* note 41, at 291–92.

446. *See* Burk, *supra* note 14, at 284, 287.

447. *See id.* at 286–87, 300 (“What is being measured in such cases is only the implicitly or explicitly agreed-upon meaning of a social practice, not a stable and durable quantity.”).

448. Yu, *supra* note 42, at 332–33; *see also* Burk, *supra* note 14, at 332.

449. U.S. CONST. art. I, § 8, cl. 8.

450. *See* Burk, *supra* note 14, at 287–88, 290.

may make equitable judgments “flatly incompatible with automated algorithmic processes.”<sup>451</sup>

Consequently, AI often results in incomplete and invalid observations, no matter how sophisticated the algorithms.<sup>452</sup> Re and Solow-Niederman warn that “AI adjudication will generate a range of concerns relating to its tendency to make the legal system more incomprehensible, data-based, alienating, and disillusioning.”<sup>453</sup>

At the same time, it is also possible that AI could “preserve or even foster equitable justice” by making more fine-grained distinctions on the facts than would a human judge.<sup>454</sup> For example, algorithms could parse an unlimited number of data points in the IP context and deliver a highly particularized determination of an infringement.<sup>455</sup> Combining both consistency and particularity could powerfully augment human decision-making. By using AI to aid in reflection and deliberation, judges would have more time to ponder specific areas requiring more equitable discretion.<sup>456</sup>

## V. CONCLUSION

AI is a technology of fundamental societal importance. It offers a cost-efficient, effective, impartial tool to make the IP system more accessible to marginalized groups while being able to correct errors faster than human-driven justice systems. At the same time, we need to be aware of bugs in the system that cause algorithmic failure, data bias, and implementation flaws. Some important biases exist within the patent and copyright laws because women and racial minorities are underrepresented in the IP system. Others stem from trade secrets and copyright laws that impede access to auditing and correcting biased algorithms and training data. Sometimes the solution to biased data is more data. At other times, less data or better data may be a more appropriate response.

As we incorporate equity into AI systems, we are, in a sense, building the car while we drive it. Equity by design embeds human oversight at key points in the AI system that require discretion to minimize algorithmic bias while maximizing its productive benefits. Equity audits help identify mistakes and improve accuracy, including anomalies that machine “intelligence” misses. When algorithms and regulatory processes are responsibly designed, they can avoid amplified systemic discrimination and unethical applications. Maximizing AI allows judges to focus on difficult cases, using the equitable judgment their comparative advantage as humans provides them to work in tandem with AI and improve outcomes for everyone in the IP justice system.

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451. See Re & Solow-Niederman, *supra* note 5, at 253.

452. See Slaughter, Kopec & Batal, *supra* note 1, at 11.

453. Re & Solow-Niederman, *supra* note 5, at 242.

454. *Id.* at 258–59.

455. See *id.* at 259.

456. See *id.* at 258–59.

