Automating the Risk of Bias

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Abstract

Artificial intelligence ("AI") is a transformative technology that has radically altered decision-making processes. Evaluating the case for algorithmic or automated decision-making ("ADM") platforms requires navigating tensions between two normative concerns. On the one hand, ADM platforms may lead to more efficient, accurate, and objective decisions. On the other hand, early and disturbing evidence suggests ADM platform results may demonstrate biases, undermining claims that this special class of algorithms will democratize markets and increase inclusion.

State law assigns decision-making authority to the boards of directors of corporations. State courts and lawmakers accord significant deference to the board in the execution of its duties. Among its duties, a board must employ effective oversight policies and procedures to manage known risks. Consequently, the board of directors and senior management of firms integrating ADM platforms must monitor operations to mitigate enterprise risks including litigation, reputation, compliance, and regulatory risks that arise as a result of the integration of algorithms.

After the recent financial crisis, firms adopted structural and procedural governance reforms to mitigate various enterprise risks; these approaches may prove valuable in mitigating the risk of algorithmic bias. Evidence demonstrates that heterogeneous teams may identify and mitigate risks more successfully than homogeneous teams. Heterogeneous teams are more likely to overcome cognitive biases such as confirmation, commitment, overconfidence, and relational biases. This Article argues that increasing gender inclusion in the development of AI technologies will introduce important and diverse perspectives, reduce the influence of cognitive biases in the design, training, and oversight of learning algorithms, and, thereby, mitigate bias-related risk management concerns.

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Introduction

Emerging technologies, such as artificial intelligence, are transforming human decision-making practices. Private firms in various sectors of the economy and local, state, and federal government agencies increasingly entrust sophisticated algorithms to decide the most important social welfare and economic questions of the day.[1] Artificial Intelligence ("AI")[2] now influences risk assessments in the administration of criminal justice, financial services, healthcare, employment, and access to government benefits and housing. Within seconds, a learning algorithm reviews exceptional volumes of data and determines whether a criminal defendant should be eligible for bail, a consumer qualifies for a residential mortgage, a mass is benign or

1 *See infra* text accompanying notes 91–102. This Article uses the terms automated decision-making ("ADM") platforms or learning algorithms to describe systems or processes that are recursively trained on large volumes of data to analyze and predict patterns and outcomes. *See infra* Section I.A.

2 Artificial intelligence ("AI") describes a "broad assemblage of technologies, from early rule-based algorithmic systems to deep neural networks, all of which rely on an array of data and computational infrastructures." Alex Campolo et al., N.Y. Univ., AI Now 2017 Report 6 n.1 (2017), https://ainowinstitute.org/AI_Now_2017_Report.pdf [https://perma.cc/4AJN-LVNE]. As described in the AI Now 2017 Report, examples of the technologies encompassed in the term AI include speech recognition, language translation, image recognition, predictions, and logical determinations traditionally associated with human reasoning and cognitive abilities. *Id.* Learning algorithms comprise one of the several different classes of algorithms that may be described as AI.

malignant, and which candidates in a pool of hundreds of job applicants are most qualified.[3]

Notwithstanding the myriad reasons to celebrate, firms adopting rapidly evolving technologies face pernicious and pervasive risks. Consumers, consumer advocates, courts, and regulators have identified several emergent and, in some cases, endemic risks that accompany the integration of nascent technologies in the digital economy.[4] Cybersecurity and privacy threats, for example, have captured authorities' attention, and rightly so. As the Target,[5] Home Depot,[6] Equifax,[7] and Facebook[8] data breaches illustrate, consumer data is perhaps the newest form of currency.

An ever-growing number of cybersecurity incidents create risk management concerns for federal[9] and local government agencies[10]

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3 For example, sophisticated algorithms enable consumers to complete the entire transaction cycle for a personal loan—underwriting, document distribution, funding, and settlement—in less than 60 seconds using their mobile devices. *See, e.g.*, GreenSky, Inc., Registration Statement (Form S-1) (May 4, 2018), https://www.sec.gov/Archives/edgar/data/1712923/000093041318001730/c88906_s1a.htm#c88906_market1 [https://perma.cc/PKN9-KLUH].

4 *See, e.g.*, Kartikay Mehrotra & Aoife White, *Facebook Must Face Lawsuit over 29 Million-User Data Breach*, BLOOMBERG (June 24, 2019), https://www.bloomberg.com/news/articles/2019-06-24/facebook-must-face-lawsuit-over-29-million-user-data-breach [https://perma.cc/2WD8-QB5S] (discussing a decision by the U.S. District Court for the Northern District of California denying Facebook's motion to dismiss class action claims alleging harm from a massive data breach affecting over 29 million users and signaling that, "[f]rom a policy standpoint, to hold that Facebook has no duty of care here would create perverse incentives for businesses who profit off the use of consumers' personal data to turn a blind eye and ignore known security risks"); *see also* Cecilia Kang, *F.T.C. Approves Facebook Fine of about $5 Billion*, N.Y. TIMES (June 12, 2019), https://www.nytimes.com/2019/07/12/technology/facebook-ftc-fine.html [https://perma.cc/5R2U-EY72].

5 Sara Germano, *Target's Data-Breach Timeline*, WALL STREET J. (Dec. 27, 2013, 6:28 PM), https://blogs.wsj.com/corporate-intelligence/2013/12/27/targets-data-breach-timeline/ [https://perma.cc/6BHZ-DZWH].

6 *The Home Depot Reports Findings in Payment Data Breach Investigation*, HOME DEPOT (Nov. 6, 2014), https://ir.homedepot.com/news-releases/2014/11-06-2014-014517315 [https://perma.cc/65H7-4T76].

7 Rebecca Shabad, *Senate Panel Holds Hearing on Equifax, Yahoo Security Breaches*, CBS NEWS (Nov. 8, 2017, 12:30 PM), https://www.cbsnews.com/live-news/senate-panel-holds-hearing-on-equifax-breach-consumer-data-security-live-updates [https://perma.cc/JH4S-L9JB]; *see also* Tara Siegel Bernard et al., *Equifax Says Cyberattack May Have Affected 143 Million in the U.S.*, N.Y. TIMES (Sept. 7, 2017), https://www.nytimes.com/2017/09/07/business/equifax-cyberattack.html [https://perma.cc/2V2V-7BVT].

8 Mike Isaac & Sheera Frenkel, *Facebook Security Breach Exposes Accounts of 50 Million Users*, N.Y. TIMES (Sept. 28, 2018), https://www.nytimes.com/2018/09/28/technology/facebook-hack-data-breach.html [https://perma.cc/PNP4-ERNG].

9 U.S. GOV'T ACCOUNTABILITY OFF., GAO-19-105, INFORMATION SECURITY: AGENCIES NEED TO IMPROVE IMPLEMENTATION OF FEDERAL APPROACH TO SECURING SYSTEMS AND PROTECTING AGAINST INTRUSIONS 1 (2018), https://www.gao.gov/assets/700/696105.pdf [https://perma.cc/SCK9-S68G] ("The risks to information systems supporting the federal government are

and their contractors,[11] healthcare providers,[12] banks,[13] and firms that collect, store, and transfer large volumes of data.[14] Successful cyberattacks enable hackers to capture consumers' confidential personal data, including but not limited to birthdates, social security numbers, and email addresses.[15] Simply stated, collecting, holding, or transferring data—a form of digital gold—creates enterprise risks.

Longstanding privacy and ethical concerns punctuate questions regarding the capture and analysis of data.[16] For example, Google recently dispatched teams of contractors who offered people on the street—a significant number of whom were dark-complexioned, homeless African Americans—a $5 gift card in exchange for allowing the contractors to take a photograph of their faces.[17] Commentators

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increasing as security threats continue to evolve and become more sophisticated. These risks include escalating and emerging threats from around the globe, steady advances in the sophistication of attack technology, and the emergence of new and more destructive attacks.").

10 Matt Chittum, *Local Governments in Region Bolster Defenses Against Constant Cyberattacks on Their Data*, ROANOKE TIMES (July 20, 2019), https://www.roanoke.com/news/local/local-governments-in-region-bolster-defenses-against-constant-cyberattacks-on/article-d80fc8c9-db08-5bfa-9d2f-8feb65818815.html [https://perma.cc/L94P-UF9C].

11 Zolan Kanno-Youngs & David E. Sanger, *Border Agency's Images of Travelers Stolen in Hack*, N.Y. TIMES (June 10, 2019), https://www.nytimes.com/2019/06/10/us/politics/customs-data-breach.html [https://perma.cc/N4BE-SSQN] (describing a cyberattack that captured tens of thousands of images of travelers and license plates stored by Perceptics, a Tennessee-based U.S. Customs and Border Protection affiliate).

12 Reed Abelson & Matthew Goldstein, *Anthem Hacking Points to Security Vulnerability of Health Care Industry*, N.Y. TIMES (Feb. 5, 2015), https://www.nytimes.com/2015/02/06/business/experts-suspect-lax-security-left-anthem-vulnerable-to-hackers.html?module=inline [https://perma.cc/22VT-76WU].

13 Stacy Cowley & Nicole Perlroth, *Capital One Breach Shows a Bank Hacker Needs Just One Gap to Wreak Havoc*, N.Y. TIMES (July 30, 2019), https://www.nytimes.com/2019/07/30/business/bank-hacks-capital-one.html [https://perma.cc/PKD6-PBH9] ("Large financial companies have to thwart hundreds of thousands of cyberattacks every single day. Data thieves have to get lucky only once.").

14 *See supra* notes 5–8.

15 Devlin Barrett, *Capitol One Says Data Breach Affected 100 Million Credit Card Applications*, WASH. POST (July 29, 2019), https://www.washingtonpost.com/national-security/capital-one-data-breach-compromises-tens-of-millions-of-credit-card-applications-fbi-says/2019/07/29/72114cc2-b243-11e9-8f6c-7828e68cb15f_story.html [https://perma.cc/H3TM-FP5D] ("[I]nvestigators say thousands of Social Security and bank account numbers were also taken."); Drew Harwell & Geoffrey A. Fowler, *U.S. Customs and Border Protection Says Photos of Travelers Were Taken in a Data Breach*, WASH. POST (June 10, 2019), https://www.washingtonpost.com/technology/2019/06/10/us-customs-border-protection-says-photos-travelers-into-out-country-were-recently-taken-data-breach/ [https://perma.cc/N5VB-Y5SN].

16 For a thorough exploration of the commodification of data and the development of capitalist surveillance, see Shoshanna Zuboff, THE AGE OF SURVEILLANCE CAPITALISM: THE FIGHT FOR A HUMAN FUTURE AT THE NEW FRONTIER OF POWER (2019).

17 *See* Isobel Asher Hamilton, *Google Suspended Facial Recognition Research for the Pixel 4 Smartphone After Reportedly Targeting Homeless Black People*, BUS. INSIDER (Oct. 7, 2019),

promptly expressed concern and regulators launched investigations, each inquiring about the legal as well as ethical implications of Google's race to capture new data sets.

As Google's facial images collection debacle illustrates, the taxonomy of enterprise risks arising from integrating new technologies expands well beyond data breaches. Civil rights activists warn that the integration of learning algorithms marks the creation of a new class of enterprise risks.[18] An algorithm is a problem-solving process with a detailed set of step-by-step instructions that enable the user to perform a specified task.[19] For example, a recipe is a simple algorithm. It has inputs (ingredients) and an instructive process that guides the baker through a series of steps required to complete a specified task (baking the cake). While basic algorithms operate as simple "if, then" statements, learning algorithms adapt to perform human-like cognitive functions, independently analyzing data to identify patterns and offer predictions with limited human guidance.[20]

Governments, businesses, educational entities, nonprofits, and other institutions are actively engaged in training algorithms to perform all kinds of tasks.[21] In some cases, learning algorithms may re-

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https://www.businessinsider.com/google-suspends-facial-recognition-research-after-daily-news-report-2019-10 [https://perma.cc/A7GY-8G4R]; Jack Nicas, *Atlanta Asks Google Whether It Targeted Black Homeless People*, N.Y. Times (Oct. 4, 2019), https://www.nytimes.com/2019/10/04/technology/google-facial-recognition-atlanta-homeless.html [https://perma.cc/LZ7Q-LCHM] (in a letter to Kent Walker, Google's legal and policy chief, Nina Hickson, Atlanta's city attorney, solicited an explanation for the campaign noting that "[t]he possibility that members of our most vulnerable populations are being exploited to advance your company's commercial interest is profoundly alarming for numerous reasons . . . [i]f some or all of the reporting was accurate, we would welcome your response as what corrective action has been and will be taken"). Presumably the need for more diverse and representative facial recognition data sets motivated Google's campaign. *See* Steve Lohr, *Facial Recognition Is Accurate, If You're a White Guy*, N.Y. Times (Feb. 9, 2018), https://www.nytimes.com/2018/02/09/technology/facial-recognition-race-artificial-intelligence.html [https://perma.cc/E6UD-4FZT].

18 *See infra* note 44 and accompanying text.

19 Joshua A. Kroll et al., *Accountable Algorithms*, 165 U. Pa. L. Rev. 633, 640 n.14 (2017).

20 *See* Liane Colonna, *A Taxonomy and Classification of Data Mining*, 16 SMU Sci. & Tech. L. Rev. 309, 313–29 (2013); Kroll, *supra* note 19, at 636.

21 *See* U.S. Dep't of Treasury, A Financial System that Creates Economic Opportunities: Nonbank Financials, Fintech, and Innovation (2018), https://home.treasury.gov/sites/default/files/2018-07/A-Financial-System-that-Creates-Economic-Opportunities—-Nonbank-Financi. . . .pdf [https://perma.cc/TLV5-39RR] [hereinafter Treasury Report]; *see also* Seth Katsuya Endo, *Technological Opacity & Procedural Injustice*, 59 B.C. L. Rev. 821, 823 (2018) (discussing use of machine-learning algorithms by the private and public sectors); Claire Cain Miller, *Algorithms and Bias: Q. and A. with Cynthia Dwork*, N.Y. Times (Aug. 10, 2015), https://www.nytimes.com/2015/08/11/upshot/algorithms-and-bias-q-and-a-with-cynthia-dwork.html [https://perma.cc/3295-ZGNV] (discussing use of machine-learning algorithms by educational institutions).

place the human decision-makers who have historically served as gatekeepers; today, algorithms may determine who is hired,[22] fired,[23] or policed,[24] predict the risk of criminal activity,[25] signal workplace collegiality,[26] count votes in political contests,[27] and choose which citizens must submit to a tax audit.[28]

Evaluating the case for algorithmic or automated decision-making platforms ("ADM") requires navigating the tensions between two normative concerns. On one hand, ADM platforms[29] are more efficient, accurate, and objective than human actors.[30] According to advocates, AI may serve as an equalizer—ADM platforms will democratize markets, expanding access to historically marginalized groups and reducing intentional and unintentional discrimination in decision-making processes.[31] In fact, advocates argue, intelligent recruitment processes—smart hiring platforms—may use learning algorithms to enhance workplace diversity and mitigate bias in recruiting, hiring, and retention decisions; advocates posit that AI will also liberate other types of decisions—like bail assessments and credit or housing decisions—from the individual prejudices of judges, loan officers, or landlords.[32] If ADM platforms perform as anticipated, they may

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22 *See infra* notes 57–60 and accompanying text.

23 See Colin Lecher, *How Amazon Automatically Tracks and Fires Warehouse Workers for 'Productivity'*, VERGE (Apr. 25, 2019, 12:06 PM), https://www.theverge.com/2019/4/25/18516004/amazon-warehouse-fulfillment-centers-productivity-firing-terminations?mod=article_inline ("The documents also show a deeply automated tracking and termination process.").

24 *See* Issie Lapowski, *How the LAPD Uses Data to Predict Crime*, WIRED (May 22, 2018, 5:02 PM), https://www.wired.com/story/los-angeles-police-department-predictive-policing/ [https://perma.cc/3J6C-S3BW].

25 *See* Julia Angwin et al., *Machine Bias*, PROPUBLICA (May 23, 2016), https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing [https://perma.cc/CZQ2-EPDP].

26 *See* Lauren Weber & Elizabeth Dwoskin, *Are Workplace Personality Tests Fair?*, WALL STREET J. (Sept. 29, 2014, 10:30 PM), https://www.wsj.com/articles/are-workplace-personality-tests-fair-1412044257 [https://perma.cc/T86H-2V4U].

27 *See* Kim Zetter, *The Crisis of Election Security*, N.Y. TIMES (Sept. 26, 2018), https://www.nytimes.com/2018/09/26/magazine/election-security-crisis-midterms.html [https://perma.cc/369U-KDSH].

28 *See* Kroll, *supra* note 19, at 658.

29 *See infra* Section I.A.

30 *See infra* Part II.

31 *See* Alex P. Miller, *Want Less-Biased Decisions? Use Algorithms*, HARV. BUS. REV. (July 26, 2018), https://hbr.org/2018/07/want-less-biased-decisions-use-algorithms [https://perma.cc/8PFS-4MGE].

32 Mark Stone, *Want a More Diverse Workforce? How AI Is Combating Unconscious Bias,* DELL TECHS. (Mar. 14, 2018), https://www.delltechnologies.com/en-us/perspectives/want-a-more-diverse-workforce-how-ai-is-combating-unconscious-bias/ [https://perma.cc/SHB4-V7CD]. *But see* Will Byrne, *Now Is the Time to Act to End Bias in AI*, FAST COMPANY (Feb. 28, 2018),

achieve the goal of greater inclusion where legal interventions have failed to provide equal opportunity and access.[33]

Last year, for example, during the largest consumer credit industry trade show in the world, Money2020,[34] PayPal Chief Executive Officer Dan Schulman emphasized the industry's obligation to leverage innovative technologies to expand access to credit to consumers with thin, impaired, or nonexistent credit histories—the "credit invisibles" and "unscorables."[35] In the hall of the Venetian Hotel in Las Vegas, adorned by handpainted frescoes and marble Corinthian columns flowering with gilded gold leaves, Schulman and the other titans of finance praised the integration of learning algorithms for the potential to ensure more objective assessments.[36]

On the other hand, early and disturbing evidence shows that relying on ADM platforms may lead to biased outcomes, undermining proponents' claims that learning algorithms will lead to greater inclusion. Even if they increase efficiency, critics argue that ADM platforms may be fueled by inaccurate or incomplete data and therefore, their decisions may not be accurate or objective.[37]

ADM platforms draw upon significant volumes of data, which may be influenced by historic or unconscious biases; firms adopting ADM platforms risk incorporating learning algorithms that may interpret and analyze this data and make decisions in a manner that replicates prejudices and perpetuates discrimination.[38] Consequently, ADM platforms risk violating federal and state antidiscrimination statutes and regulations, such as Title VII of the Civil Rights Act of 1964,[39] the Equal Credit Opportunity Act,[40] and the Fair Housing

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https://www.fastcompany.com/40536485/now-is-the-time-to-act-to-stop-bias-in-ai [https://perma.cc/Z6AQ-D453].

33 *See infra* Section II.A; *see also* FED. TRADE COMM'N, BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION? UNDERSTANDING THE ISSUES 6 (2016), https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf [https://perma.cc/93BB-MX22].

34 Rachel O'Dwyer, *Algorithms Are Making the Same Mistakes Assessing Credit Scores that Humans Did a Century Ago*, QUARTZ (May 14, 2018), https://qz.com/1276781/algorithms-are-making-the-same-mistakes-assessing-credit-scores-that-humans-did-a-century-ago/ [https://perma.cc/BC5U-2YHB].

35 *Id.*

36 *Id.*

37 *Id.*

38 *See infra* notes 49–58 and accompanying text.

39 42 U.S.C. § 2000e (2012).

40 15 U.S.C. § 1691(b) (2012). For a careful analysis of concerns related to financial technology or "fintech" lenders' use of ADM platforms, see Matthew Adam Bruckner, *Fintech's Promises and Perils: The Promise and Perils of Algorithmic Lenders' Use of Big Data*, 93 CHI.-

Act,[41] all of which prohibit intentional discrimination and unintentional discrimination that has a disparate effect on legally protected classes.[42]

Even when well-intentioned developers aspire to create ADM platforms that are more inclusive, bias may creep in and compromise the outcomes.[43] Offering evidence of bias resulting from the adoption of ADM platforms in the criminal justice system, Michelle Alexander proclaims that ADM platforms are arguably the "newest Jim Crow"[44]

KENT L. REV. 3, 5 (2018). *See generally* Christopher K. Odinet, *Consumer Bitcredit and Fintech Lending*, 69 ALA. L. REV. 781 (2018).

41 42 U.S.C. § 45 (2012).

42 *See* FEDERAL TRADE COMMISSION, *supra* note 33, at 5–12. "Disparate treatment" may be "overt" (when the employer, creditor, or landlord openly discriminates on a prohibited basis) or it may be found through comparing the treatment of applicants who receive different treatment for no discernable reason other than a prohibited basis. In the latter case, it is not necessary that the employer, creditor, or landlord act with any specific intent to discriminate.

43 *See generally* Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CAL. L. REV. 671 (2016).

44 *See* Michelle Alexander, *The Newest Jim Crow*, N.Y. TIMES (Nov. 8, 2018), https://www.nytimes.com/2018/11/08/opinion/sunday/criminal-justice-reforms-race-technology.html [https://perma.cc/3967-QNNJ]; *see also* VIRGINIA EUBANKS, AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR (2018) (arguing that the collection and commodification of data and related abuses have imposed a new regime of surveillance, profiling, punishment, containment, and exclusion that Eubanks describes as the "digital poorhouse"—technology's touted benefits, including more efficient delivery of services to the poor, are not realized and the use of data worsens inequality); SAFIYA UMOJA NOBLE, ALGORITHMS OF OPPRESSION: HOW SEARCH ENGINES REINFORCE RACISM (2018).

The Jim Crow era centered on the structural exclusion of and legally sanctioned discrimination against black Americans. *See* Margaret Hu, *Algorithmic Jim Crow*, 86 FORDHAM L. REV. 633, 650–63 (2017) (arguing that the Department of Homeland Security's vetting and screening protocols risk introducing an algorithmically driven and technologically enhanced form of Jim Crow). *See generally* Gabriel J. Chin, *Jim Crow's Long Goodbye*, 21 CONST. COMMENT. 107 (2004) (examining the legislative response to *Brown v. Board*, including the implications of the fact that many racially discriminatory laws still remain on the books today); Gabriel J. Chin & Randy Wagner, *The Tyranny of the Minority: Jim Crow and the Counter-Majoritarian Difficulty*, 43 HARV. C.R.-C.L. L. REV. 65 (2008); Rachel D. Godsil, *Race Nuisance: The Politics of Law in the Jim Crow Era*, 105 MICH. L. REV. 505 (2006); Trina Jones, Brown *II: A Case of Missed Opportunity?*, 24 L. & INEQ. 9 (2006); Benno C. Schmidt, Jr., *Principle and Prejudice: The Supreme Court and Race in the Progressive Era, Part 1: The Heyday of Jim Crow*, 82 COLUM. L. REV. 444 (1982).

The central purpose of Jim Crow "was to maintain a second-class social and economic status for blacks while upholding a first-class social and economic status for whites." Hu, *supra* at 651 (citation omitted). At the height of the Jim Crow era, discrimination was enforced by not only law but public etiquette as well, encouraging white Americans to take the law into their own hands and enforce it themselves, especially in Southern states. *Id.* In fact, in the South, the discriminatory effects of Jim Crow were felt in every aspect of American life. *Id.* at 652 ("Jim Crow penetrated every facet of life for Southern African Americans: it was an integral part of the social, political, and legal fabric of Southern society.").

While the North presented a less explicit Jim Crow, the effects were still significant in hous-or, as Ruha Benjamin explains, "Jim Code."[45]

As a result of these concerns, relying on ADM platforms may create a new class of risk management concerns for the firms integrating complex algorithms into their business models.[46] First, algorithms interpret source data. Although developers may design ADM platforms with a desire to enhance objectivity and consequently reduce bias, algorithms at the center of ADM platforms may incorporate bias in the source data—commonly described as big data—that train learning algorithms to independently draw conclusions.[47] Because many firms outsource key elements in the platform development process including data collection, data cleaning, data partitioning, model selection, and model training, bias in the source data may not be immediately detected.[48]

As the popular computer science maxim explains, "garbage in, garbage out," meaning biased inputs (source data) will lead to biased or erroneous outputs.[49] The notorious Northpointe, Inc.'s Correc-

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ing, education, employment, and economic settings. *Id.* Historians argue that the Southern Jim Crow was more prevalent within the framework of the South due to white Southerners' attempts to preserve the old master/slave system of the past. *Id.* "Jim Crow established restrictions on marriage, voting, education, employment, housing, travel, and enforced segregation in public spaces." *Id.* at 652–53 (footnotes omitted). These social codes served to perpetuate a culture of violence, racism, and fear that permeated the way of life for African Americans living in the South. *Id.* at 653.

As Michelle Alexander explains, predictive, risk assessment algorithms or ADM platforms may "appear colorblind on the surface but they are based on factors that are not only highly correlated with race and class, but are also significantly influenced by pervasive bias." Alexander, *supra*.

45 Ruha Benjamin, Race After Technology: Abolitionist Tools for the New Jim Code (2019).

46 For a comprehensive survey of the difficulties that arise from using sophisticated algorithms in automated decision-making, see Cathy O'Neil, Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy (2016); Frank Pasquale, The Black Box Society: The Secret Algorithms that Control Money and Information (2015).

47 *See infra* Section II.A.

48 Decisions regarding these elements—quantity, validity, and generalizability—significantly impact the performance of ADM platforms. Other underlying issues that might be equally important include gathering, merging, and measuring data, collecting a sufficient amount of data, ensuring that the variables for which data are collected accurately and precisely measure what they are supposedly measuring (variables' measurement validities), and ensuring generalizability or the ability of the algorithm trained on a particular dataset to generate accurate predictions when deployed on different data. *See, e.g.*, David Lehr & Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. Davis L. Rev. 653, 703–04 (2017).

49 *See* Barocas & Selbst, *supra* note 43. *See generally* Ifeoma Ajunwa, *Algorithms at Work: Productivity Monitoring Applications and Wearable Technology as the New Data-Centric Research Agenda for Employment and Labor Law*, 63 St. Louis U. L.J. 21 (2019); Ifeoma Ajunwa,

tional Offender Management Profiling for Alternative Sanctions ("COMPAS") recidivism prediction platform offers a disturbing example of these concerns.[50] Activists swiftly objected to the risk assessment platform's incorporation of unreliable and inaccurate data, and demanded reforms designed to address the platform's racially discriminatory scoring methodology.[51]

Second, ADM platforms rely on a special class of algorithms that "learn" to make decisions independently; in other words, the algorithms learn to make decisions that reach beyond explicitly programmed instructions.[52] Learning algorithms function autonomously, independently selecting and analyzing variables, adopting processes, and drawing conclusions.[53] Inaccuracies and biases in data may be amplified when evaluated by ADM platforms.[54] Consequently, critics argue that ADM platforms must be viewed as an art, not a science;[55] critics demand ethical checks and balances to address early evidence of algorithmic bias.[56]

The spectacular failure of Amazon's automated employment recruiting platform illustrates critics' concerns. Amazon developed an ADM platform to evaluate, score, and rank job applicants.[57] Amazon's resume review platform relied on a machine learning algorithm capable of processing thousands of job applications in seconds.[58]

Genetic Testing Meets Big Data: Tort and Contract Law Issues, 75 Ohio St. L.J. 1225 (2014); Ifeoma Ajunwa et al., *Limitless Worker Surveillance*, 105 Cal. L. Rev. 735 (2017); Hu, *supra* note 44; Nancy Leong & Aaron Belzer, *The New Public Accommodations: Race Discrimination in the Platform Economy*, 105 Geo. L.J. 1271 (2017).

50 *See* Andrews Guthrie Ferguson, The Rise of Big Data Policing: Surveillance, Race, and the Future of Law Enforcement (2017); Randy Rieland, *Artificial Intelligence Is Now Used to Predict Crime. But Is It Biased?*, Smithsonian (Mar. 5, 2018), https://www.smithsonianmag.com/innovation/artificial-intelligence-is-now-used-predict-crime-is-it-biased-180968337/ [https://perma.cc/A3X5-S792] ("Both PredPol and CrimeScan limit their projections to where crimes could occur, and avoid taking the next step of predicting who might commit them—a controversial approach that the city of Chicago has built around a 'Strategic Subject List' of people most likely to be involved in future shootings, either as a shooter or victim.").

51 *See, e.g.*, Angwin et al., *supra* note 25 (describing the limitations of risk assessment platforms developed to predict recidivism and highlighting the weakness and inaccuracies in the information gathered and analyzed).

52 *See* Harry Surden, *Machine Learning and Law*, 89 Wash. L. Rev. 87, 88 (2014).

53 *See id.* at 89.

54 *See* Barocas & Selbst, *supra* note 43, at 683–84.

55 *See* Cain Miller, *supra* note 21; Weber & Dwoskin, *supra* note 26.

56 *See* Cain Miller, *supra* note 21.

57 *See* Jeffrey Dastin, *Amazon Scraps Secret AI Recruiting Tool that Showed Bias Against Women*, Reuters (Oct. 9, 2018), https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G [https://perma.cc/H65U-YLLK].

58 *See id.*

The algorithm evaluated candidates' educational or experiential qualifications and ranked candidates based on training data. The training data included the data collected from candidates hired in previous searches.[59] The algorithms in Amazon's platform independently made inferences and drew conclusions, moving beyond explicit instructions regarding the methodology for ranking candidates.[60]

Programmers intended for the platform to engage in an unbiased analysis, identifying the best candidates in competitive pools of applicants for software development positions.[61] Notwithstanding programmers' intentions, the platform began to "penalize[] resumes that included the word 'women's,' as in 'women's chess club captain'" and "downgrade[] graduates of two all-women's colleges."[62] Notwithstanding the team's immediate efforts to edit the program to address gender bias, Amazon recognized the risk that the platform might begin to discriminate on the basis of other attributes, disproportionately impacting legally protected groups and violating antidiscrimination law.[63]

Amazon's frustrations with its automated hiring platform illustrate endemic challenges that haunt the development of ADM platforms. As indicated above, the case for ADM platforms requires carefully considering normative concerns including access, fairness, and equity.

Beyond costly antidiscrimination litigation, firms must navigate reputation and regulatory risks. Amazon's hiring platform makes plain that firms that integrate ADM platforms must develop internal governance policies to address this growing body of risk management concerns.[64]

How might firms gain the benefits of integrating ADM platforms while mitigating the risk that these platforms may replicate biases,[65]

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59 Lehr & Ohm, *supra* note 48, at 673. Supervised and unsupervised algorithms comprise a subset of the technologies commonly described as AI.

60 *See* Dastin, *supra* note 57.

61 *See id.*

62 *Id.*

63 *See id.*

64 *See infra* Section III.A.

65 Aliya Ram, *AI Risks Replicating Tech's Ethnic Minority Bias Across Business*, FIN. TIMES (May 30, 2018), http://www.ft.com/content/d61e8ff2-48a1-11e8-8c77-ff51caedcde6 [https://perma.cc/2QZX-A5PK]; *see also* Dina Bass & Ellen Huet, *Researchers Combat Gender and Racial Bias in Artificial Intelligence*, BLOOMBERG (Dec. 4, 2017, 7:45 AM), https://www.bloomberg.com/news/articles/2017-12-04/researchers-combat-gender-and-racial-bias-in-artificial-intelligence [https://perma.cc/2EY5-R64X]; Sascha Eder, *How Can We Eliminate Bias in Our Algorithms?*, FORBES (June 27, 2018), https://www.forbes.com/sites/theyec/2018/06/27/how-can-we-eliminate-bias-in-our-algorithms/#3e41743e337e [https://perma.cc/ZES3-MGSW];

impede firms' compliance with antidiscrimination statutes, and amplify the marginalization of legally protected groups?[66] This Article examines the risk of algorithmic bias and inquires whether increasing diversity among developers, senior managers, and members of the boards of directors of firms adopting learning algorithms may mitigate the risk that ADM platforms will perpetuate bias.

Commentators posit that a lack of diversity in the technology industry creates blind spots. Data scientists admit that ADM platforms may reflect developers' conscious and unconscious biases in myriad ways.[67] For example, teams of programmers that lack gender diversity may fail to identify under and overrepresentation of subjects in data

Natasha Lomas, *UK Report Urges Action to Combat AI Bias*, TechCrunch (Apr. 16, 2018, 10:36 AM), https://techcrunch.com/2018/04/16/uk-report-urges-action-to-combat-ai-bias/ [https://perma.cc/M3P4-LXTS]; Robin Nunn, *Workforce Diversity Can Help Banks Mitigate AI Bias*, Am. Banker (May 30, 2018), https://www.americanbanker.com/opinion/workforce-diversity-can-help-banks-mitigate-ai-bias [https://perma.cc/W7F8-HASK]; Eric Rosenbaum, *Silicon Valley is Stumped: AI Cannot Always Remove Bias from Hiring*, CNBC (May 30, 2018), https://www.cnbc.com/2018/05/30/silicon-valley-is-stumped-even-a-i-cannot-remove-bias-from-hiring.html [https://perma.cc/5F76-NRNT]; Stone, *supra* note 32; Jonathan Vanian, *IBM Debuts Tools to Help Prevent Bias in Artificial Intelligence*, Fortune (Sept. 19, 2018), http://fortune.com/2018/09/19/ibm-artificial-intelligence-bias/ [https://perma.cc/3G79-SJ8U]; Liz Webber, *These Entrepreneurs Are Taking on Bias in Artificial Intelligence*, Entrepreneur (Sept. 5, 2018), https://www.entrepreneur.com/article/319228 [https://perma.cc/TEK8-5HKP].

66 *See* Anupam Chander, *The Racist Algorithm?*, 115 Mich. L. Rev. 1023, 1024–26 (2017); Christina Couch, *Ghosts in the Machine*, PBS (Oct. 25, 2017), https://www.pbs.org/wgbh/nova/article/ai-bias [https://perma.cc/PX6D-GVVV]; Dave Gershgorn, *Congress Is Worried About AI Bias and Diversity*, Quartz (Feb. 15, 2018), https://qz.com/1208581/diversity-and-bias-in-ai-has-reached-us-congress/ [https://perma.cc/8ZZH-ERME]; Gideon Mann & Cathy O'Neil, *Hiring Algorithms Are Not Neutral*, Harv. Bus. Rev. (Dec. 9, 2016), https://hbr.org/2016/12/hiring-algorithms-are-not-neutral [https://perma.cc/UH3L-YH29]; Carlos Melendez, *Is There Such a Thing as a Prejudiced AI Algorithm*, Forbes (Aug. 15, 2018), https://www.forbes.com/sites/forbestechcouncil/2018/08/15/is-there-such-a-thing-as-a-prejudiced-ai-algorithm/#6121e8922dc3 [https://perma.cc/9PJM-HSZ3]; Ramona Pringle, *When Technology Discriminates: How Algorithmic Bias Can Make an Impact*, CBC (Aug. 10, 2017), https://www.cbc.ca/news/technology/algorithms-hiring-bias-ramona-pringle-1.4241031 [https://perma.cc/5LSA-ZEHE]; Kriti Sharma, *Can We Keep Our Biases from Creeping into AI?*, Harv. Bus. Rev. (Feb. 9, 2018), https://hbr.org/2018/02/can-we-keep-our-biases-from-creeping-into-ai [https://perma.cc/YJX7-MHC8]; Jackie Snow, *"We're in a Diversity Crisis": Cofounder of Black in AI on What's Poisoning Algorithms in Our Lives*, Tech. Rev. (Feb. 14, 2018), https://www.technologyreview.com/s/610192/were-in-a-diversity-crisis-black-in-ais-founder-on-whats-poisoning-the-algorithms-in-our/ [https://perma.cc/7DN9-YHJX]; James Vincent, *The Tech Industry Doesn't Have a Plan for Dealing with Bias in Facial Recognition*, Verge (July 26, 2018), https://www.theverge.com/2018/7/26/17616290/facial-recognition-ai-bias-benchmark-test [https://perma.cc/VFG2-F2LM].

67 Sharma, *supra* note 66.

sets.[68] Once integrated into ADM platforms, data sets that are not sufficiently diverse may lead to biased outcomes.[69]

The reputations of an increasing number of firms in the technology industry are marred by the lack of diversity in the rank-and-file employees and senior leadership of the firms.[70] The leadership ranks of the technology industry are remarkably male[71] and exceptionally homogenous.[72] In fact, evidence suggests that a "bro" culture permeates the industry.[73] Bro culture fosters exclusivity[74] and masculinity.[75] Bro culture is so pervasive in the technology industry that women entrepreneurs embrace venture beards—hiring, promoting, or appointing men to join them at fundraising pitches with venture capital firms to prevent discrimination or harassment.[76]

The epidemic of underrepresentation of women in the technology sector underscores these challenges. Notwithstanding the national spotlight on the lack of diversity in the technology sector, there has been limited progress to address gender balance concerns.[77] In fact, some technology firms are actively concealing information regarding

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68 *See id. See also* Joy Buolamwini & Timnit Gebru, *Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification*, 81 PROC. MACHINE LEARNING RES. 1 (2018), http://proceedings.mlr.press/v81/buolamwini18a/buolamwini18a.pdf [https://perma.cc/8CX2-AMWM] (finding imbalance in representation of gender and darker complexioned subjects and proposing alternative approach to data set for facial recognition data sets); Couch, *supra* note 66 (describing the flawed benchmarks in facial recognition software that include disproportionate percentages of photos of men or fail to reflect sufficient age, gender, or racial diversity to accurately perform on certain groups such as older people, women, or those with darker skin tones).

69 *See* Melendez, *supra* note 66.

70 Gillian B. White, *Melinda Gates: The Tech Industry Needs to Fix Its Gender Problem—Now*, ATLANTIC (Mar. 16, 2017), https://www.theatlantic.com/business/archive/2017/03/melinda-gates-tech/519762/ [https://perma.cc/K967-7JVY]. In an interview, Melinda Gates explains that the absence of women in the technology industry creates risks, including the risk that hidden bias may be coded into the system and "we won't even realize all the places that we have it." *Id.*

71 *See* Claire Cain Miller, *Google Releases Employee Data, Illustrating Tech's Diversity Challenge*, N.Y. TIMES (May 28, 2014), https://bits.blogs.nytimes.com/2014/05/28/google-releases-employee-data-illustrating-techs-diversity-challenge challenge [https://perma.cc/LF7C-NRDN].

72 Sharma, *supra* note 66.

73 Cain Miller, *supra* note 71.

74 *See* Cathy O'Neil, *Amazon's Gender-Biased Algorithm Is Not Alone*, BLOOMBERG (Oct. 16, 2018), https://www.bloomberg.com/opinion/articles/2018-10-16/amazon-s-gender-biased-algorithm-is-not-alone [https://perma.cc/357G-DKAN] (describing Amazon's failed attempt at automated hiring through machine learning).

75 *See* Benjamin Edwards & Ann McGinley, *Venture Bearding*, 52 U.C. DAVIS L. REV. 1873, 1893 (2019).

76 *See* Edwards & McGinley, *supra* note 75.

77 Bourree Lam, *The Department of Labor Accuses Google of Gender Pay Discrimination*, ATLANTIC (Apr. 7, 2017), https://www.theatlantic.com/business/archive/2017/04/dol-google-pay-discrimination/522411/ [https://perma.cc/E6T4-XLD3].

their (lack of) diversity. As Jamillah Williams explains, technology firms have adopted complex and sophisticated legal strategies to veil their lack of gender and racial diversity.[78]

In part, the problem may be the pipeline. Women comprise less than twenty percent of those seeking computer science undergraduate and graduate degrees or holding software programming positions.[79] The numbers are so dismal that one commentator asks, "where are the women?"[80] Even more disturbing, some accounts suggest that women often pretend to be men to obtain work as programmers.[81]

While women are hiding their identity to gain access to opportunities in the AI community, others are unapologetic about concerns that women and diverse programmers may experience exclusion. In 2018, four programmers published an article chronicling the debate about the acronym for one of the largest and most popular international AI conferences—the Neural Information Processing Systems Conference or "NIPS." Offering examples of overt sexual harassment at computational conferences, the authors provided detailed accounts of pervasive "sexist hostility" and "crude" behavior. Frustrations peaked in December 2017 when keynote speaker Elon Musk remarked that there could be no NIPs without tits.[82]

This Article contends that the increased participation of women on corporate boards, as managers, and in key decision-making positions may enhance risk management oversight and mitigate the risk of

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78 Jamillah B. Williams, *Diversity as a Trade Secret*, 107 GEO. L.J. 1685 (2019).

79 *Women in Computer Science: Getting Involved in STEM*, COMPUTER SCI., https://www.computerscience.org/resources/women-in-computer-science/ [https://perma.cc/GDH3-MDB4].

80 Tom Simonite, *AI Is the Future—But Where Are the Women?*, WIRED (Aug. 17, 2018, 7:00 AM), https://www.wired.com/story/artificial-intelligence-researchers-gender-imbalance/ [https://perma.cc/W2TT-YVZ6].

81 Lauren Camera, *Women Can Code—As Long as No One Knows They're Women,* U.S. NEWS (Feb. 18, 2016, 2:35 PM), https://www.usnews.com/news/blogs/data-mine/2016/02/18/study-shows-women-are-better-coders-but-only-when-gender-is-hidden [https://perma.cc/D6V9-TET2].

82 DANIELA WITTEN ET AL., WHAT'S IN A NAME? THE NEED TO NIP NIPS 2 (2018), http://tensorlab.cms.caltech.edu/users/anima/pubs/NIPS_Name_Debate.pdf [https://perma.cc/Z4UW-BL5M] ("There has been substantial recent controversy surrounding the use of the acronym 'NIPS' for the Neural Information Processing Systems conference, stemming from the fact that the word 'nips' is common slang for nipples, and has historically been used as a racial slur targeting people of Japanese origin. Here, we outline the ways in which this acronym has contributed to a hostile environment towards women in machine learning."). In November of 2018, the conference board agreed to a new acronym "NeurIPS" which many believe will create a more inclusive environment in machine learning. *Id.* at 3. *See also* Timnit Gebru (@timnitGebru), TWITTER (Dec. 10, 2017, 6:08 PM), https://twitter.com/timnitgebru/status/939995193943646208?lang=en [https://perma.cc/H4AD-NMN8].

firms adopting ADM platforms may lead to discrimination against members of protected classes.[83] Enhancing gender diversity among the members of the board, management, senior developers, and the general leadership ranks of technology firms may lead technology firms to ask important questions such as whether data sets are complete or accurate, or whether the infrastructure or mechanics of programming fail to consider significant or underrepresented populations.[84]

State law delegates decision-making authority within firms to the boards of directors; boards manage enterprise risks and compliance with state and federal laws.[85] For decades, corporate governance experts have debated the business case or financial benefit of diversity. This Article surveys the empirical evidence and concludes that the presence of a critical mass of women on boards of directors may influence financial performance. In truth, however, a myopic focus on firms' economic performance fails to take into account the wealth of benefits that diverse decision-making yields.[86] This Article contends that expanding the diversity in the talent pool in the oversight, management, and development of ADM platforms may offer a pathway toward mitigating the risk that these platforms will operate in a manner that leads to discriminatory outcomes.[87]

This Article makes three critical contributions. First, this Article examines the rising significance of ADM platforms. In light of the rapid pace of adoption and the diversity of government agencies and market sectors integrating these technologies, resolving normative questions regarding the use and limits of ADM platforms is paramount. Consequently, policymakers should be concerned with and undertake measures to ensure equity and accessibility to the resources and opportunities created by these platforms.

Second, this Article contends that disparate impact claims arising from algorithmic bias create risk management concerns for the firms that integrate ADM technology. To date, scholars proposing reforms

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83 *See infra* Section IV.A.

84 Sharma, *supra* note 66 (explaining that the "fairly culturally homogenous" AI talent pool is a small community of highly credentialed PhDs); *see also* Liza Mundy, *Why Is Silicon Valley So Awful to Women?*, Atlantic (Apr. 2017), https://www.theatlantic.com/magazine/archive/2017/04/why-is-silicon-valley-so-awful-to-women/517788/ [https://perma.cc/VWY5-WGY8]; White, *supra* note 70.

85 *See infra* Section III.A.; Kristin Johnson, *Addressing Gaps in the Dodd-Frank Act: Directors' Risk Management Oversight Obligations*, 45 U. Mich. J.L. Ref. 55, 78–92 (2011).

86 *See infra* Part IV.

87 *See* Sharma, *supra* note 66.

to address concerns regarding algorithmic bias have focused on externally imposed state and federal regulation.[88] This Article argues that firms may mitigate the threat of algorithmic bias by developing internal structural and process-oriented corporate governance solutions to mitigate the endemic risks that arise from relying on learning algorithms. These internal governance solutions should supplement rather than supplant state and federal regulation of the integration and use of ADM platforms.

Third, relying on empirical studies in corporate governance, this Article advocates for firms to focus on the role of human agents and enhance leadership diversity in the firms integrating algorithmic platforms. This Article draws on empirical studies and argues that increased gender diversity will enable firms to better address group decision-making limitations identified in psychology literature.[89] Acknowledging the limits of existing studies and the need for continued research,[90] this Article concludes that a careful investigation of the risk management benefits of enhanced gender representation in leadership and decision-making positions may offer important guidance

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88 *See infra* note 120 and accompanying text.

89 *See infra* Section IV.A; *see also* Laura St. Claire et al., *Braving the Financial Crisis: An Empirical Analysis of the Effect of Female Board Directors on Bank Holding Company Performance* (Office of the Comptroller of the Currency, Economics Working Paper 2016-1), https://www.occ.gov/publications-and-resources/publications/economics-working-papers/files/2010-2019/economic-working-paper-2016-1.html [https://perma.cc/H5GF-4WFE] (providing an additional empirical study on female corporate directors); Cristina Banahan & Gabriel Hasson, *Across the Board Improvements: Gender Diversity and ESG Performance*, HARV. L. SCH. F. CORP. GOVERNANCE & FIN. REG. (Sept. 6, 2018), https://corpgov.law.harvard.edu/2018/09/06/across-the-board-improvements-gender-diversity-and-esg-performance/#4 [https://perma.cc/8ETV-58BG] (examining the relationship between board gender diversity and environmental and social management and concluding that companies with gender diverse boards are associated with better performance on Institutional Shareholder Services, Inc.'s environmental and social risk management measures). The Banahan and Hasson study concluded that gender diverse boards manage risk better. *Id.* According to the study, "[g]ender diversity in corporate decision-making is a crucial factor in effective leadership because it helps companies be more attentive and responsive to risk." *Id.* Further, "Gender diverse boards offer more comprehensive understanding of key company stakeholders." *Id.* According to Banahan and Hasson "women may also provide additional insight into consumer trends and consumer priorities for the companies of the boards they serve." *Id.* Gender diversity increased board attendance and effectiveness. *Id.*

90 Sarah Harvey et al., *Decision Diversion in Diverse Teams: Findings from Inside a Corporate Boardroom*, *in* 3 ACADEMY MANAGEMENT DISCOVERIES 358, 359 (2017) (offering a longitudinal study of the meetings of a corporate board over a five year period, which examines the microprocesses that occur after a change in the composition of the board, and identifies a microprocess that the authors describe as decision diversion that arises as the board negotiates subgroup member interests and task performance).

for improving firms' ability to address algorithmic bias and mitigate related risk management concerns.

The Article proceeds in four parts. Part I introduces the ADM platforms that now captivate popular culture. With limited human intervention, these platforms engender personalized news streams,[91] direct commercial flights,[92] drive automobiles,[93] reply to email messages,[94] determine eligibility for welfare benefits,[95] identify your preferred television series and movies,[96] and offer real time traffic analysis.[97] For litigants, ADM technology may predict the relevance of documents in civil litigation.[98] Government agencies have adopted ADM technology platforms to tally votes,[99] select returns for tax audits,[100] determine eligibility for public assistance,[101] and identify individuals for jury service.[102]

There is little room to dispute that ADM technology, at least in its current stage of development, creates risk exposure for adopting firms. Scholars exploring algorithmic bias offer a range of solutions.[103]

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91 *See* Guatam Narula, *Everyday Examples of Artificial Intelligence and Machine Learning*, EMERJ (Jan. 9, 2019), https://emerj.com/ai-sector-overviews/everyday-examples-of-ai/ [https://perma.cc/XFE8-FS5Q].

92 *See id.*; *see also* John Markoff, *Planes Without Pilots*, N.Y. TIMES (Apr. 6, 2015), https://www.nytimes.com/2015/04/07/science/planes-without-pilots.html?_r=0 [https://perma.cc/L7V9-D72Z] (discussing how AI is used to help fly planes).

93 *See* Narula, *supra* note 91 ("In the future, AI will shorten your commute even further via self-driving cars that result in up to 90% fewer accidents, more efficient ride sharing to reduce the number of cars on the road by up to 75%, and smart traffic lights that reduce wait times by 40% and overall travel time by 26% in a pilot study.").

94 *Id.* ("Can your inbox reply to emails for you? Google thinks so, which is why it introduced smart reply to Inbox in 2015, a next-generation email interface. Smart reply uses machine learning to automatically suggest three different brief (but customized) responses to answer the email.").

95 *See* Virginia Eubanks, *Caseworkers vs. Computers* (Dec. 11, 2013), https://virginia-eubanks.com/2013/12/11/caseworkers-vs-computers/ [https://perma.cc/G2LT-3JB8].

96 *See* Endo, *supra* note 21.

97 Narula, *supra* note 91 ("Reducing commute times is no simple problem to solve. A single trip may involve multiple modes of transportation . . . construction; accidents; road or track maintenance; and weather conditions can constrict traffic flow with little to no notice.").

98 Endo, *supra* note 21, at 834.

99 *See* Zetter, *supra* note 27.

100 *See* Kimberly A. Houser & Debra Sanders, *The Use of Big Data Analytics by the IRS: Efficient Solutions or the End of Privacy as We Know It?*, 19 VAND. J. ENT. & TECH. L. 817, 831 (2017).

101 *See* Eubanks, *supra* note 95.

102 *See Federal Courts Using Technology to Improve Juror Experience*, U.S. COURTS (May 5, 2017), https://www.uscourts.gov/news/2017/05/05/federal-courts-using-technology-improve-juror-experience [https://perma.cc/XX7E-ZF9V].

103 *See, e.g.*, Barocas & Selbst, *supra* note 43, at 720; Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 8, 32

Three central themes emerge among the proposed solutions: transparency, explainability, and accountability. A number of measures focus on developers and firms' creation of ADM platforms.[104] However, laudable proposals for intervention overlook existing and possibly more expedient internal corporate governance mechanisms that have long served to facilitate accountability for and careful oversight of endogenous and exogenous risks.

Part II examines the risk of bias created by integrating ADM platforms. Part III argues that corporate governance structures and processes employed to identify, assess, and manage risks may serve to mitigate bias in ADM platforms. Upon examining the rationale for process-oriented and structure reforms, this Article argues that firms regularly rely on corporate governance strategies to mitigate risk exposure. This Part demonstrates that firms have already integrated structural reforms that will enable greater internal oversight of ADM platforms.

Part III acknowledges some challenges that may impede the success of proposed structural and process-oriented reforms and identifies a number of remaining questions. Specifically, this Part recognizes that structural and process-oriented reforms face endemic cognitive biases and that these biases influence group decision-making, including leadership and senior programming decisions. Risk exposure related to bias claims may provide incentives for directors, senior managers, and developers to overcome the kinds of challenges that typically stymie organizational reforms.

Part IV contends that there are several pathways for achieving greater gender balance in firms adopting ADM platforms and argues that these pathways are consistent with commonly adopted structural and process-oriented reforms. This Part discusses California's gender equity leadership mandate for firms organized or doing business in California. While this and other proposals may not survive legal challenges, each creates an opportunity to explore an alternative rationale

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(2014); Mikella Hurley & Julius Adebayo, *Credit Scoring in the Era of Big Data*, 18 YALE J.L. & TECH. 148, 196 (2016); Odinet, *supra* note 40, at 843–57.

104 *See* Barocas & Selbst, *supra* note 43, at 675 ("Each of these steps creates possibilities for a final result that has a disproportionately adverse impact on protected classes, whether by specifying the problem to be solved in ways that affect classes differently, failing to recognize or address statistical biases, reproducing past prejudice, or considering an insufficiently rich set of factors."); Rebecca Greenfield & Riley Griffin, *Artificial Intelligence Is Coming for Hiring, and It Might Not Be That Bad*, BLOOMBERG (Aug. 8, 2018), https://www.bloomberg.com/news/articles/2018-08-08/artificial-intelligence-is-coming-for-hiring-and-it-might-not-be-that-bad [https://perma.cc/V84J-DSUR].

for and methodology to achieve greater inclusion and the potential for better governance to mitigate the risk that ADM platforms will operate in a manner that results in perilous forms of bias.

I. Digitized Decision-making

Similar to algorithms developed thousands of years ago, AI enhances the accuracy and efficiency of decision-making processes.[105] Unlike the earliest algorithms, however, AI enables machines or computers to imitate human cognitive intelligence.[106] Machine learning is a subset of AI methods that trains algorithms to improve on ADM processes, meaning the algorithm may assess the shortcomings in its decision-making process in early iterations and improve upon its analysis and predictions in later iterations.[107] This Part examines the application and implications of standard algorithms and machine learning algorithms as well as the limitations of this intriguing and rapidly evolving technology.

A. Adopting Algorithms

Early algorithms followed a simple but detailed series of commands.[108] According to Pedro Domingos, these algorithms followed three logical operations—"AND, OR, and NOT."[109] The algorithms completed specified tasks based on a limited set of instructions.[110] For example, financial market participants have long relied on algorithms to navigate the complex risks related to securities and commodities trading, securities underwriting, consumer lending, and syndicated commercial lending. While computer scientists' experiments with algorithms date back to the 1940s, the financial services industry intimately embraced algorithms 30 years later.[111]

In the mid-1970s, Wall Street traders began to develop and adapt trading algorithms based on the "designated order turnaround" or "DOT" system.[112] Around the same time, Fischer Black, Robert

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105 *See* Michael L. Rich, *Machine Learning, Automated Suspicion Algorithms, and the Fourth Amendment*, 164 U. Pa. L. Rev. 871, 880 (2016).

106 *See* Colonna, *supra* note 20.

107 *See* Rich, *supra* note 105.

108 *See id.*

109 Pedro Domingos, The Master Algorithm: How the Quest for the Ultimate Learning Machine Will Remake Our World 2 (2015).

110 Programmers coded the algorithms to respond to inquiries regarding a clearly defined data set or variables. *See id.*

111 Kristin N. Johnson, *Regulating Innovation: High Frequency Trading in Dark Pools*, 42 J. Corp. L. 833, 842–45 (2017).

112 *Id.* at 862.

Merton, and Myron Scholes developed a mathematical model (the "Black-Scholes Model") that gained international attention for predicting pricing in options markets.[113]

An instant success among elite Wall Street financial institutions, the Black-Scholes Model was a siren, enticing quantitative analysts to abandon math and science graduate teaching programs and join the race to craft the earliest computerized algorithms in finance.[114] While mathematical models for predicting pricing had long delivered outsized profits, the introduction of computer software programs designed to execute analytical processes ushered in a cornucopia of new financial products, business units, and revenue streams.[115]

During the last 20 years, two transformational developments in computer science engineering altered the prevalence of algorithms in markets—the aggregation of big data and the evolution of machine learning. First, algorithms that aggregate large volumes of current and historic market information have enhanced market participants' ability to engage in data analytics.[116] Access to big data enabled market participants to predict prepayment and default risk in credit markets or price movements in equity markets with greater precision.[117] Machines capable of consuming a greater diversity and larger quantity of variables, or big data, informs investment banking and conventional depository institutions' risk management and investment decision-making.[118] Second, as algorithms evolve beyond simple "if, then" statements towards machines mimicking human thinking or "artificial intelligence," market participants began developing automated systems.[119] This Part examines the impact of these two phenomena.

Although the phrase "big data" is ubiquitous in academic literature, the popular press, and conversations regarding the future of various government regulations,[120] there is little precision and much

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113 Merton and Scholes later received the Nobel Prize for their invaluable contribution to the development of the discipline of economics. *See* Press Release, Nobel Prize (Oct. 14, 1997), https://www.nobelprize.org/prizes/economics/1997/press-release/ [https://perma.cc/269H-E53Y].

114 Scott Patterson, The Quants: How a New Breed of Math Whizzes Conquered Wall Street and Nearly Destroyed It 2–12 (2010).

115 *See id.* (discussing several tycoons who made their way based on mathematical algorithms and the effect they had on the financial markets).

116 *See* Bruckner, *supra* note 40.

117 *See id.*

118 *See* Pasquale, *supra* note 46, at 4–5.

119 *See* Pasquale, *supra* note 46, at 129–31.

120 *See* Andrew Guthrie Ferguson, *Big Data and Predictive Reasonable Suspicion*, 163 U. Pa. L. Rev. 327, 383–84 (2015) (discussing how "big data invites provocative questions about whether such predictive tips should factor into the reasonable suspicion calculus").

confusion regarding the meaning of the term.[121] Pondering the divergent uses of the same term, Michael Rich observes that big data is frequently used interchangeably and confusingly with terms such as "data mining" and "knowledge discovery in databases."[122] Consequently, numerous scholars and commentators' analysis of algorithms and machine learning begins with a simple question regarding the fuel fed to these complex analytical machines: What, they ask, is big data?[123]

The rapid evolution of the notion of big data stymies efforts to adopt a universally understood definition.[124] According to many, big data "is a generalized, imprecise term that refers to the use of large data sets in data science and predictive analytics."[125] In other words, big data plays a significant role in the proliferation of predictive algorithms, yet, its meaning remains elusive.[126] Commentators sketch a portrait of big data that reflects involved and complex processes and methods, significant quantities of data, and rapid distribution.[127] In other words, big data is high volume, high variety, and high velocity.[128]

As Julie Cohen explains, big data is a "combination of a technology and a process."[129] Cohen depicts the technology component of big data as "a configuration of information-processing hardware capable of sifting, sorting, and interrogating vast quantities of data in very short times."[130] In conjunction with the information processing technology element of big data, Cohen identifies "a process component"

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121 *See* Rich, *supra* note 105.

122 *Id.*

123 *See* Margaret Hu, *Small Data Surveillance v. Big Data Cybersurveillance*, 42 PEPP. L. REV. 773, 776, 777 n.4 (2015) ("'Big data' is difficult to define, as it is a newly evolving field and the technologies that it encompasses are evolving rapidly as well.").

124 *See id.*

125 *Id.* at 794.

126 *See The Big Data Conundrum: How to Define It?*, MIT TECH. REV. (Oct. 3, 2013), http://www.technologyreview.com/view/519851/the-big-data-conundrum-how-to-define-it/ [https://perma.cc/3RTJ-YLB7].

127 In her analysis of national security cybersurveillance, Margaret Hu proposes juxtaposing early understandings of human-engineered intelligence, surveillance, and sensory gathered data—all forms of small data—with the attributes of big data. *See* Hu, *supra* note 123, at 800–04.

128 *See* Doug Laney, *3D Data Management: Controlling Data Volume, Velocity, and Variety*, META GRP. (Feb. 6, 2001), http://blogs.gartner.com/doug-laney/files/2012/01/ad949-3D-Data-Management-Controlling-Data-Volume-Velocity-and-Variety.pdf [https://perma.cc/UZH4-5QZH].

129 Julie E. Cohen, *What Privacy is For*, 126 HARV. L. REV. 1904, 1920 (2013).

130 *Id.*

that "involves mining the data for patterns, distilling the patterns into predictive analytics, and applying the analytics to new data."[131]

Some describe big data as "the storage and analysis of large or complex data sets using a series of techniques."[132] Smart phones, laptops, tablets, and personal mobile devices instantaneously and continuously transmit information, generating reams of big data.[133] Increasingly, the records in these data sets number in the billions.[134] These data sets aggregate records from, among other data sources, individual internet usage patterns, consumption, and retail shopping habits.[135] Algorithms reviewing gathered data may begin to mine it and predict certain patterns regarding the individual whose data is collected.[136]

Big data is "exhaustive in scope, striving to capture entire populations of systems," and "flexible, with traits of extensionality . . . and scalability."[137] The large scale of big data is found in the quantity and variety of information available to be processed; most agree that big data relies on machine learning, supercomputing, and AI tools, which allow big data to exceed the ability of human capacity.[138] In fact, common definitions of big data explain that it "expressly or implicitly precludes human storage and processing capacity."[139] To the contrary, "small data" includes things humans can analyze, create, and perceive with human senses or based on human judgment.[140]

According to Dave Farber, the "Grandfather of the Internet," corporations and government agencies are the predominant consumer of big data; these two major consumers of big data have starkly con-

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131 *Id.*

132 Hu, *supra* note 123, at 794 ("'Big Data' is shorthand for the combination of a technology and a process. The technology is a configuration of information-processing hardware capable of sifting, sorting, and interrogating vast quantities of data in very short times.").

133 *See id.* at 788 n.38.

134 *See id.* at 805.

135 *See, e.g.*, Noreen Malone, *The Algorithm Knows Me. So Why Does It Keep Shaming Me?*, N.Y. MAG. (Oct. 11, 2018), http://nymag.com/intelligencer/2018/10/algorithm-shame-the-feeling-of-being-seen-by-the-algorithm.html [https://perma.cc/KL82-W45D] (discussing how algorithms draw data on individuals concerning internet usage and consumer product consumption).

136 *See* Hu, *supra* note 123, at 791–92 (collecting sources on "predictive technologies" using big data).

137 *Id.* at 795.

138 *See id.* at 796.

139 *See id.* at 798 ("[I]f a human can comprehend the data without computing and algorithmic assistance, it is not big data.").

140 *Id.* at 795.

trasting incentives.[141] Corporations, according to Farber, use the data for commercially beneficial insights while government agencies examine it for evidence of suspicious activity.[142] The unquenchable thirst for big data has spawned an interest in alternative sources of data, such as individual social media profiles, streamed music preferences, and friendship and kinship networks.[143] Increasingly, processes that combine analytical evaluation of big data and small or alternative data have become the definition of efficient decision-making and production.[144]

B. Adapting Algorithms: Machine Learning, Deep Learning, and Neural Networks

Parallel to advances in data aggregation and mining technology, developers and their benefactors invested significant human capital and financial resources in the development of learning algorithms.[145] Engineers and later computer scientists began developing the methods now commonly referred to as "artificial intelligence" or "AI"; these methods involve supervised and unsupervised learning or profoundly complex analysis (advanced regressions and categorization of data).[146] AI processes involve computers or other machines analyzing vast quantities of data and engaged in reinforced learning.[147] AI technologies may aggregate big data[148] or analyze information gathered and processed through voice or image data.[149]

Machine learning automatically detects patterns in data, and upon discovering patterns, it applies these patterns to predict future outcomes based on the supplied data.[150] These methods engage in

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141 John Horgan, *U.S. Never Really Ended Creepy "Total Information Awareness" Program*, SCI. AM. (June 7, 2013), http://blogs.scientificamerican.com/cross-check/2013/06/07/u-s-never-really-ended-creepy-total-information-awareness-program/ [https://perma.cc/3TK9-43V9]; *see also* Hu, *supra* note 123, at 791.

142 *Id.* at 797.

143 *See, e.g.*, Malone, *supra* note 135 (discussing how algorithms use data from social networks and other online sources to draw conclusions about individuals).

144 *See* Hu, *supra* note 123, at 798–99.

145 Surden, *supra* note 52, at 89–90 (explaining that "'[m]achine learning' refers to a subfield of computer science concerned with computer programs . . . [that] are capable of changing their behavior to enhance their performance on some task through experience").

146 *See* TREASURY REPORT, *supra* note 21, at 53.

147 *See id.*

148 *See* Angwin et al., *supra* note 51.

149 *See* TREASURY REPORT, *supra* note 21.

150 KEVIN P. MURPHY, MACHINE LEARNING: A PROBABILISTIC PERSPECTIVE 1 (2012).

complex decision making and apply logic to resolve indicated questions.[151]

As Michael Rich explains, classical machine learning involves an algorithm engaged in "continuous improvement on a given task" or "learning"; this, he says,

> differs from the more holistic concept referred to when people speak of human learning. In particular, machine learning does not require a computer to engage in higher-order cognitive skills like reasoning or understanding of abstract concepts. Rather, machine learning applies inductive techniques to often-large sets of data to 'learn' rules that are appropriate to a task. In other words, the 'intelligence' of a machine learning algorithm is oriented to outcomes, not process: a 'smart' algorithm reaches consistently accurate results on the chosen task even if the algorithm does not 'think' like a person.[152]

Machine learning is concerned with the development of algorithms and techniques for building computer systems that can automatically improve with experience and solve problems, particularly the complicated, ill-defined ones.[153] Learning algorithms model human cognitive processes and analyze complex data sets to predict future outcomes.[154] Through the wonder of AI technology, machines and computers see, hear, think, and make decisions in a manner similar to humans.[155] Machine learning technologies reflect efforts to train a nonhuman machine, computer, or robot to understand data and evolve in its ability to evaluate the data and predict outcomes.

Data scientists have explored the foundation for statistical analysis through multivariate data in two phases: features and classification. Feature selection reduces dimensions of or eliminates relevant features from an original dataset.[156] Classification sorts raw data or selected features using algorithms.[157]

Classification is a supervised machine learning process that is distinct from a learning process algorithm; it learns from data already labeled with the target "feature."[158] "Features, in turn, are the 'lan-

151 *See id.*

152 Rich, *supra* note 105, at 880 (footnotes omitted).

153 *See* Hurley & Adebayo, *supra* note 103, at 159–60.

154 *See* Rich, *supra* note 105, at 881.

155 Treasury Report, *supra* note 21, at 53.

156 *See* Rich, *supra* note 105, at 881.

157 *See id.*

158 *Id.*

guage' that machine learning algorithms uses [sic] to describe the objects within its domain."[159] The only limitation placed on features is that they must be measurable; the program then creates a model based on the data set that is later used to predict the proper classification of future objects.[160] The process can be further explained as follows: the initial dataset is subdivided into a training set, verification set or validation set, and a test set.[161]

The algorithm begins by analyzing the training set, thereby learning the initial group classification rules.[162] "These rules are then applied to a validation or verification set," and the results are then "used to optimize the rules' parameters."[163] Finally, "the optimized rules are applied to the test set," the results of this stage establishing a confidence level and support level for each rule.[164] Rules with low support levels are considered less statistically significant.[165] Confidence levels are based on how often objects in the test set follow the rule thus measuring the strength of the algorithm's prediction.[166]

The key to developing the algorithms used in these situations is training by evaluating the output of each algorithm with the desired result; this allows the machine to learn by making its own connections within available data. This process occurs with little human interference, being that the very nature of machine learning is one that takes the human element largely out of embedding correlations and inferences in an algorithm.[167]

"[B]y exposing so-called 'machine learning' algorithms to examples of the cases of interest (previously identified instances of fraud, spam, default, and poor health) the algorithm 'learns' which related attributes or activities can serve as potential proxies for those qualities or outcomes of interest."[168] This enables algorithms that analyze data to "become more accurate over time when completing a task."[169]

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159 *Id.*

160 *Id.*

161 *Id.* at 871.

162 *Id.* at 882.

163 *Id.*

164 *Id.*

165 *Id.* ("[T]o restrict which rules the algorithm will use to ensure predictions are made only on the basis of statistically significant correlations, programmers often require rules to meet a minimum support level.").

166 *Id.*

167 *See* Lehr & Ohm, *supra* note 48, at 664.

168 Barocas & Selbst, *supra* note 43, at 678.

169 Rich, *supra* note 105, at 880.

Machine learning methods are becoming more pervasive throughout society.[170] Such methods are used in a variety of classification tasks from identifying spam emails to diagnosing diseases.[171] Reducing the role of human agents or failing to ensure that there is a "human in the loop" increases the likelihood that data mining systems will reproduce the historic biases embedded in the data.[172]

This Part has explored the technology that creates and big data that fuels ADM platforms. As discussed above, there is significant potential for ADM technology to create a pathway for inclusiveness. Yet, as the next Part explains, early evidence suggests that without effective oversight this nascent technology may create enterprise risks for businesses integrating ADM platforms, including the regulatory, litigation, and reputational risks that arise as a result of algorithms operating in a manner that leads to bias against marginalized and vulnerable consumers.

II. Risking Bias

ADM technology engenders important benefits—faster, more efficient, and more accurate data analytics that reduce transaction costs and a number of significant business and legal risks.[173] Fintech lenders, for example, laud ADM as a pathway to increase credit access for those who have been marginalized by traditional credit scoring and lending models.[174] As this Part discusses, however, the unmonitored integration of ADM platforms influencing access to employment, credit, and housing opportunities or government benefits leads to noteworthy concerns.

Arguing that corporations or governments may attempt to hide behind the complexity of the underlying algorithms to exploit, discriminate, or engage in other unethical behavior, commentators have raised alarms.[175] Even when developers have laudable intentions such

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170 Bruce Schneier, *Autonomous Everything: How Algorithms Are Taking Over Our World*, Literary Hub (Oct. 1, 2018), https://lithub.com/autonomous-everything-how-algorithms-re-taking-over-our-world/ [https://perma.cc/E5SQ-HWZ5].

171 Rich, *supra* note 105, at 882.

172 Andrew D. Selbst, *Disparate Impact in Big Data Policing*, 52 Ga. L. Rev. 109, 115–16 (2017).

173 *See* Mary Ellen Biery, *3 Benefits of Automating Loan Decisions*, Abrigo (June 2, 2019), https://www.abrigo.com/blog/2018/09/17/3-benefits-of-automating-loan-decisions/ [https://perma.cc/CN5W-ZHMU].

174 *See* Ashoka, *Banking the Unbanked: A How-to*, Forbes (June 14, 2013), https://www.forbes.com/sites/ashoka/2013/06/14/banking-the-unbanked-a-how-to/#1e9291885727 [https://perma.cc/N8QJ-4JVW].

175 Eubanks, *supra* note 44, at 11–12; Noble, *supra* note 44.

as promoting access to resources or reducing discrimination, analysis of facially neutral data may lead to outcomes that negatively affect protected classes. As the earlier examples of Amazon's hiring platform and the risk assessment algorithm deployed by COMPAS indicate, bias may creep into ADM processes.[176]

Over the last several years, scholars and data scientists have developed a carefully crafted and detailed portrait of the potential for big data analytics to lead to biased, unfair, or prejudicial outcomes. Deconstructing the technical aspects of ADM, scholars have identified several stages in the development process of ADM platforms where programmers may unintentionally incorporate bias: inputs, training, and programming.

Input bias stems from the limitations inherent in source data. Data sets used to train machine learning algorithms may be incomplete or reflect historical biases.[177] As data sets are programmed into an ADM platform, bias in the data sets becomes hardwired into the platform. Training bias arises as a result of the "categorization of the baseline data or the assessment of whether the output matches the desired result."[178] Programming bias arises from the original design or the self-modification of the algorithm "through successive contacts with human users, the assimilation of existing data, or the introduction of new data."[179]

Firms that integrate data sets into ADM platforms often purchase the data sets from third parties who have collected the underlying data.[180] The third-party vendors who aggregate data may intend for others to use the data for specific types of analysis. Third party vendors who create data sets may be unaware of developers' intentions regarding the application of the acquired data. Consequently, third party vendors may fail to emphasize, and developers may ignore, the limits of acquired data sets.[181]

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176 *See supra* notes 57–63 and accompanying text.

177 *See* Bass & Huet, *supra* note 65. In some instances, the biases arise because the data set is flawed (i.e., fails to include a specific kind of data). For example, communities and activists sharply criticized Google after an early stage facial recognition software began classifying African-Americans in photographs as gorillas because of the limited examples of individuals with darker complexions in the data sets used to train its proprietary search platform. *See id.*

178 Kevin Petrasic et al., *Algorithms and Bias: What Lenders Need to Know*, WHITE & CASE (2017), https://www.whitecase.com/publications/insight/algorithms-and-bias-what-lenders-need-know [https://perma.cc/WT7E-ZAXG].

179 *Id.*

180 Lisa Rice & Deidre Swesnik, *Discriminatory Effects of Credit Scoring on Communities of Color*, 46 SUFFOLK U. L. REV. 935, 950 (2013).

181 *Id.*; *see also* Bass & Huet, *supra* note 65.

Data scientists and commentators have discovered that unanticipated uses of data sets may result in correlations between characteristics that unintentionally serve as proxies for the characteristics ascribed to protected classes. According to Barocas and Selbst:

> [A]n algorithm is only as good as the data it works with. Data is frequently imperfect in ways that allow these algorithms to inherit the prejudices of prior decision makers. In other cases, data may simply reflect the widespread biases that persist in society at large. In still others, data mining can discover surprisingly useful regularities that are really just preexisting patterns of exclusion and inequality.[182]

As a result, even when predictive analytics do not expressly consider a protected characteristic such as race, data sets integrated into ADM platforms may still perform in a manner that has a disparate impact on protected groups.[183] To address concerns regarding bias, scholars, commentators, and regulators propose a number of solutions designed to engender algorithmic accountability. Danielle Citron and Frank Pasquale emphasize the need for "technological due process" or transparency and human oversight of ADM platforms to ensure equitable outcomes.[184] While commentators use varying language to describe efforts intended to ensure accountability,[185] proposed re-

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182 Barocas & Selbst, *supra* note 43, at 671. According to Barocas and Selbst:

> Unthinking reliance on data mining can deny historically disadvantaged and vulnerable groups full participation in society. Worse still, because the resulting discrimination is almost always an unintentional emergent property of the algorithm's use rather than a conscious choice by its programmers, it can be unusually hard to identify the source of the problem or to explain it to a court.

Id.

183 *See id.*; *see also* Moritz Hardt, *Approaching Fairness in Machine Learning*, MOODY RD (Sept. 6, 2016), http://blog.mrtz.org/2016/09/06/approaching-fairness.html [https://perma.cc/M8CJ-TMLX].

184 Citron & Pasquale, *supra* note 103.

185 There are ways to make algorithms more explainable. First, you can use a simpler class of models—one with a less complex optimization process. Lehr & Ohm, *supra* note 48, at 692. Additionally, an analyst can generate graphical plots that indicate how important different input variables were to the predictions and how changes in the values of input variables tend to be translated into changes in the outcome variable. Further, you can use model-agnostic approaches. *Id.* at 693. Model-agnostic approaches are essentially black box explainers and may, in principle, be applied to any model. Additionally, you can use sensitivity analysis. Andrew D. Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085, 1114 (2018). This is an approach that is applied in many domains to understand the behavior of not just models, but any opaque, complex system. *Id.* The simplest approach is to marginally alter (perturb) a single input feature and measure the change in model output. This gives a local feature specific, linear approximation of the model's response. By repeating this process for many values, a more extensive picture of model behavior can be built up. Most explanations are limited to a list or graphical representation of the main features that influenced a decision and

forms typically encourage one of two normative principles: transparency or explainability.[186]

Transparency may refer to a number of different types of reforms. Some proposals equate transparency with greater access to information regarding programming code or data.[187] The details regarding these algorithms and their operation are often carefully guarded and rarely disclosed.[188] Consequently, many describe these algorithms shrouded in secrecy as black boxes.[189]

Responding to the opacity that characterizes ADM platforms, consumers, consumer advocates, regulators, and other stakeholders call for transparency and demand that firms embracing complex algorithms reveal the details of the operational mechanics and effects of their ADM platforms.[190] A number of reform proposals introduce monitoring requirements including voluntary or federally mandated audits of ADM processes.[191] An important set of proposals suggests a sliding scale for evaluating ADM processes, demanding transparency where the platforms have the potential to significantly influence markets and cause noteworthy harm.[192]

Others have proposed incorporating audits executed by internal compliance programs or third party auditors.[193] An audit may identify data that correlates with protected characteristics and may therefore serve as a proxy for an attribute of legally protected classes.[194] Federal regulatory agencies and private actors have endorsed auditing programs.[195] The Office of Technology Research and Investigation of the Federal Trade Commission has proposed a transparency-driven regu-

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their relative importance. Presenting feature importance in these ways largely ignores the details of interactions between features, so even the richest explanations based on this approach are limited to relatively simple statements.

186 *Id.*; *see also* Selbst & Barocas, *supra* note 185, at 1090. In some instances, scholars and commentators describe transparency and explainability as distinguishable. In other instances, the terms are used almost interchangeably. *Id.*

187 *See id.* at 1093.

188 *See id.* at 1092.

189 *See id.* at 1117.

190 *See* Citron & Pasquale, *supra* note 103, at 8.

191 *See id.* at 25.

192 *See* Julie Brill, Commissioner, Fed. Trade Comm'n, Remarks at the NYU Conference on Algorithms and Accountability: Scalable Approaches to Transparency and Accountability in Decision-making Algorithms (Feb. 28, 2015), https://www.ftc.gov/system/files/documents/public_statements/629681/150228nyualgorithms.pdf [https://perma.cc/6JQ7-8GKG].

193 *See* Barocas & Selbst, *supra* note 43.

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

195 *See* Brill, *supra* note 192.

latory approach.[196] Academics and advocates similarly demand disclosure[197] and offer suggestions regarding the implementation of data and algorithmic audits. Removing the veil of secrecy, advocates argue, better enables regulators to determine whether the ADM platform will engender biased outcomes.[198]

Frank Pasquale—author of *The Black Box Society*, demands greater accountability from firms developing proprietary ADM platforms.[199] Pasquale argues that reformers must demand the elimination of ADM platforms that engender biased outcomes.[200] According to Pasquale,

> access to data is just the first and smallest step toward fairness in a world of pervasive digital scoring, where many of our daily activities are processed as 'signals' for rewards or penalties, benefits or burdens. Critical decisions are made not on the basis of the data per se, but on the basis of data analyzed algorithmically . . . . Failing clear understanding of the algorithms involved—and the right to challenge unfair ones—disclosure of underlying data will do little to secure reputational justice.[201]

Other proposed reforms demand greater algorithmic accountability than may be required under common perceptions of transparency and explainability. Some seek regular disclosures regarding the classes and categories of the data ADM platforms collect, the sources of this data, the collection methods used, and the particular data points their model treats as significant.[202] Borrowing from existing remedies to bias, some advocate for "algorithmic impact assessments"—requiring public disclosure of the ADM platforms and allowing outside researchers to independently analyze the platforms for bias.[203] Proponents of reform also aim to require developers and users to maintain certain standards of accuracy and conduct regular reviews of their data to self-certify that they are in compliance.[204]

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196 *Id.* (arguing that "[c]onsumers should be able to exercise appropriate control over information that goes into the pipelines that feed the algorithms that end up having an effect on their lives" and advocating for legislation to address the lack of transparency in AI and concerns regarding the role of data brokers).

197 *See* O'Neil, *supra* note 46.

198 *See* Kim, *supra* note 194.

199 *See* Pasquale, *supra* note 46, at 150.

200 *See id.* at 153.

201 *Id.* at 21–22.

202 *See* Hurley & Adebayo, *supra* note 103, at 197.

203 *See* Rieland, *supra* note 50.

204 *See* Hurley & Adebayo, *supra* note 103, at 198–99.

These policies shift the burden to the company and developer to ensure proper use of data sets.[205] These safeguards would ultimately result in what has been called "technological due process," or "procedures ensuring that predictive algorithms live up to some standard of review and revision to ensure their fairness and accuracy."[206]

In a few instances, industry participants have galvanized around establishing industry standards regarding notions of transparency. The National Institute of Standards and Technology ("NIST") tests the accuracy of facial recognition systems using the Face Recognition Vendor Test ("FRVT").[207] The FRVT tests the accuracy of facial recognition systems in different scenarios.[208]

The FRVT is, however, entirely voluntary, meaning vendors are not required to submit their algorithms for testing.[209] In fact, to date, only smaller firms have submitted algorithms to NIST for testing and commercial firms, claiming to protect proprietary technology, have not.[210] NIST also has limited resources and therefore, likely lacks capacity to execute wide scale testing. Many argue that such an approach would require legislative action and federal funding. Finally, deep learning algorithms will not be subject to testing methodologies such as FRVT.[211] Deep learning algorithms train on data sets that are continuously evolving, and therefore, cannot be easily transferred for testing.[212]

Each of these proposals invites external oversight of ADM platforms. While valuable, external reforms have notable limitations. Creating a comprehensive response to the growing dominance of algorithmic platforms will simply require time, careful investigation regarding data collection, cleansing, integration, and platform operational mechanics. Reforms may require the development of national or international standards for audits, certification, or disclosure rules, which may take years to implement. Voluntary disclosure reforms may

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205 *Id.*

206 Citron & Pasquale, *supra* note 103, at 19 (citing Danielle Keats Citron, *Technological Due Process*, 85 Wash. U. L. Rev. 1249, 1260–63 (2008)).

207 *Face Recognition Vendor Test*, NIST (Apr. 2, 2010), https://www.nist.gov/programs-projects/face-recognition-vendor-test-frvt [https://perma.cc/EGQ4-8Y3H].

208 *Id.*

209 *Id.*

210 *See* Patrick Grother et al., *Ongoing Face Recognition Vendor Test (FRVT) Part 2: Identification*, NIST (Nov. 2018), https://doi.org/10.6028/NIST.IR.8238 [https://perma.cc/RDX6-ETGT].

211 *See id.* (discussing the specific comparison sets used and limited nature of the testing that may be indicator of difficulty dealing with more complex algorithms).

212 *See supra* Section I.B.

be difficult to enforce and may fail to create sufficient incentives for firms to comply. A more expedient path may exist for reforming ADM platforms.

The next Part argues that corporate governance reforms have long enabled regulators to introduce relatively prompt and often effective self-regulation and disclosure by publicly traded firms subject to federal regulatory oversight.

III. Structural and Process-Oriented Reforms

Conventional enterprise risk management theory encourages firms that integrate ADM platforms to mitigate the risk that algorithms will operate in a biased manner. This Part argues that firms are already adapting to address the risk of bias, and an emphasis on risk management through corporate governance may offer an expeditious path to address concerns regarding bias.

This Part begins by examining the structure of corporate boards and describing the role of directors and managers. Next, this Part argues that structural reforms must be accompanied by process-oriented reforms. This Part concludes by acknowledging the limits to both structural and process-oriented reforms.

A. Managing Risk: Corporate Governance Reforms

State law assigns decision-making authority to the boards of directors of corporations.[213] State statutes direct the owners of the corporation to elect a board of directors and empower the board to make important decisions on behalf of the owners.[214] Moreover, state courts and lawmakers accord significant deference to boards of directors regarding the execution of their duties.[215] The board may rely on briefings from senior executive officers before making important decisions, but decision-making authority remains with the board.[216]

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213 *See, e.g.*, Del. Code Ann. tit. 8, § 141(a) (2018). Section 141(a) of Delaware General Corporation Law, for example, recognizes the board of directors as the primary decision-making authority in the corporation and provides that a corporation's "business and affairs . . . shall be managed by or under the direction of a board of directors." *Id.*

214 *See, e.g.*, *id.*

215 *See, e.g.*, Shlensky v. Wrigley, 237 N.E.2d 776, 781 (Ill. App. Ct. 1968) ("Directors are elected for their business capabilities and judgment and the courts cannot require them to forego their judgment because of the decisions of directors of other companies. Courts may not decide these questions in the absence of a clear showing of dereliction of duty on the part of the specific directors.").

216 *See* Tamar Frankel, *Corporate Boards of Directors: Advisors or Supervisors?*, 77 U. Cin. L. Rev. 501, 504 (2008).

Among other duties, boards manage the internal affairs of corporations by monitoring a corporation's performance, assisting in strategic decisions, and offering advice to the executive officers of the corporation.[217] The board's monitoring role encompasses oversight and management of known risks.[218] For firms integrating ADM platforms, concerns that the businesses' operations may result in bias against a legally protected class and result in litigation alleging discrimination is a known risk[219] that the board must manage[220] and, preferably, mitigate.[221]

B. Structural Board Reforms

The internal structural organization of a firm creates a framework for the business to make decisions. For Delaware corporations, the internal structural organization consists of the board of directors and officers of the corporation.[222] These individuals have authority to make key decisions regarding the firm's operations and are therefore accountable for the risks the firm takes and the results that follow.[223]

In December 2007, a global economic recession ensconced financial markets, reducing U.S. real gross domestic product by 4.3% and doubling unemployment.[224] During the crisis, U.S. households' net worth fell by nearly $15 trillion.[225] On September 15, 2008, after losing $2.8 billion in a single quarter and notwithstanding the firm's $639 billion in assets, Lehman Brothers filed for Chapter 11 protection,

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217 Colin B. Carter & Jay W. Lorsch, Back to the Drawing Board 67–68 (2004) (discussing three key functions of a board: monitoring performance, making key decisions, and giving advice).

218 Johnson, supra note 91, at 78–92.

219 Risk, broadly defined, describes an element of uncertainty regarding future outcomes. Risks arise in response to endogenous and exogenous conditions. Philippe Jorion, Value at Risk: The New Benchmark for Managing Financial Risk 3 (3d ed. 2007); *see also* Frank H. Knight, Risk, Uncertainty and Profit 15 (1921) (describing risk as calculable or measurable outcomes that may be expressed as numerical probabilities and distinguishing risk from uncertainty, which refers to random outcomes that occur in an unpredictable manner and may not be quantified).

220 Risk management refers to efforts to measure, monitor, and mitigate risk. Risk management focuses on estimating the probability and magnitude of risks that lead to losses. Risk management strategies typically analyze important classes of risk including market risk, credit risk, and cyber risk. *See generally* Jorion, *supra* note 219.

221 *See* Petrasic et al., *supra* note 178.

222 Del. Code Ann. tit. 8, §§ 141(a), 142(a) (2018).

223 *See id.*

224 Robert Rich, *The Great Recession: December 2007–June 2009*, Fed. Res. Hist. (Nov. 22, 2011), https://www.federalreservehistory.org/essays/great_recession_of_200709 [https://perma.cc/NFL5-UUQF].

225 *Id.*

marking the largest corporate bankruptcy in the history of the nation.[226] Eleven days later, another large financial institution that had been in operation for over a century—Washington Mutual—entered into receivership with the Federal Deposit Insurance Corporation.[227]

Responding to the catalysts that triggered the financial crisis, Congress enacted the nearly 1,000 page Dodd-Frank Wall Street Reform and Consumer Protection Act ("Dodd-Frank Act").[228] The preamble of the Dodd-Frank Act affirms congressional intentions to "promote the financial stability of the United States by improving accountability and transparency in the financial system."[229] Notwithstanding its unprecedented length, scope, and breadth, the outline for regulation imposed by the Dodd-Frank Act generally aims to prioritize financial market firms' accountability and risk management oversight.[230]

Section 972 of the Dodd-Frank Act introduces a significant structural postcrisis reform requiring publicly traded firms to "comply-or-explain" their decision to allow the same person to hold the position of Chief Executive Officer ("CEO") and serve as Chairman of the Board. Under Section 972 and the final rule adopted by the Securities Exchange Commission implementing this provision, publicly traded companies must disclose the decision to allow one person to serve as both CEO and Chairman of the board of directors ("CEO duality").[231]

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226 Jonathan Stempel, *Lehman Payout Tops $80 billion, Creditors Get Another $17.9 Billion*, REUTERS (Mar. 27, 2014), https://www.reuters.com/article/us-lehman-bankruptcy/lehman-payout-tops-80-billion-creditors-get-another-17-9-billion-idUSBREA2Q1DD20140327 [https://perma.cc/C8MU-EBV3].

227 *Status of Washington Mutual Bank Receivership*, FDIC (Mar. 22, 2018), https://www.fdic.gov/bank/individual/failed/wamu-settlement.html [https://perma.cc/7S8N-YGBR].

228 Dodd-Frank Wall Street Reform and Consumer Protection Act, Pub. L. No. 111-203, § 929-Z, 124 Stat. 1376, 1871 (2012) (codified at 15 U.S.C. § 780).

229 *Id.*

230 *See id.* Similar to legislative action adopted in the wake of the Enron, Tyco, and Worldcom accounting scandals in the late 1990s, Congress abandoned a long history of respecting corporate governance as the purview of state legislatures and imposed federal statutes mandating structural board reforms. *See* MARC I. STEINBERG, THE FEDERALIZATION OF CORPORATE GOVERNANCE 20–24 (2018); *see also* Dan Ackman, *WorldCom, Tyco, Enron—R.I.P.*, FORBES (July 1, 2002, 9:32 AM), https://www.forbes.com/2002/07/01/0701topnews.html#4e9ebdb15397 [https://perma.cc/4DDZ-F5J3]; Floyd Norris, *A Crime So Large It Changed the Law*, N.Y. TIMES (July 14, 2005), https://www.nytimes.com/2005/07/14/business/a-crime-so-large-it-changed-the-law.html [https://perma.cc/78MB-84B3].

231 17 C.F.R. § 229.407(h) (2012). Section 229.407(h) obligates companies to

> [b]riefly describe the leadership structure of the [company's] board, such as whether the same person serves as both principal executive officer and chairman of the board, or whether two individuals serve in those positions, and, in the case of a [company] that is an investment company, whether the chairman of the board is an

Decades prior to the recent financial crisis, a growing trend favored CEO duality.[232] In the years immediately before the financial crisis, CEO duality had become far less popular.[233] More than other postcrisis corporate governance reforms, Section 972 aimed to influence the structure of the board of directors of publicly traded companies.

While requiring disclosure does not prohibit publicly traded companies from adopting a particular approach, the increased transparency creates pressure for firms adopting CEO duality to defend their decision. Firms would also have to explain how they would address conflicts of interest that arise because the CEO also serves as Chairman of the Board.

Section 972 reflects legislators and regulators' willingness to implement corporate governance reforms that alter the structure of the board of directors. Two critical observations presumably motivated legislators and regulators' efforts to steer publicly traded companies away from CEO duality. First, risk management demands practices that constitute effective corporate governance.[234] Second, because structural reforms may enhance corporate governance, they may also improve risk management oversight.[235]

An example illustrates the rationale for concluding that CEO duality undermined good corporate governance and plagued numerous financial institutions in the years leading to the recent financial crisis. Consider Countrywide Financial Corporation ("Countrywide"), a mortgage lender that originated exceptional volumes of subprime mortgage loans prior to the recent financial crisis.[236] The company's annual report on Form 10-K filed with the Securities and Exchange Commission reveals that Angelo Mozilo, a cofounder of Countrywide, served as CEO and Chairman of the board of directors of the com-

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> "interested person" of the [company] as defined in section 2(a)(19) of the Investment Company Act (15 U.S.C. § 80a-2(a)(19)).

Id.

232 *See Spencer Stuart Board Index*, SPENCERSTUART (2016), https://www.spencerstuart.com/~/media/pdf%20files/research%20and%20insight%20pdfs/spencer-stuart-us-board-index-2016.pdf [https://perma.cc/Y7D5-P3ME].

233 *See id.*

234 *See* Paul Rose, *Regulating Risk by "Strengthening Corporate Governance*,*"* 17 CONN. INS. L.J. 1, 1 (2011).

235 *See id.*

236 *See* Jeff Madrick & Frank Partnoy, *Should Some Bankers Be Prosecuted?*, N.Y. REV. BOOKS (Nov. 10, 2011), https://www.nybooks.com-articles-2011-11-10-should-some-bankers-be-prosecuted-? [https://perma.cc/RC4D-T6CB].

pany for the decade leading to the financial crisis.[237] Prior to his elevation to the two positions (CEO and Chairman) Mozilo held the title of President at Countrywide.[238]

Veteran bankers acknowledged that industry participants were blinded by their eagerness for a "high and quick return."[239] The Financial Crisis Inquiry Commission Report documents veteran bankers' reservations and discomfort regarding the "pure lunacy" of mortgage markets and investment banks' "voracious" appetite for mortgage-backed investment opportunities.[240] Mozilo was publicly excoriated as one of the real villains of the subprime scandal; postcrisis revelations of his greed and rejection of risk management best practices in pursuit of higher equity returns shocked the nation.[241] His absolute and near-authoritarian position at Countrywide eliminated any check on his avarice as the mortgage originator lurched toward calamity.

The Dodd-Frank Act's structural reforms signal a marked shift in the trend against duality. Traditional agency theory posits that managers are agents of the corporation and should endeavor to maximize the interest of the shareholders who are the corporation's principals.[242] Scholars and commentators point to traditional agency theory and argue that CEO duality stymies the effectiveness of the board by endorsing an inherent conflict for the CEO and Chairman.[243] For publicly traded companies, the board is a critical vehicle for monitoring compliance with affirmative legal obligations and other critical nonle-

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237 Countrywide Fin. Corp., Annual Report (Form 10K/A) (2007), http://fcic-static.law.stanford.edu/cdn_media/fcic-docs/2008-04-24%20Countrywide%202007%2010-K.pdf [https://perma.cc/PTQ6-C2XK].

238 *Id.*

239 NAT'L COMM'N ON THE CAUSES OF THE FIN. AND ECON. CRISIS IN THE U.S., THE FINANCIAL CRISIS: INQUIRY REPORT 4 (2011) [hereinafter INQUIRY REPORT].

240 *See id.* at 4 n.7.

241 ANDREW ROSS SORKIN, TOO BIG TO FAIL: THE INSIDE STORY OF HOW WALL STREET AND WASHINGTON FOUGHT TO SAVE THE FINANCIAL SYSTEM AND THEMSELVES 251–52 (2009); *see also* BETHANY MCLEAN & JOE NOCERA, ALL THE DEVILS ARE HERE 304 (2011) ("In January 2008, Bank of America acquired Countrywide for $4 billion; less than a year earlier its market capitalization had been more than six times that amount, at nearly $25 billion. During the second half of 2007, Countrywide took $5.2 billion in write-downs and increases to loan loss reserves, according to a shareholder lawsuit later filed against the company. The write-downs essentially wiped out Countrywide's earnings for 2005 and 2006.").

242 *See* Michael C. Jensen & William H. Meckling, *Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure*, 3 J. FIN. ECON. 305, 308–10 (1976).

243 *See* Dan R. Dalton et al., *The Fundamental Agency Problem and Its Mitigation*, *in* THE ACADEMY OF MANAGEMENT ANNALS 1, 1 (2007); Dan R. Dalton et al., *Meta-Analytic Reviews of Board Composition, Leadership Structure, and Financial Performance*, 19 STRATEGIC MGMT. J. 269, 282 (1998).

gal expectations that expose the company to undesirable risks.[244] Proponents of Section 972 contend that nonduality—separation of the CEO and chair positions—reduces agency costs, provides a necessary check for monitoring and disciplining the CEO, and better aligns senior executives' and long-term shareholders' interests.[245]

While the normative appeal for nonduality is clear, critics challenge the presumption that adoption of Section 972 engenders the anticipated results. Stephen Bainbridge posits that "proponents of a mandatory nonexecutive chairman of the board have overstated the benefits of splitting the positions, while understating or even ignoring the costs of doing so."[246] Empirical evidence suggests nonduality has little effect on firms' performance.[247] According to one study, "there is no difference in performance between firms with total nonduality during the period and firms with total duality."[248]

More concretely, critics claim that there is little evidence that board independence and decision-making improve a company's performance. Studies evaluating board independence among firms that adopt duality and firms that separate the roles and require a different person to serve in each role reveal mixed and inconclusive results.[249] In his testimony before Congress on the question of duality, John Coates explained that "[t]he only clear lesson from these studies is that there has been no long-term trend or convergence on a split chair/CEO structure."[250]

Notwithstanding the lack of evidence that nonduality enhances firm performance, few would dispute that separating the roles improves risk management oversight. Like his peers with dual CEO and

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244 *See* Arthur R. Pinto, *Corporate Governance: Monitoring the Board of Directors in American Corporations*, 46 Am. J. Comp. L. 317, 326–27 (1998) (discussing the board's fiduciary duty to shareholders and how the board is meant to monitor the company's managers).

245 *See* Jianyun Tang, *CEO Duality and Firm Performance: The Moderating Roles of Other Executives and Blockholding Outside Directors*, 35 Eur. Mgmt. J., 362, 363 (2017).

246 Stephen M. Bainbridge, *Dodd-Frank: Quack Federal Corporate Governance Round II*, 95 Minn. L. Rev. 1779, 1799 (2011).

247 B. Ram Baliga et al., *CEO Duality and Firm Performance: What's the Fuss?*, 17 Strategic Mgmt. J. 41, 49–50 (1996); *see* Brian K. Boyd, *CEO Duality and Firm Performance: A Contingency Model*, 16 Strategic Mgmt. J. 301, 302 (1995); Robert W. Rutledge et al., *The Effects of Board Independence and CEO Duality on Firm Performance: Evidence from the NASDAQ-100 Index with Controls for Endogeneity*, 18 J. Applied Bus. & Econ. 49 (2016); Tang, *supra* note 245, at 369.

248 Baliga et al., *supra* note 247.

249 *See Protecting Shareholders and Enhancing Public Confidence by Improving Corporate Governance*: Hearing Before the Subcomm. on Sec., Ins., & Inv. of the Comm. on Banking, Hous., & Urban Affairs, 111th Cong. 47–48 (2009) (statement of John C. Coates).

250 *Id.*

board chair appointments, Angelo Mozilo exerted extraordinary influence over the direction of Countrywide. In defense of his decisions to direct the company to adopt excessively risky mortgage underwriting policies, engage in predatory tactics to entice customers to enter into undesirable mortgage arrangements, and commit blatant fraud, Mozilo explained that a "gold rush" mentality consumed the company and its competitors; according to Mozilo, he and the industry were entrenched in a culture characterized by competition to capture a greater portion of mortgage-lending market share.[251]

C. Process-Oriented Reforms

Structural reforms focus on the organizational framework that a business or organization adopts to make decisions.[252] In other words, how does a corporate board assign decision-making authority or responsibility? The examples in the previous Section explore the structures that a corporate board may utilize to assign accountability.

Process-oriented reforms examine the practices adopted to achieve business outcomes. For many years, scholars advanced the notion that group decisions are qualitatively better than individual decisions because groups benefit from deliberative processes.[253] Individuals making decisions have natural cognitive limits that impede rational efficient decision making.[254] According to experimental psychologists and behavioral economists, groups aggregate individual members' knowledge, interests, and skills and consequently their decisions are qualitatively better that the decisions of the average individual group member.[255]

Individuals making decisions have significant memory and computational skill deficits.[256] As individuals, humans have limited expertise, memory, and analytical and computational abilities.[257] Yet, individuals have a natural tendency to overestimate the quality of their own judgments and abilities.[258] Group deliberative processes overcome the bounded rationality that limits an individual's decision-

251 *See* INQUIRY REPORT, *supra* note 239, at 5, 105.

252 *See supra* Section III.B.

253 *See* Marlene A. O'Connor, *The Enron Board: The Perils of Groupthink*, 71 U. CIN. L. REV. 1233, 1243 (2003).

254 *See* Stephen M. Bainbridge, *Why a Board? Group Decision-Making in Corporate Governance*, 55 VAND. L. REV. 1, 21 (2002).

255 *Id.*

256 *Id.* at 20.

257 *Id.*

258 *Id.* at 29–30.

making process.[259] Because of this, groups tend to commit fewer errors and discover more mistakes than the average individual group member.[260]

The benefits of group decision-making assume that groups engage in an honest, robust exchange of ideas.[261] When groups engage in candid decision-making processes, the groups benefit from the rich diversity of talents, strengths, ideas, and personal and professional experiences of their members.[262]

There is also a compelling efficiency rationale for adopting a collective decision-making process. For a business to gain the best outcome when a task is assigned, it may be difficult to identify the individual who will outperform her peers in advance of the task.[263] A group decision-making process offers the benefit of capturing the skills of the strongest member of the group without the necessity of having to identify the strongest member at the outset.[264] However, the presumed attributes and benefits often fail to materialize and instead, group decision-making engenders a number of concerns.[265]

Studies by behavioral economists reveal that several significant cognitive biases and other structural dynamics may influence the effectiveness of deliberative, group decision-making processes. In the context of boards of directors, the impact of cognitive biases and structural dynamics create notable limitations.

Four significant cognitive biases—commitment bias, confirmation bias, overconfidence, and structural bias—limit group decision-making processes. First, the theory of commitment bias posits that people have a natural propensity to identify information that supports a previously adopted strategy or course of action.[266] Once a person has chosen a course of action, commitment bias suggests that the person will continue to act in a manner consistent with the chosen course even if later discovered information suggests that one should follow a differ-

259 *Id.* at 21.

260 O'Connor, *supra* note 253.

261 *See* Bainbridge, *supra* note 254, at 21.

262 *See Managing Group Decision Making*, LUMEN, https://courses.lumenlearning.com/boundless-management/chapter/managing-group-decision-making/ [https://perma.cc/E3PH-BPCT].

263 *See* Bainbridge, *supra* note 254, at 25–26.

264 *Id.* at 26.

265 *See id.* at 31–32.

266 *See* THERESA F. KELLY & KATHERINE L. MILKMAN, ESCALATION OF COMMITMENT 1 (2011), https://static1.squarespace.com/static/5353b838e4b0e68461b517cf/t/53850248e4b0342df68aa930/1401225800241/escalation-of-commitment.pdf [https://perma.cc/54UL-UYSN].

ent course.[267] Commitment bias may make it difficult for a director to appreciate evidence that her decisions or the group's earlier decisions were misguided.

Second, confirmation bias describes a tendency to disregard information that contradicts an established conclusion and unconsciously gravitate to information that confirms a previously articulated opinion.[268] Because of confirmation bias, groups will perceive information as supporting earlier decisions where an objective review of the same information suggests cause to question, reevaluate, or abandon earlier conclusions.[269] Confirmation bias leads an individual or group to disregard information that contradicts their perceptions and established conclusions.[270]

Third, overconfidence bias describes a tendency to overestimate a group's abilities or the abilities of the leadership of a group.[271] Overconfidence leads group members to defer to leadership without rigorously debating the issue and to adopt overly optimistic opinions regarding the performance of group leaders.[272] Overconfidence compromises objective decision-making.[273]

Fourth, structural bias impedes a director's ability to exercise objective judgment in circumstances that involve persons with whom a director has a relationship.[274] Structural bias refers to the tendency of group members to abandon their own individual perceptions regarding a particular issue and adopt an opinion that is the group consensus on the matter even if they possess information that conflicts with or contradicts the group's opinion.[275]

Relational ties and affiliations stymie board members' ability to evaluate one another's opinions and actions objectively. Board members are generally selected from a small pool of qualified candidates. The small pool of director candidates also suggests that directors will

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267 *Id.*

268 *See id.* at 2.

269 *See id.*

270 *Id.*

271 *See* Amel Baccar et al., *Managerial Optimism, Overconfidence and Board Characteristics: Toward a New Role of Corporate Governance*, 7 Austl. J. Basic & Applied Sci. 287, 288 (2013).

272 *See id.*

273 *See id.* ("CEOs will never invest in optimal way [sic] under the effect of such biases.").

274 Antony Page, *Unconscious Bias and the Limits of Director Independence*, 2009 U. Ill. L. Rev. 237, 248.

275 *See* Luiz Félix et al., *Predictable Biases in Macroeconomic Forecasts and Their Impact Across Asset Classes*, Ctr. Fin. Stud. (June 2018), https://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=EEAESEM2018&paper_id=577 [https://perma.cc/58VG-QCCL].

likely participate in similar educational and professional circles and share multiple affiliations with one another. The limited pool of qualified candidates often ensures that board members will have relationships with other board members prior to serving on a board. Or, through their service, board members may develop intimate personal relationships with one another.

Because of structural bias, interactions and affiliations may color board members' ability to engage in the rigorous debate necessary to generate the benefits of deliberative decision-making. Consequently, structural bias may limit the effectiveness of group decision-making in the boardroom.

Structural dynamics may further deteriorate objective decision-making by reinforcing cognitive biases. According to scholars, "herding" can amplify the effects of cognitive biases.[276] Herding describes the tendency of group members to adopt the decisions of other members in a group, disregarding information in their possession or even their own judgments that may be contrary to the group's opinion.[277] The group may defer to the judgment of a dominant board member who is perceived as better informed. In other instances, a board member may free-ride on the information offered by another board member in an effort to appear to be a team player that can "get-along." Board members herding behind a popular or dominant perspective undermine the benefits of group decision-making, leading to less effective, suboptimal decisions.

IV. Disrupting Bias

Part II explains that businesses and government agencies integrating existing ADM platforms may find that relying on this nascent technology results in legally prohibited discrimination or undesirable bias. Failing to effectively address the risk of bias creates ethical concerns. These normative concerns regarding fairness ought to be sufficient to inspire firms to engage in efforts to mitigate bias. Yet, early evidence indicates that firms, captivated by the benefits of ADM technology, may resist regulatory oversight that imposes monitoring obligations and contend that oversight imposes costs that stymie innovation.

Firms must, however, balance concerns regarding the costs of regulatory oversight with the risk management consequences of de-

276 *See id.* at 5.

277 *See id.* at 2 n.1.

ploying deeply flawed technologies. More concretely, social media exposés and public accountability campaigns demanding that firms and regulators address bias and implement appropriate guardrails will most certainly create reputation and litigation costs that impact firms' economic success. These concerns, and the costs that they create, may be characterized as governance and risk management challenges. Viewing these concerns through a risk management lens should lead regulated firms and regulators to consider long-adopted tools to begin to remedy bias concerns.

As discussed in Part III, scholars, consumer advocates, and policymakers have advanced a number of thoughtful proposals to address governance and risk management challenges. Proposed reforms aim to assist in managing and mitigating the risk of bias.[278] These proposals emphasize accountability by requiring greater transparency and imposing internal structural and process-oriented governance reforms similar to those described in Part II.

Because the concerns regarding algorithmic bias discussed in Part II create a risk management challenge, it is not surprising that suggestions regarding how to mitigate this risk may invoke internal corporate governance solutions. Early reform proposals similarly suggest internal, corporate governance solutions, including self-monitoring through auditing[279] or creating internally or independently prepared algorithmic impact statements.[280]

This Part draws on the structural and process-oriented reforms discussed in Part III to address concerns that ADM platforms may lead to bias and create enterprise risks. This Part contends that firms integrating ADM platforms will benefit from adopting measures that enhance gender diversity among developers, senior managers, and board members. Ensuring greater gender balance in the leadership of

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278 *See, e.g.*, Jamillah B. Williams, *Accountability as a Debiasing Strategy: Testing the Effect of Racial Diversity in Employment Committees*, 103 Iowa L. Rev. 1593, 1605 (2018) (discussing how the Rooney Rule is used to help mitigate discriminatory bias).

279 *See, e.g.*, Chander, *supra* note 66, at 1044 ("An affirmative action approach would seek to ensure that the data used to train an algorithm are evaluated for being embedded with viral discrimination."); Megan Garcia, *How to Keep Your AI From Turning into a Racist Monster*, Wired (Feb. 13, 2017), https://www.wired.com/2017/02/keep-ai-turning-racist-monster/ [https://perma.cc/VDE3-SCG5] (suggesting companies internally audit their algorithms in search of bias); Greenfield & Griffin, *supra* note 104 ("Pymetrics, an AI hiring startup, has programmers audit its algorithm to see if its giving preference to any gender or ethnic group."); Vincent, *supra* note 66 (analyzing the Face Recognition Vendor Test administered by the National Institute of Standards and Technology, which tests the accuracy of facial recognition systems).

280 *See supra* notes 228–30.

the firms developing and integrating ADM platforms may mitigate the risk of bias.[281]

A. Mitigating the Risk of Bias: The Promise of Greater Gender Inclusion

For decades, scholars and commentators have advocated for greater gender diversity on corporate boards and among senior managers.[282] Early debates often centered on the business case for diversity measured by firms' performance.[283] A well-established literature of peer-reviewed and academic studies analyzing historic data, however, establishes the limitations of arguments that claim that adding women to the board or senior ranks makes firms more profitable.[284]

In the context of developing AI or, more specifically, the nascent, rapidly evolving subset of learning algorithms, the focus of the debate

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281 David Danks & Alex John London, *Algorithmic Bias in Autonomous Systems*, INT'L JOINT CONF. ON ARTIFICIAL INTELLIGENCE (2017), https://www.cmu.edu/dietrich/philosophy/docs/london/IJCAI17-AlgorithmicBias-Distrib.pdf [https://perma.cc/LTH2-MSN3]. Danks and London propose a taxonomy of bias introducing the following categories of bias: (1) training data bias, (2) algorithmic focus bias, (3) algorithmic processing bias, (4) transfer context bias, and (5) misinterpretation bias. *Id.* For purposes of the discussion here, the term "bias" generally describes training data which captures training data or input data bias. As Danks and London explain,

> this type of algorithmic bias (again, whether statistical, moral, legal, or other) can be quite subtle or hidden, as developers often do not publicly disclose the precise data used for training the autonomous system. If we only see the final learned model or its behavior, then we might not even be aware, while using the algorithm for its intended purpose, that biased data were used.

Id. References to bias may also describe algorithm focus bias which is the use of input variables that are not legally permitted to be used for certain types of predictions or judgments. *Id.* Presumably, rational market participants will exclude legally impermissible variables to avoid liability in antidiscrimination suits.

282 *See generally* Rohini Anand, *A Retrospective View of Corporate Diversity Training from 1964 to the Present*, 7 ACAD. MGMT. LEARNING & EDUC. 356 (2008), https://www.wintersgroup.com/corporate-diversity-training-1964-to-present.pdf [https://perma.cc/QG42-CLHB].

283 *See, e.g.*, Vanessa Fuhrmans, *Companies with Diverse Executive Teams Posted Bigger Profit Margins, Study Shows*, WALL STREET J. (Jan. 18, 2018, 7:41 PM), https://www.wsj.com/articles/companies-with-diverse-executive-teams-posted-bigger-profit-margins-study-shows-1516322484 [https://perma.cc/T7C2-2F8N].

284 Jan Luca Pletzer et al., *Does Gender Matter? Female Representation on Corporate Boards and Firm Financial Performance—A Meta-Analysis*, NAT'L CTR. BIOTECHNOLOGY INFO. (June 18, 2015), https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4473005 [https://perma.cc/83BY-RSPW] ("The main finding of the current study, based on data from 20 studies (34 effect sizes) published only in peer-reviewed academic journals, is that the relationship between the percentage of female directors on corporate boards and firm financial performance is consistently small and non-significant."); Corrine Post & Kris Byron, *Women on Boards and Firm Financial Performance: A Meta-Analysis*, 58 ACAD. MGMT. J. 1546, 1546–71 (2015) (a meta-analysis synthesizing 140 studies of board gender diversity including a combined sample of more than 90,000 firms from more than 30 countries).

must shift. The discipline producing AI and the firms integrating this technology will profoundly impact myriad elements in society. The significance of the technology compels a thoughtful discussion and evaluation of the "humans in the loop" and the lack of diversity among programmers and senior management exacerbate the likelihood that learning algorithms will function in a manner that leads to bias. As one commentator poignantly intimates, if AI is the future, where are the women?[285]

Early evidence demonstrates that technology firms may be among the least diverse in the economy. Exploring the declining numbers of women in computer science, Clive Thompson reports that women comprised 27% of computing and mathematical professions in 1960 and, by 1990, women held 35% of these positions.[286] However, by 2013, the number of women in computing and mathematics professions declined to a stunning 26%, a level of representation lower than gender representation in the profession in 1960.[287]

An informal investigation of presenters at the leading AI conferences suggests that women comprise only 22% of AI professionals.[288] A survey of university professors teaching courses in AI at a small sample of universities reveals that "on average 80% of AI professors are male."[289]

Before reaching the importance of gender diversity on the development of AI and the potential for gender diversity to reduce the risk of bias, a cursory review of the existing literature evaluating greater

285 Simonite, *supra* note 80.

286 Clive Thompson, *The Secret History of Women in Coding*, N.Y. TIMES (Feb. 13, 2019), https://www.nytimes.com/2019/02/13/magazine/women-coding-computer-programming.html [https://perma.cc/97U7-5UVH].

287 *Id.*

288 THE GLOBAL GENDER GAP REPORT, WORLD ECON. F. (2018), http://www3.weforum.org/docs/WEF_GGGR_2018.pdf [https://perma.cc/8KSA-76H4] ("[O]nly 22% of AI professionals globally are female, compared to 78% who are male."). According to the WEF Global Gender Gap Report

> [w]omen employed in the Software and IT Services Industry make up 7.4% of the AI talent pool—or just one-quarter of the male AI talent pool . . . [w]omen in the Education sector comprise 4.6% of that talent pool, or just under one-third of the male AI talent pool in this sector.

Id.; *see also* Alicia Clegg, *Will AI Bring Gender Equality Closer?*, FIN. TIMES (Mar. 7, 2019), https://www.ft.com/content/f5b416ba-185e-11e9-b191-175523b59d1d [https://perma.cc/PYL3-468Q] (asking whether "the age of intelligent machines [will] bring[] gender equality nearer or turn[] back the clock").

289 YOAV SHOHAM ET AL., ARTIFICIAL INTELLIGENCE INDEX, 2018 ANN. REP. 25 (including data collected using faculty rosters on September 21, 2018 from selected schools with easily accessible AI faculty rosters namely UC Berkeley, Stanford, UIUC, CMU, UC London, Oxford, and ETH Zurich).

gender inclusion illustrates the benefits and the limits of framing the discussion in terms of financial performance or mandating gender equity. For decades, commentators and academics have studied the impact of increasing gender diversity in corporate leadership. The studies often evaluate the benefits of leadership diversity measured by accounting and profitability metrics such as return on equity ("ROE"), return on sales ("ROS"), and return on invested capital ("ROIC").[290]

Consulting firms McKinsey & Company[291] and Catalyst,[292] and financial firm Credit Suisse,[293] for example, each published studies demonstrating that firms perform better with gender-diverse leadership. Yet, academic studies present a far less compelling case for gender diversity on corporate boards, revealing that there is no clear relationship between diverse gender representation and corporate financial performance.[294] A number of peer-reviewed academic studies find a

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290 The Credit Suisse Research Institute, established in 2008, similarly examined the relationship between gender diversity and financial performance in a sample of 2,360 companies located in countries around the world and concluded that companies with at least one woman on the board would have outperformed their competitors in terms of share price performance, after controlling for biases from the skew in female representation in certain industries and regions. THE CS GENDER 3000: THE REWARD FOR CHANGE, CREDIT SUISSE 1, 23 (2016) [hereinafter CS GENDER 3000]. The study found that companies with at least one woman director had higher net income growth during a six year period than companies with no woman directors (14% versus 10%, respectively) and that the average ROE of companies with at least one woman on the board over the past six years is 16%, which was 4% higher than the average ROE of companies with no female board representation (12%). *Id.*

291 *See* VIVIAN HUNT ET AL., DELIVERING THROUGH DIVERSITY, MCKINSEY & CO. 8, 10–11 (2018) (noting that the study "observe[s] a positive correlation between greater levels of gender diversity and higher likelihood of financial outperformance across geographies at the executive level").

292 Catalyst, *The Bottom Line: Corporate Performance and Women's Representation on Boards*, CHUBB CORP. (2007), https://www.catalyst.org/wp-content/uploads/2019/01/The_Bottom_Line_Corporate_Performance_and_Womens_Representation_on_Boards.pdf [https://perma.cc/Q4HL-Q9CH] (measuring the Return on Equity, Return on Sales, and Return on Invested Capital (among other factors) by Women's Representation on the Board). In 2007 and 2011, a research center, Catalyst, published two of the most cited recent studies on gender diversity and board performance. The 2007 Catalyst study—a univariate analysis using board data—compared the means of two groups over a four-year period (2001–2004) and analyzed return on equity ("ROE"), return on sales ("ROS"), and return on investment income ("ROIC") in the sample group of Fortune 500 companies. *Id.* The study ranked the companies based on ROE, ROS, and ROIC and considered differences between the identified firms that had significant gender diversity on the boards and those that did not. *Id.* The study found that companies in the highest quartile (companies with the highest average percentage of women board directors) outperformed companies in the lowest quartile (companies with the lowest average percentage of women board directors) by 53% in ROE, 42% in ROS, and 66% in ROIC. *Id.*

293 CS GENDER 3000, *supra* note 290.

294 *See, e.g.*, Toyah Miller & María del Carmen Triana, *Demographic Diversity in the Boar-*

positive relationship[295] while others find no significant relationship[296] or a negative relationship between gender diversity on boards and firm financial performance.[297]

In recent years, scholars have emphasized the perils of focusing on financial performance to the exclusion of other concerns. In the context of ADM, for example, myopically focusing on short-term profit maximization may lead to unfathomable reputational, regulatory, and litigation risks.

As the literature has developed, studies have focused on the various benefits of gender diverse boards and leadership. Studies have found that women perform the same functions differently and at times, more effectively, than men.[298] Research suggests that increased sex diversity facilitates "higher quality decisions through improved

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droom: Mediators of the Board Diversity–Firm Performance Relationship, 46 J. MGMT. STUD. 755, 755 (2009) (surveying the literature and concluding that studies draw differing conclusions regarding the impact of gender diversity on firm's financial performance); Post & Byron, *supra* note 284.

295 *See, e.g.*, David A. Carter et al., The Diversity of Corporate Board Committees and Financial Performance 20–23 (2007), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=972763 [https://perma.cc/83HW-XMXA].

296 *See, e.g.*, Reidar Øystein Strøm, *Female Leadership, Performance, and Governance in Microfinance Institutions*, 42 J. BANKING & FIN. 60, 73 (2014) (a study investigating the relationship between female leadership, firm performance, and corporate governance in a global panel of 329 microfinance institutions in 73 countries from 1998–2008).

297 *See, e.g.*, Charles B. Shrader et al., *Women in Management and Firm Financial Performance: An Exploratory Study*, 9 J. MANAGERIAL ISSUES 355, 365 (1997) (indicating that results of the study do not support the conclusion that "higher percentages of women managers on the top management team or on the board of directors were disproportionately associated with higher financial performance.").

298 *See* SCOTT E. PAGE, THE DIFFERENCE: HOW THE POWER OF DIVERSITY CREATES BETTER GROUPS, FIRMS, SCHOOLS, AND SOCIETIES 314 (2007); Darren Rosenblum & Daria Roithmayr, *More than a Woman: Insights into Corporate Governance after the French Sex Quota*, 48 IND. L. REV. 889, 905 (2015) ("More generally, research has suggested that sex diversity matters because women bring with them different approaches to decision-making, offering fresh descriptive categories, and novel decision-making frameworks, heuristics, and classification systems."); DAVID A.H. BROWN ET AL., WOMEN ON BOARDS: NOT JUST THE RIGHT THING . . . BUT THE BRIGHT THING, CONF. BOARD CAN., 5–6 (2002), http://www.conferenceboard.ca/e-library/abstract.aspx?did=374 [https://perma.cc/7UEE-6LJW] (Carnegie Mellon study found that, all else being equal, teams with more women scored higher than teams with fewer women); *see also* Joan MacLeod Heminway, *Women in the Crowd of Corporate Directors: Following, Walking Alone, and Meaningfully Contributing*, 21 WM. & MARY J. WOMEN & L. 59, 79–84 (2014). It should be noted, however, that sex diversity should not be seen as essentializing either sex. These studies were not yet able to assert the rationale for differences in performance. They do, however, observe the correlation between sex and performance-based outcomes. *See, e.g.*, Lisa M. Fairfax, *Clogs in the Pipeline: The Mixed Data on Women Directors and Continued Barriers to Their Advancement*, 65 MD. L. REV. 579, 602–05 (2006).

monitoring, mitigating groupthink[299] and boosting collective intelligence."[300]

In a 2014 study evaluating the relationship between female leadership and the stability of financial institutions during the recent financial crisis,[301] evidence suggests that having women in leadership positions positively influenced capital ratios and default risk.[302] The study found that, "while neither CEO nor Chair gender is related to bank failure in general" there is "strong evidence that smaller banks with female CEOs and board Chairs were less likely to fail during the financial crisis."[303] Finally, a growing body of literature focuses on the number of women directors and not merely evidence that boards included a token woman director.

A 2016 study by economists at the Federal Reserve suggests that measuring noneconomic factors in the structure and dynamics of the board may prove exceptionally valuable. Economists examined the largest 90 U.S. bank holding companies from 1994–2014—a group comprised of 55 of the largest publicly traded bank holding companies as measured by total assets and constituting 63% of the banking industry during the period of the financial crisis (2008–2012).[304] According to their study, financial institution boards with three or more women "braved the crisis better" than boards with fewer or no women.[305]

Finally, if we perceive bias as a concern that may be addressed through risk management practices, then gender balance may offer a

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299 *See* Akshaya Kamalnath, *The Corporate Governance Case for Board Gender Diversity: Evidence from Delaware Cases*, 82 ALB. L. REV. 23, 27 (2019) ("Groupthink results in defective decision-making by the group, even when individual members of the group are both qualified and conscientious."); O'Connor, *supra* note 253, at 1259, 1306 (describing groupthink as a "concurrence-seeking tendency" often seen in members of cohesive groups; the tendency fosters over-optimism, lack of vigilance, and an irrational belief in the group's morality).

300 Rosenblum & Roithmayr, *supra* note 298, at 904.

301 Ajay Palvia et al., *Are Female CEOs and Chairwomen More Conservative and Risk Averse? Evidence from the Banking Industry during the Financial Crisis*, 131 J. BUS. ETHICS 577, 592 (2015) ("From a public policy perspective, the documented benefits of female leadership for bank stability may be of interest to regulators when setting future policies for promoting gender equality and the advancement of women in business."). *See generally* Thorsten Beck et al., *Gender and Banking: Are Women Better Loan Officers?*, 17 REV. FIN. 1279 (2013); Andrea Bellucci et al., *Does Gender Matter in Bank-Firm Relationships? Evidence from Small Business Lending*, 34 J. FIN. & BANKING 2968 (2010); Maureen I. Muller-Kahle & Krista B. Lewellyn, *Did Board Configuration Matter? The Case of US Subprime Lenders*, 19 CORP. GOVERNANCE: INT'L. REV. 405, 405 (2011).

302 Palvia et al., *supra* note 301, at 592.

303 *Id.* at 577.

304 Laura St. Claire et al., *supra* note 89 at 2.

305 *Id.* at 22–24.

valuable tool for mitigating bias. Gender diversity may alter boards' processes—creating an informal process-styled reform. According to theorists, women participating on boards are more attentive and responsive, demonstrate a better understanding of corporate and outside stakeholders, and offer insight regarding consumer markets.[306] Simply stated, gender diverse boards manage risk better than homogenous boards.[307]

The next Section advocates for greater gender diversity in the developer, senior management, and board ranks of firms adopting ADM platforms and assesses the impact of California's new law mandating gender diversity on the boards of corporations incorporated or headquartered in the state.[308]

B. Diversifying the Leadership and Developers of Automated Decision-Making Platforms

As the previous Section explains, evaluating gender diverse leadership through the lens of firm performance may result in a narrow and incomplete portrait of the benefits and limits of greater gender inclusion. A more nuanced perspective would consider that there are many types of risk that may impact firm performance. As discussed in Part II, for example, the risk of bias may lead to litigation, reputation, and other types of risks. Growing reliance on learning algorithms across various sectors of the economy—in healthcare, government services, and policing—heightens concerns that arbitrary, unfair, or biased outcomes will become embedded in social and economic systems.[309]

This Section argues that increasing gender inclusion in the development cycle of AI technologies will introduce important and diverse perspectives, reduce the influence of cognitive biases in the design, training, and oversight of learning algorithms, and, thereby, enhance

306 *See* Banahan & Hasson, *supra* note 89.

307 *See id.*

308 *See* Lori Ioannau, *Silicon Valley's Achilles' Heel Threatens to Topple Its Supremacy in Innovation*, CNBC (June 20, 2018, 9:55 AM), https://www.cnbc.com/2018/06/20/silicon-valleys-diversity-problem-is-its-achilles-heel.html [https://perma.cc/4E2A-N9XW] ("The lack of workforce diversity and unconscious bias is a systemic problem in Silicon Valley."); Vanian, *supra* note 65 ("Joy Buolamwini, the MIT researcher who probed Microsoft and IBM's facial-recognition tech (along with China's Megvii), recently told Fortune's Aaron Pressman that a lack of diversity within development teams could also contribute to bias because more diverse teams could be more aware of bias slipping into the algorithms.").

309 *See* Ellora Thadaney Israni, *When an Algorithm Helps Send You to Prison*, N.Y. TIMES (Oct. 26, 2017), https://www.nytimes.com/2017/10/26/opinion/algorithm-compas-sentencing-bias.html [https://perma.cc/KKQ4-SR6F].

fairness and reduce the likelihood of bias and threat that firms integrating ADM platforms will violate antidiscrimination statutes. The proposed approaches for enhancing gender inclusion parallel the kinds of approaches adopted to improve group decision-making on corporate boards.[310] Both structural and process-oriented reforms may offer valuable pathways to enhance gender diversity and mitigate the risk of bias.

Process-oriented reforms are quickly gaining ground among firms integrating ADM platforms. As Part II explains, industry best practices encourage developing internal and independent auditing for bias. Several popular examples illustrate the potential for bias to creep into learning algorithms and firms' decisions to adopt process-oriented reforms such as auditing; consider, for example, Facebook's employment[311] and housing advertisements[312] and Amazon's hiring algorithm.[313] In these instances, firms self-regulated, altering the learning algorithms employed or retiring them from service to minimize liability.

Some of the challenges that gave rise to these examples are the result of firms' reliance on homogenous groups of developers; within these groups, the literature demonstrates that cognitive biases (confirmation bias, relational bias)[314] will impair group decision-making and influence teams' ability to recognize the limitations of their developments. The homogeneity of the people "in the loop" in AI may unintentionally exacerbate the effects of underrepresentation and reinforce unconscious bias in the development of learning algo-

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310 *See* Erik Larson, *When It Comes to Business Decisions, Diversity Is Not Propaganda*, FORBES (Oct. 24, 2018, 9:07 AM), https://www.forbes.com/sites/eriklarson/2018/10/24/when-it-comes-to-decisions-diversity-is-not-propaganda/#253d4fa81d7f [https://perma.cc/ZQW3-YZBQ].

311 *See, e.g.*, Noam Scheiber, *Facebook Accused of Allowing Bias Against Women in Job Ads*, N.Y. TIMES (Sept. 18, 2018), https://www.nytimes.com/2018/09/18/business/economy/facebook-job-ads.html?searchResultPosition=1 [https://perma.cc/3NMY-PBJT] (detailing accusations against Facebook that allege that the social media platform helped employers to exclude female candidates from recruiting campaigns for truck driver and window installer positions).

312 *See, e.g.*, Charles V. Bagli, *Facebook Vowed to End Discriminatory Housing Ads. Suit Says It Didn't*, N.Y. TIMES (Mar. 27, 2018), https://www.nytimes.com/2018/03/27/nyregion/facebook-housing-ads-discrimination-lawsuit.html [https://perma.cc/G59T-358B] ("Facebook, an advertising behemoth with more than two billion users a month, provides advertisers with the ability to customize their messages and target who sees them by selecting from preset lists of demographics, likes, behaviors and interests, while excluding others.").

313 See *supra* notes 57–60 and accompanying text.

314 *See supra* Section III.C.

rithms.[315] As Kriti Sharma explains, the "tech industry remains very male and fairly culturally homogeneous."[316]

In one of the more notorious examples of underrepresentation in training data sets leading to racial and gender bias, Joy Buolamwini and Timnit Gebru explored the overrepresentation of white males and the underrepresentation of women, particularly women with darker complexions, in three widely adopted commercial datasets.[317] Buolamwini and Gebru's study examines the limits of existing facial recognition training data sets.[318] Buolamwini and Gebru's study revealed that the data sets were overwhelmingly composed of images of subjects with pale, fair, or lighter skin complexions.[319] The disproportionate representation of lighter-complexioned males, and the absence of sufficient samples of facial images of darker complexioned females, lighter females, and darker complexioned males leads to disturbingly high error rates when the technology is adopted and used by a representative population with a more diverse range of skin tones.[320] Buolamwini and Gebru's central concern is that learning algorithms are deeply influenced by the data that programmers' use to train algorithms.

Failing to use diverse, representative data sets may lead to large numbers of consumers being unable to use the technology, or worse—grave errors, mistakes, and inaccurate results may lead to under-represented subjects suffering significant losses.[321] Buolamwini and Gebru's observations regarding the limits of widely-adopted facial recognition data sets becomes even more salient when one considers

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315 *See* Bass & Huet, *supra* note 65 ("Bias can surface in various ways. Sometimes the training data is insufficiently diverse, prompting the software to guess based on what it 'knows.' In 2015, Google's photo software infamously tagged two black users 'gorillas' because the data lacked enough examples of people of color. Even when the data accurately mirrors reality the algorithms still get the answer wrong, incorrectly guessing a particular nurse in a photo or text is female, say, because the data shows fewer men are nurses. In some cases the algorithms are trained to learn from the people using the software and, over time, pick up the biases of the human users.").

316 Sharma, *supra* note 66.

317 Buolamwini & Gebru, *supra* note 68.

318 Jonathan Vanian, *Unmasking A.I.'s Bias Problem*, FORTUNE (June 25, 2018), https://fortune.com/longform/ai-bias-problem/ [https://perma.cc/CM5P-C7GZ].

319 *Id. (*explaining that lighter-skinned subjects represented 79.6% and 86.2% in the IJB-A and Adience data sets, respectively).

320 *Id.*

321 INIOLUWA DEBORAH RAJI & JOY BUOLAMWINI, CONF. ON ARTIFICIAL INTELLIGENCE, ETHICS, AND SOC'Y, ACTIONABLE AUDITING: INVESTIGATING THE IMPACT OF PUBLICLY NAMING BIASED PERFORMANCE RESULTS OF COMMERCIAL AI PRODUCTS (2019), https://dam-prod.media.mit.edu/x/2019/01/24/AIES-19_paper_223.pdf [https://perma.cc/2PR9-JTNA].

the consequences of the application of facial recognition technology in areas such as criminal justice or policing.[322]

It is fair to suggest that male programmers may also encourage and propose the creation of more representative data sets or other reforms that mitigate bias. As Part III explains, the value of different perspectives may alter group dynamics and enable group members who share similar backgrounds or experiences and those from different backgrounds to identify better solutions to common challenges.[323] However, as AI Now explains in their recent report on diversity in AI, the concerns related to underrepresentation and the significance of AI in an increasing number of social welfare demands indicate that it would be imprudent to simply rely on "cognitive diversity" or "viewpoint diversity" to overcome concerns regarding bias in AI.[324]

Where, one might ask, will we find these diverse developers and senior programmers? A quick glance at the statistics demonstrates that enhancing the gender balance in AI may prove more challenging than advocates admit. Many who agree that diversity will enhance decision-making and mitigate the risk of bias point to the remarkably small pool of talent capable of developing, programming, coding, or supervising the creation of ADM platforms.[325] Women comprise only 18% of computer science undergraduate degrees,[326] and representation among those enrolled in graduate school programs, holding software and coding programming positions, and in senior executive and board positions is similarly low.[327]

Because the technology industry emphasizes specific undergraduate credentials and successful completion of graduate school (often doctoral) programs, creating a diverse pipeline must begin during the

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322 Lucas D. Introna & Helen Nissenbaum, N.Y. Univ. Ctr. for Catastrophe Preparedness and Response, Facial Recognition Technology A Survey of Policy and Implementation Issues (2009), https://nissenbaum.tech.cornell.edu/papers/facial_recognition_report.pdf [https://perma.cc/74FL-XYL8].

323 John R. Smith, *IBM Research Releases "Diversity in Faces" Dataset to Advance Study of Fairness in Facial Recognition Systems*, IBM (Jan. 29, 2019), https://www.ibm.com/blogs/research/2019/01/diversity-in-faces/ [https://perma.cc/V8QT-VWH5].

324 Sarah West, Meredith Whittaker & Kate Crawford, Discriminating Systems: Gender, Race, and Power in AI, AI Now 29 (Apr. 2019) (criticizing suggestions that "cognitive diversity" or "viewpoint diversity" may serve as a substitute for gender and racial diversity).

325 *See* Larson, *supra* note 310.

326 *Women in Computer Science: Getting Involved in STEM*, Computer Sci., https://www.computerscience.org/resources/women-in-computer-science/ [https://perma.cc/GDH3-MDB4].

327 Jessica Bateman, *Sexist Robots Can Be Stopped by Women Who Work in AI*, Guardian (May 29, 2017), https://www.theguardian.com/careers/2017/may/29/sexist-robots-can-be-stopped-by-women-who-work-in-ai [https://perma.cc/65MN-BEJ9].

earliest education stages.[328] To address the limited number of women currently in the pipeline, technology firms are revisiting traditional assumptions regarding qualifications. According to Danielle Brown, Google's Vice President and Chief Diversity Officer, Google now looks at skill, qualification, and census data to determine "what percentage of people have those degrees and skills and who is out there and in the marketplace."[329]

While Google's promise signals that diverse participation in developing AI will require creative and alternative approaches to recruiting and retention, Jamillah Williams' thoughtful analysis of the technology industry's successful use of trade secret law to shroud the embarrassing dearth of diverse employees at the programming, development, and senior management levels reveals the difficulty of holding technology firms accountable and obtaining data regarding the diversity of the humans with the most significant role in developing AI and similarly important technologies.[330]

Diverse programmers are launching affinity group networks to address the dearth of women and diverse developers. For example, *Women in AI* has directly engaged in efforts to facilitate mentoring and placement programs.[331] Timnit Gebru, machine vision researcher, created *Black in AI*.[332] According to Gebru, the AI community is in a diversity crisis.[333] Notwithstanding critic's arguments that the affinity group networks are unnecessary and exclusionary,[334] both groups have hosted parallel events at the annual NeurIPS conference.

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328 *See* Janice Gassam, *Five Reasons Why the Pipeline Problem is Just a Myth*, FORBES (Dec. 18, 2018, 8:39 PM), https://www.forbes.com/sites/janicegassam/2018/12/18/5-reasons-why-the-pipeline-problem-is-just-a-myth/#4085ef16227a [https://perma.cc/5FLH-H9MA] ("When looking at the number of students from underrepresented backgrounds taking AP computer science courses in the state of California, Black and Hispanic students make up 60% of California's student population, yet only 16% of the population taking AP computer science courses. These underrepresented groups are also less likely to have access to and exposure to computer science at home and elsewhere.").

329 Nitasha Tiku, *Google's Diversity Stats Are Still Very Dismal*, WIRED (June 14, 2018), https://www.wired.com/story/googles-employee-diversity-numbers-havent-really-improved/ [https://perma.cc/U9JS-V7KN] ("In January, [Brown] says Google adopted a new strategy aiming to grow the representation of women globally and of black and Latinx employees in the US to 'reach or exceed available talent pools in all levels.'").

330 *See generally* Jamillah B. Williams, *Diversity as a Trade Secret*, 107 GEO. L.J. 1685 (2019).

331 *See What is Wai2Go?*, Women in AI, https://www.womeninai.co/wai2go ("Through training and mentoring, we aim at raising awareness and empowering women for action in the field of AI.").

332 *See* Snow, *supra* note 66.

333 *Id.*

334 Jeremy Kahn and Dina Bass, *Black AI Workshop Becomes Latest Flashpoint in Tech's*

At least one state legislature has adopted a formal mandate requiring publicly traded firms to appoint women to the boards of corporations in its jurisdiction. In an attempt to address the lack of diversity in corporate boardrooms, on September 30, 2018, California Governor Jerry Brown signed a bill into law mandating gender diversity on the boards of publicly traded companies.[335] The statute requires publicly held firms incorporated or headquartered in California to appoint at least one self-identified woman to the board of directors by the end of 2019.[336] By December 31, 2021, the California statute requires corporations with six or more directors to have a minimum of three women directors; corporations with five directors to have at least two women directors; and corporations with four or fewer directors to have at least one woman director on their board.[337] The Cali-

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Culture War, BLOOMBERG (Oct. 20, 2017), https://www.bloomberg.com/news/articles/2017-10-20/black-ai-workshop-becomes-latest-flashpoint-in-tech-s-culture-war [https://perma.cc/23YY-NQQ2].

335 CAL. CORP. CODE § 301.3 (West 2019) ("No later than the close of the 2021 calendar year, a publicly held . . . corporation shall comply with the following: (1) If its number of directors is six or more, the corporation shall have a minimum of three female directors. (2) If its number of directors is five, the corporation shall have a minimum of two female directors. (3) If its number of directors is four or fewer, the corporation shall have a minimum of one female director.").

336 *Id.* The statute requires the Secretary of State to "name and shame" or publish on the internet periodic reports documenting, among other things, the number of corporations in compliance with these provisions. Michael Disotell et al., *All Aboard! California Law Requires More Female Representation on Boards of Directors*, JD SUPRA (Dec. 5, 2018), https://www.jdsupra.com/legalnews/all-aboard-california-law-requires-more-29383/ [https://perma.cc/2MQ4-Y9FW]. The bill would also authorize the Secretary of State to impose fines for violations of the bill, as specified, and would provide that moneys from these fines are to be available, upon appropriation, to offset the cost of administering the bill. *Id.*

337 CAL. CORP. CODE § 301.3(b) (WEST 2019). According to Professor Joseph A. Grundfest of Stanford Law School, the amendment is unconstitutional as applied to all but 72 publicly traded corporations headquartered in California due to the internal affairs doctrine. Joseph A. Grundfest, *Mandating Gender Diversity in the Corporate Boardroom: The Inevitable Failure of California's SB 826*, at 2 (Stan. Law Sch. Working Paper No. 232) (2018), https://ssrn.com/abstract=3248791 [https://perma.cc/U25V-XL69] ("As the United States Supreme Court has explained, a corporation's internal affairs, such as rules regulating the composition of its board of directors and shareholder elections, are governed by the corporation's state of incorporation, and not by the state in which it is headquartered."); *see also* CTS Corp. v. Dynamics Corp. of Am., 481 U.S. 69, 89 (1986) (holding that "the law of the incorporating State generally should 'determine the right of a shareholder to participate in the administration of the affairs of the corporation'" (quoting RESTATEMENT (SECOND) OF CONFLICT OF LAWS § 304 (1971))); Edgar v. Mite Corp., 457 U.S. 624, 645–46 (1982) (holding that the composition of a corporation's board of directors must be governed by a single jurisdiction to avoid conflicting demands). Grundfest also argues that SB 826 violates the Commerce Clause because it applies to corporations headquartered in California but that are chartered outside of California. Grundfest, *supra*.

Put more succinctly, SB 826 interferes with a corporation's internal governance and shareholder voting in violation of the internal affairs doctrine. For example, a corporation headquarfornia statute mandating gender diversity faces myriad legal challenges, including claims asserting violations of state and federal constitutional laws.[338] Notwithstanding these concerns, Darren Rosenblum argues that the statute may curb male overrepresentation on California's corporate boards.[339] According to Rosenblum, even without the quota firms now have

> a fiduciary duty to diversify. A decade ago, after the demise of Lehman Brothers, commentators asked, "Would the firm have disappeared had it been Lehman Sisters?" Today we can pose the same question about companies caught in the crosshairs of sexual harassment controversies.[340]

Whether greater gender inclusion is mandated or voluntary or the result of structural or process-oriented reforms, there are several significant barriers that may impede gender diverse groups of programmers or gender diverse boards from achieving bias-mitigating goals. Culture is a pernicious and pervasive issue that may undermine the benefits of increasing gender diversity.

In a recent study, Lauren Camera explores bias against women in computer science and coding through an experiment evaluating commercial interest in women coders; to execute the experiment she selectively masks or reveals the gender of the coders.[341] Camera's strong evidence of explicit bias is disturbing; it also suggests that the bro culture at some technology firms may be sufficient to ensure that even women who succeed in gaining a highly-coveted position with an elite technology firm may be quickly driven out.

Evidence from a growing number of technology firms reveals a deeply disconcerting bro culture characterized by claims of sexual harassment and discriminatory practices.[342] Recent examples include a

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tered in California but chartered in Delaware would be required to have a minimum number of women directors by California, while Delaware permits any number of women directors consistent with the board's judgment. When faced with this conflict, settled law is clear, the Delaware law controls. *See CTS Corp*, 481 U.S. 69; *Edgar*, 457 U.S. 624. While the bill's sponsor seeks to overcome this conclusion, it is clear that no California state statute can override the internal affairs doctrine. *See* VantagePoint Venture Partners 1996 v. Examen, Inc., 871 A.2d 1108, 1113 (Del. S. Ct. 2005).

338 *See* Levi Sumagaysay, *California Sued Over Law Requiring Women on Corporate Boards*, MERCURY NEWS (Aug. 9, 2019 12:11 PM), https://www.mercurynews.com/2019/08/09/california-sued-over-law-requiring-women-on-corporate-boards/ [https://perma.cc/SK34-D6VM].

339 Darren Rosenblum, *California Dreaming?*, 99 B.U. L. REV. 1435, 1439 (2019).

340 *Id.* at 1456.

341 Camera, *supra* note 81.

342 Sarah Myers West et al., *Discriminating Systems: Gender, Race, and Power in AI*, AI

class action suit led by Microsoft employees,[343] a federal investigation of gender discrimination at Uber,[344] an audit of Google's pay practices by the Department of Labor,[345] and general tales of discriminatory attitudes and exclusionary and alienating practices.[346] Marked by a spirit of masculinity and a lack of gender and racial diversity, bro culture in technology mirrors the culture commonly associated with Wall Street firms just a few decades ago—winning at all costs and rewarding those who break the rules and get away with it.[347]

While greater inclusion has a number of benefits, increasing the number of women or diverse developers, senior managers, and board members can exacerbate existing cultural norms if women and diverse team members embrace "bro culture." As Professors Carbone, Cahn, and Levitt explain, this culture fosters a competitive environment to the disadvantage of women, and most men, "by selecting for narcissists who thrive in such [tournament-like] environments at the expense of others and making it harder for women and other outsiders to play by the same rules as insider men."[348] Simply placing women in corporate leadership positions does not automatically allow for effective change.[349] Many of the same problems that arise with men in leadership could arise with women if there is no change to an existing exclusionary culture.

Now (Apr. 4, 2019), https://ainowinstitute.org/discriminatingsystems.pdf [https://perma.cc/PE9X-2NVE].

343 *See* Second Amended Class Action Complaint, Moussouris v. Microsoft Corp., No. 2:15-cv-01483-JLR (W.D. Wash. Apr. 6, 2016); *see also Microsoft Gender Discrimination Class Action Lawsuit*, Microsoft Gender Case (2019), https://microsoftgendercase.com/ [https://perma.cc/ND79-5DVJ] ("On September 16, 2015, a gender discrimination class action lawsuit was filed against Microsoft Corporation. The class action, *Moussouris v. Microsoft Corporation*, was brought by a former female Microsoft technical professional on behalf of herself and all current and former female technical professionals employed by Microsoft in the U.S. On October 27, 2015, an amended complaint was filed, adding current Microsoft employees Holly Muenchow and Dana Piermarini as named plaintiffs, in addition to Ms. Moussouris.").

344 Greg Bensinger, *Uber Faces Federal Investigation over Alleged Gender Discrimination*, Wall Street J. (July 16, 2018, 6:47 PM), https://www.wsj.com/articles/uber-faces-federal-investigation-over-alleged-gender-discrimination-1531753191 [https://perma.cc/6VJS-RL6V].

345 Bourree Lam, *The Department of Labor Accuses Google of Gender Pay Discrimination*, Atlantic (Apr. 7, 2017), https://www.theatlantic.com/business/archive/2017/04/dol-google-pay-discrimination/522411/ [https://perma.cc/E6T4-XLD3].

346 Mark S. Luckie, *Facebook is failing its black employees and its black users*, Facebook (Nov. 27. 2018), https://www.facebook.com/notes/mark-s-luckie/facebook-is-failing-its-black-employees-and-its-black-users/1931075116975013/ [https://perma.cc/34EJ-UNXG].

347 *See* June Carbone et al., *Women, Rule-Breaking, and the Triple Bind*, 87 Geo. Wash. L. Rev. 1105, 1123 (2020) ("It also produces the intense distrust of anyone perceived to be an outsider who might not be so willing to look the other way.").

348 *Id.*

349 *Id.*

Recent examples of women executives at financial market firms illustrate these concerns. In the run up to the recent financial crisis, Zoe Cruz, former female co-president of prominent investment banking firm Morgan Stanley, served as the head of institutional securities and wealth management, earning over $30 million a year.[350] When the financial crisis began, Cruz discovered a phenomenon described as the "glass cliff."[351] Faced with billions of dollars in losses, the board and managers at Morgan Stanley quickly elected to blame Cruz and the unit that she supervised for massive losses in the firms subprime mortgage portfolio.[352] Cruz, however, had performed no worse than others on Wall Street and she arguably reacted at the onset of the crisis in a manner that mitigated the firm's losses.[353] Nevertheless, Morgan Stanley's board of directors requested her resignation.[354]

In addition to concerns that women will perform in a manner that is self-interested, many argue that even if women have a desire to adopt more ethical approaches, they may lack the ability to challenge the established culture within a firm.[355] Sallie Krawcheck, former Chief Financial Officer and head of wealth management at Citigroup, was forced out after she attempted to take significant steps toward protecting customers during the 2008 financial crisis.[356] These conflicting strategies demonstrate that regardless of the approach taken, female executives face a significant disadvantage. Cruz played the game with the boys and was still fired, whereas Krawcheck was more reserved, fought for her customers, and was still terminated.[357]

Finally, including more women in board leadership may not be effective if the culture does not address tokenism.[358] For companies to

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350 Joe Hagan, *Only the Men Survive*, N.Y. MAG. (Apr. 25, 2008), http://nymag.com/news/business/46476/ [https://perma.cc/A8LD-DQT8].

351 DEBORAH RHODE, WOMEN AND LEADERSHIP 63–64 (2019).

352 Hagan, *supra* note 350.

353 *Id.*

354 *Id.*; *see also* Carbone et al., *supra* note 347 ("Downturns are a particularly treacherous time for female executives, particularly executives who took the same kind of risks that the men did.").

355 *See* Carbone et al., *supra* note 347.

356 Jeff John Roberts, *I Was Fired for Being a Woman, Salli Krawcheck Tells Crowd*, FORTUNE (Oct. 8, 2016), https://fortune.com/2016/10/08/sallie-krewcheck-fired/ [https://perma.cc/H4UK-JCUX].

357 *Id.*

358 *See* Gassam, *supra* note 328 ("A token is defined as 'someone who is included in a group to make people believe that the group is trying to be fair and include all types of people when this is not really true.' Lack of representation in an organization can lead to feelings of tokenism."); *see also* Deborah L. Rhode & Amanda K. Packel, *Diversity On Corporate Boards: How Much Difference Does Difference Make?*, 39 DEL. J. COR. L. 377, 408 (2011).

retain the diverse employees they hire, they must address the overall culture instead of focusing on filling diversity quotas.[359] Management must do more to make these employees feel valued within the organization, whether that be implementing inclusive policies, or ensuring resources are put into place to address unfair treatment.[360] For diverse candidates to be able to contribute and make a difference to the board, it has been argued that such diverse candidates should constitute a "critical mass," in other words, the minimum number required to ensure that the woman or diverse director does not experience the effects of tokenism.[361] Creating an atmosphere where they can succeed will help to ensure the longevity of women developers, senior managers, and board members' service.

Conclusion

The applications of automated decision technologies increase daily. Government agencies, private sector firms, universities, and even nonprofits are actively engaged in integrating ADM platforms to perform tasks traditionally done by humans.[362] Parallel to the growing reliance on ADM platforms, many express concerns that ADM platforms will replicate historic biases and further marginalize legally protected groups.

This Article argues that increasing gender diversity may offer a pathway for firms to mitigate the risk management concerns created by integrating ADM platforms. Referring to corporate governance reforms adopted in the wake of the recent financial crisis, this Article argues that structural and process-oriented board reforms may enable firms to enhance gender balance at the developer, senior executive

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359 *See id.* ("Research indicates that tokenism is positively correlated with turnover intentions in organizations with gender inequity."); *see also* Jori Ford, *Most Tech Companies Are Going About Diversity All Wrong*, Entrepreneur (July 26, 2018), https://www.entrepreneur.com/article/317289 [https://perma.cc/AKQ9-DJ9G] ("When you bake diversity into your organization's mission and core values, it guides the company's vision and actions. As a result, customers and other stakeholders understand that diversity is an essential component of company culture.").

360 *See* Gassam, *supra* note 328.

361 Rosenblum & Roithmayr, *supra* note 298, at 905 ("Business sociologist Rosabeth Moss Kanter identifies the key threshold that constitutes a critical mass as thirty-five percent."); Mariateresa Torchia et al., *Women Directors on Corporate Boards: From Tokenism to Critical Mass*, 102 J. Bus. Ethics 299, 299 (2011).

362 *See* Treasury Report, *supra* note 21; *see also* Endo, *supra* note 21; Cain Miller, *supra* note 21.

and board level. Greater diversity in leadership may enhance decision-makers' ability to identify and address the risk of algorithmic bias.