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AI Lending and ECOA: Avoiding Accidental Discrimination

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I. INTRODUCTION

An unmarried woman has an ongoing credit arrangement with her local lender. Some time later, after that woman marries, her lender notifies her that her new marital status means that she must reapply before she can continue accessing her existing credit. Moreover, that new application must be submitted under her husband's name, and any income the wife contributes—even if she earns more than her husband—likely will not be considered. If the woman and her husband become separated and divorced, that credit account will stay in his name. She will have to apply for a new credit account, but her application will be penalized by her status as a divorcée. Even if nothing has changed, if she is working the same job, getting paid the same salary, has no additional children who are dependents, and has no new financial obligations, she may be unable to get the same credit arrangement she had before she was married.

In the early 1970s, such a situation was not unheard of and was one of the motives behind the Equal Credit Opportunity Act ("ECOA").[1] In their original report, the drafters of the ECOA clarified their belief that lenders should make decisions regarding creditworthiness solely on financial considerations and not based on membership in any class.[2] While the ECOA has been expanded and

1. The scenario described above is but one of several examples of discrimination cited by the Senate Committee on Banking, Housing and Urban Affairs in proposing the addition of Title III—Equal Credit Opportunity to the Truth in Lending Act. Additional examples include different creditworthiness standards between women and men, refusals to consider alimony and child support as valid sources of income, considering a woman's use of birth control in credit determinations, and more. COMM. ON BANKING, HOUS., & URB. AFFS, TRUTH IN LENDING ACT AMENDMENTS, S. REP. NO. 93-278, at 16–17 (1973).

2. *See id.* at 19 (stating that rational considerations of creditworthiness include weighing expendable income and assets against anticipated obligations and that there is no rational basis in refusing to apply "ordinary criteria" because of characteristics unrelated to creditworthiness).

revised over time,[3] it has maintained the central principle that nobody should be denied credit based on factors unrelated to creditworthiness.[4]

Meanwhile, the twenty-first century has seen the development of computerized, algorithmic lending programs that use artificial intelligence ("AI") and "Big Data" to guide determinations about an applicant's creditworthiness.[5] This technology has the potential to help realize the ECOA's goal of ensuring that no credit applicant is denied credit based on factors unrelated to creditworthiness.[6] However, the nature of these algorithms also creates a significant risk that discrimination arising both from historical practices and from new and unexpected sources becomes a central—and potentially unidentifiable—part of the algorithms.[7] While the rewards to lenders adopting these tools are enticing, there are genuine risks that lenders should consider when pursuing these rewards.

This Note considers how, by aligning the interests of lenders with the goals of the ECOA, AI lending programs can offer a win–win scenario that benefits both lenders and consumers. Part II gives an overview of the purpose and requirements of the ECOA. Part III introduces algorithms—particularly AI algorithms—and the fundamentals of how lenders use them. Part IV looks at the benefits and risks posed by using AI algorithms in making credit decisions. Part V highlights recent attention paid to AI by government entities. Finally, Part VI considers different approaches that both regulators and lenders can take to get the most benefit out of AI lending algorithms while minimizing their inherent risks.

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3. Notably, particularly for this note, the ECOA was amended in 1976 to expand the protections against discrimination to include age, race, color, religion, national origin, receipt of public assistance benefits, and exercise of rights under the Consumer Credit Protection Act as well as to add in the requirement of notice for adverse actions. Equal Credit Opportunity Act Amendments of 1976, Pub. L. No. 94-239, 90 Stat. 251 (codified as amended at 15 U.S.C. § 1691).

4. *See* S. REP. NO. 93-278, at 19 ("All people with independent incomes must be assured equal access to the credit economy."); *see also* COMM. ON BANKING, HOUS., & URB. AFFS, EQUAL CREDIT OPPORTUNITY ACT AMENDMENTS OF 1976, S. REP. NO. 94-589, at 3 (1976) ("[I]t must be established as clear national policy that no credit applicant shall be denied the credit he or she needs and wants on the basis of characteristics that have nothing to do with his or her creditworthiness.").

5. Matthew Adam Bruckner, *The Promise and Perils of Algorithmic Lenders' Use of Big Data*, 93 CHI.-KENT L. REV. 3, 13 (2018).

6. *See infra* Part IV.A.

7. *See infra* Part IV.B.

II. Introduction to the Equal Credit Opportunity Act

While the ECOA[8] was written to ensure that nobody is denied equal access to credit because of characteristics unrelated to creditworthiness, the original statute left out a number of groups historically subjected to discrimination.[9] The protections in the original text of the ECOA extended only to discrimination based on sex or marital status.[10] One early academic commentator suggested that this limited scope may have been Congress's way of essentially testing whether the ECOA was workable before expanding its scope to cover additional groups.[11] Shortly after the initial passage of the ECOA, the 1976 ECOA Amendments (the "1976 Amendments") introduced, among other things, a prohibition of credit discrimination based on race, color, religion, national origin, and age.[12]

The 1976 Amendments recognized that credit decisions based on characteristics unrelated to creditworthiness harm both the consumer and the creditor.[13] For consumers, the fact that credit was extensively used in significant purchases such as homes and cars meant that credit was a necessity and not a luxury.[14] For creditors, such "irrational discrimination" meant they limited their potential customer base and failed to realize the benefit of some of their best classes of customers.[15]

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8. Equal Credit Opportunity Act, 15 U.S.C. § 1691 (2018). The regulation promulgated by the ECOA is Regulation B, 12 C.F.R. § 1002 (2022).

9. *See* Gail R. Reizenstein, *A Fresh Look at the Equal Credit Opportunity Act*, 14 AKRON L. REV. 215, 223 (1980) ("[The ECOA] create[d] a legal right of equal access to credit . . . . [However,] the original Act failed to . . . recognize other groups historically denied credit . . . .").

10. Equal Credit Opportunity Act, Pub. L. No. 93-495 § 701(a), 88 Stat. 1521, 1521 (1974) (amended 1976).

11. Kathryn P. Taylor, *Equal Credit for All - An Analysis of the 1976 Amendments to the Equal Credit Opportunity Act*, 22 ST. LOUIS U. L.J. 326, 332 (1978).

12. Equal Credit Opportunity Act Amendments of 1976, Pub. L. No. 94-239 (codified as amended at 15 U.S.C. § 1691).

13. *See* COMM. ON BANKING, HOUS., AND URB. AFFS, EQUAL CREDIT OPPORTUNITY ACT AMENDMENTS OF 1976, S. REP. NO. 94-589, at 3 (1976) (commenting on the necessity of credit for consumers and entrepreneurs as well as the loss to creditors for engaging in "irrational discrimination").

14. *Id.*

15. *See id.* ("Discrimination against the elderly was the most often cited abuse, despite the fact that in the experience of many creditors their older customers were their best customers."); *see also* Reizenstein, *supra* note 9, at 223 ("[S]tudies have shown that [women] (especially single women) are in fact better credit risks than men."); *id.* at 223 n.8 (giving as an example a 1964 study showing 2% of men while only 0.75% of women defaulted).

As a whole, the 1976 Amendment sought to find a balance between (1) the societal benefits that come from preventing discrimination with (2) the ability of creditors to make sound judgments regarding creditworthiness in a way that benefits both lenders and borrowers.[16]

In order to meet this underlying goal, the ECOA sets forth two major provisions that lenders must comply with. The first provision prohibits creditors from discriminating based on an applicant's status as a protected class member, deriving income from any public assistance program, or exercising their rights under the Consumer Credit Protection Act.[17] The second provision requires creditors who take an adverse action against an applicant to provide a statement of why that action was taken.[18]

Under the first provision, Regulation B[19] (the ECOA's implementing regulation) defines discrimination to include any treatment of one applicant that is less favorable than another applicant and prohibits discrimination on any prohibited basis.[20] Regulation B additionally provides that discrimination can be found under either of two theories of liability: disparate treatment or disparate impact.[21]

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16. S. REP. NO. 94-589, at 4.

17. Equal Credit Opportunity Act, 15 U.S.C. § 1691(a) (2018). The third discrimination prohibition category (exercising rights under the CCPA) was included to prevent retaliatory credit actions being taken against one who had, for example, sued under causes of action created by the ECOA, the Fair Credit Reporting Act, and the Truth in Lending Act. S. REP. NO. 94-589, at 5.

18. 15 U.S.C. § 1691(d)(2).

19. Regulation B, 12 C.F.R. § 1002 (2022).

20. *See id.* § 1002.2(n) (definition of "discrimination"); § 1002.2(z) (definition of "prohibited basis"); § 1002.4(a) (prohibiting discrimination against an applicant on a prohibited basis). While the ECOA itself does not define "discrimination" it does have two subsections that list activities that *are not* discrimination. *See* 15 U.S.C. § 1691(b)–(c) (laying out certain activities that are expressly allowed and that address denying entry into special credit programs aimed at disadvantaged classes, provided the decision follows the rules of the specific program). Perhaps the most direct congressional statement of what discrimination is comes from the original report proposing the ECOA which stated that discrimination "occurs when a credit applicant is not evaluated pursuant to a creditor's ordinary credit criteria, but is judged—and frequently denied credit—not individually, but because of membership in a class." COMM. ON BANKING, HOUS., AND URB. AFFS, TRUTH IN LENDING ACT AMENDMENTS, S. REP. NO. 93-278 at 19 (1973).

21. *See, e.g.*, CONSUMER FIN. PROT. BUREAU, CFPB CONSUMER LAWS AND REGULATIONS: ECOA 1 (2013), https://files.consumerfinance.gov/f/201306_cfpb_laws-and-regulations_ecoa-combined-june-2013.pdf [https://perma.cc/Y5XL-VB9K] (discussing the two theories of liability). There is an argument that, because the ECOA does not mention disparate impact and the Supreme Court has not yet considered a disparate impact claim under the ECOA, there may be little chance of a disparate impact claim succeeding. *See* Mikella Hurley & Julius Adebayo, *Credit Scoring in the Era of Big Data*, 18 YALE J.L. &

Official guidance states that both theories of liability can be satisfied even when there is no intent to discriminate unless the creditor's actions or practice has a legitimate, nondiscriminatory reason.[22] In addition to discrimination arising from actions taken against specific applicants, discrimination can occur when a lender makes statements, creates ads, or otherwise communicates in any way that would discourage potential credit applicants from applying for credit.[23] The CFPB continues to consider and address new conceptions of discrimination. For example, in 2021, the CFPB stated that sex discrimination encompasses both sexual orientation and gender identity[24] and clarified in a 2022 advisory opinion that protections for applicants extend to credit applicants and existing credit customers.[25]

For the second ECOA provision, Regulation B defines "adverse action" to include (i) a refusal to grant credit within the amount or terms requested by the applicant, (ii) a termination or unfavorable change in the terms of an account, or (iii) a refusal to increase the amount of credit in response to an application to do so.[26] After an adverse action is taken, a creditor must send to the applicant within thirty days either a statement of the specific reasons for the adverse action or a disclosure

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TECH. 148, 193–95 (2016) (discussing the uncertainty of success with disparate impact claims). *But see* Talia B. Gillis & Jann L. Spiess, *Big Data and Discrimination*, 86 UNIV. CHI. L. REV. 459, 461 n.6 (2019) (arguing that the Supreme Court's decision in *Tex. Dep't of Hous. and Cmty. Affs v. Inclusive Cmtys. Project, Inc.*, 576 U.S. 519 (2015) upholding disparate impact under the closely related Fair Housing Act, along with statements made by the CFPB, support the availability of disparate impact claims). An analysis of these arguments is outside of the scope of this note, and this note presumes that disparate impact would be upheld by courts.

22. *See* 12 C.F.R. § 1002.4(a)(1)–(2) (Supp. I 2022) (discussing the scope of the anti-discrimination provision and examples of disparate treatment); *id.* § 1002.6(a)(2) (Supp. I 2022) (discussing congressional intent that the effects test developed under Title VII of the Civil Rights Act case law apply to the ECOA).

23. *Id.* § 1002.4(b). For example, in 2022, the CFPB filed suit against Trident Mortgage Company for violations of the ECOA and the Fair Housing Act for locating the vast majority (fifty-one out of fifty-three) of its offices outside of majority-minority neighborhoods and targeting its marketing campaigns specifically to majority-white neighborhoods. *CFPB, DOJ Order Trident Mortgage Company to Pay More Than $22 Million for Deliberate Discrimination Against Minority Families*, CONSUMER FIN. PROT. BUREAU: NEWSROOM (July 27, 2022), https://www.consumerfinance.gov/about-us/newsroom/cfpb-doj-order-trident-mortgage-company-to-pay-more-than-22-million-for-deliberate-discrimination-against-minority-families/ [https://perma.cc/W75K-UNVK].

24. Equal Credit Opportunity (Regulation B); Discrimination on the Bases of Sexual Orientation and Gender Identity, 86 Fed. Reg. 14363, 14363 (Mar. 16, 2021).

25. Equal Credit Opportunity (Regulation B); Revocations or Unfavorable Changes to the Terms of Existing Credit Arrangements, 87 Fed. Reg. 30097, 30099 (May 18, 2022).

26. 12 C.F.R. § 1002.2(c).

that the applicant has a right to a statement of specific reasons if such statement is requested within sixty days of the notice.[27]

During the process of amending the ECOA, the Committee stated that the adverse action notification requirement was "among the most significant parts of the bill" and "essential to achieve the anti-discrimination goals of the legislation."[28] Two primary rationales for the adverse action notification were given. First, the Committee asserted that creditors would be less likely to act improperly if they had to explain why they made their decisions.[29] Second, the Committee noted that applicants who were properly denied credit would be able to identify and fix the reasons they were denied if those reasons were explained to them.[30]

While the ECOA was originally placed under the jurisdiction of the Federal Reserve Board ("FRB"), since the enactment of the Dodd–Frank Act in 2010, rulemaking authority for all consumer finance laws has been delegated to the Consumer Finance Protection Bureau ("CFPB").[31] However, multiple agencies are tasked with monitoring or enforcing the ECOA and Regulation B within their spheres of jurisdiction. For example, agencies responsible for overseeing the ECOA and Regulation B compliance include:

- the CFPB for banks, savings associations, and credit unions with total assets of over $10 billion;
- the Federal Trade Commission (FTC) for affiliates of such financial institutions who are not themselves banks, savings associations, or credit unions as well as retailers, finance companies, and all other unlisted creditors;
- the Office of the Comptroller of the Currency (OCC) for national banks, federal savings associations, and federal branches of foreign banks;
- the FRB for state member banks, branches and agencies of foreign banks (other than those under other agency's jurisdictions), commercial lending companies owned or

27. § 1002.9(a).

28. COMM. ON BANKING, HOUS., & URB. AFFS, EQUAL CREDIT OPPORTUNITY ACT AMENDMENTS OF 1976, S. REP. NO. 94-589, at 7 (1976).

29. *Id.*

30. *Id.*

31. Dodd–Frank Wall Street Reform and Consumer Protection Act ("Dodd–Frank") § 1061(b), 12 U.S.C. § 5581(b) (2018).

controlled by foreign banks, and organizations operating under the Federal Reserve Act;
- the Federal Deposit Insurance Corporation (FDIC) for nonmember insured banks, insured state branches of foreign banks, and insured state savings associations;
- the National Credit Union Administration (NCUA) for federal credit unions;
- the U.S. Small Business Administration (SBA) for small business investment companies;
- the Farm Credit Administration (FCA) for federal land banks, federal land bank associations, federal intermediate credit banks, and production credit associations;
- the Securities and Exchange Commission (SEC) for brokers and dealers;
- the Department of Transportation (DOT) for air carriers and creditors subject to Surface Transportation Board; and
- the Packers and Stockyards Division of the U.S. Department of Agriculture (USDA) for creditors subject to the Packers and Stockyards Act.[32]

While each of these agencies has the authority to take specific actions, such as issuing citations for violations or referring creditors with a pattern of potentially discriminatory behaviors to the Department of Justice,[33] the primary enforcement authority is delegated to the CFPB and FTC.[34]

III. Introduction to AI Algorithmic Lending Practices

At a foundational level, an algorithm is nothing more than a set of instructions.[35] A basic algorithm simply takes in an input, performs a function, and returns an output.[36] Even complex algorithms that perform complicated tasks can often be distilled down to a set of directions, each of which is relatively simple.[37] While algorithms are

32. 12 C.F.R. § 1002 App. A (2022).

33. *See, e.g.*, 2022 CONSUMER FIN. PROT. BUREAU FAIR LENDING REP. 33–36 (listing the most frequently cited violations); *id.* at 36 (listing referrals to the Department of Justice).

34. 12 C.F.R. § 1002.16(a)(2).

35. Robin Feldman & Kara Stein, *AI Governance in the Financial Industry*, 27 STAN. J.L. BUS. & FIN. 94, 101 (2022).

36. Bruckner, *supra* note 5, at 9.

37. *Id.*

commonly thought of as modern, cutting-edge tech developments, lenders have been using algorithms for decades.[38]

Perhaps the best-known example of an algorithm used in lending decisions is the credit score, and no credit modeling system is more widely used than the FICO score.[39] Introduced in 1989, the FICO score was created to be a standardized approach for rating the creditworthiness of credit applicants that eliminates the subjective (and frequently biased) reliance on in-person application processes.[40] To create a credit score, the FICO system aggregates data on an applicant from different financial sources, runs that data through its algorithm, and outputs that applicant's score.[41] While the exact formula is not known, FICO focuses on five categories of factors: the applicant's payment history, the amounts an applicant owes to existing creditors, the length of the applicant's credit history, recent credit inquiries, and the specific mixture of credit the applicant currently has.[42] It is believed that FICO uses fewer than fifty individual data points for any specific applicant in creating the applicant's credit score.[43]

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38. *Id.* at 11.

39. *See id.* ("[A] FICO score is an algorithmic output."); *see also* U.S. DEP'T OF THE TREASURY, A FINANCIAL SYSTEM THAT CREATES ECONOMIC OPPORTUNITIES: NONBANK FINANCIALS, FINTECH, AND INNOVATION 134 (July 2018) [hereinafter FINTECH AND INNOVATION] https://home.treasury.gov/sites/default/files/2018-07/A-Financial-System-that-Creates-Economic-Opportunities---Nonbank-Financi . . . .pdf [https://perma.cc/TG5C-NDSC] (stating that FICO scores are "reportedly used by some 90% of top lenders.").

40. Lorena Rodriguez, Note, *All Data is Not Credit Data: Closing the Gap Between the Fair Housing Act and Algorithmic Decisionmaking in the Lending Industry*, 120 COLUM. L. REV. 1843, 1852 (2020). Note, though, that despite the goals and promises of FICO, whether credit scores have actually resulted in fair, unbiased credit is debated by some commentators. Some have questioned whether the scores themselves might be biased or discriminatory. *See, e.g.*, *id.* at 1853 ("While FICO's credit-scoring system is supposed to be unbiased and objective, some scholars have argued that the five factors have a disparate impact on consumers of color."); DOWSE B. (BRAD) RUSTIN IV ET AL., PRICING WITHOUT DISCRIMINATION: ALTERNATIVE STUDENT LOAN PRICING, INCOME-SHARE AGREEMENTS, AND THE EQUAL CREDIT OPPORTUNITY ACT 6 (2017) ("While scoring-based models eliminate a user's ability to inject bias into the scoring system, the models do not guarantee that the scoring criteria will not disparately affect a protected class."). Others have found evidence that, even if the scoring is fair, actual credit decisions continue to be inequitable. *See* Janine S. Hiller, *Fairness in the Eyes of the Beholder: AI; Fairness; and Alternative Credit Scoring*, 123 W. VA. L. REV. 907, 922 (2021) (citing a study showing Latino and African American borrowers were charged higher rates than white borrowers with the same FICO score).

41. RUSTIN, *supra* note 40, at 5.

42. Rodriguez, *supra* note 40, at 1852.

43. Bruckner, *supra* note 5, at 11.

Compared to the algorithm used by FICO, the AI lending algorithms considered in this note have one fundamental difference: the ability to "learn" and "improve" on their own.[44] While a traditional algorithm requires having a human programmer create a series of discrete steps that the algorithm follows to come to a result, an AI algorithm is given past data sets with real-world results and is programmed to look for patterns from which it can predict results from future data sets.[45] AI software[46] is, in effect, programmed not to *perform* a specific task but rather to *learn* how to perform a task.[47] For example, in a lending context, instead of programming the software with a formula for calculating default risk, the AI would be given data on past credit customers—including information on which customers defaulted—and the AI looks for patterns to identify what characteristics correlate to chances of default.[48] In short, human programmers develop an AI, and that AI then creates the algorithm used to evaluate credit applicants.

In order to trust an AI's results, the AI must be tested against another known data set (minus the information on defaults) with the output compared to the real-world results.[49] Importantly, though, even after the AI consistently achieves acceptably accurate results, these results must continue to be verified to ensure that no unexpected problems arise.[50] For example, the AI might start making unexpected

44. FINTECH AND INNOVATION, *supra* note 39 at 53.

45. *See, e.g.*, Feldman, *supra* note 35, at 101 ("[D]eep learning means using past data to train a model that can, on its own, make predictions on future data and direct choices based on those predictions."); Yavar Bathaee, *The Artificial Intelligence Black Box and the Failure of Intent and Causation*, 31 HARV. J.L. & TECH. 889, 900 (2018) ("The goal of tuning a machine-learning algorithm is to ensure that the trained model will generalize, meaning that it has predictive power when given a test dataset (and ultimately live data)."); Bruckner, *supra* note 5, at 10 ("The paramount value of learning algorithms is 'to detect patterns in data in order to automate complex tasks or make predictions.'").

46. It is, perhaps, useful to clarify some terminology here. Through this note, I will use "AI" when referring to the underlying software processes that self-train as described in this section (note, though, that other sources may refer to these same processes by other names such as machine learning and predictive analytics). I will use "AI algorithms" to refer to the algorithms that are developed through AI processes. I will refer to "AI lending algorithms" as the specific tool used by lenders.

47. Bruckner, *supra* note 5, at 9.

48. Gillis, *supra* note 21, at 463.

49. *See, e.g.*, Bathaee, *supra* note 45, at 900–01 (describing the machine-learning training process).

50. ORG. FOR ECON. COOP. & DEV., ARTIFICIAL INTELLIGENCE, MACHINE LEARNING AND BIG DATA IN FINANCE: OPPORTUNITIES, CHALLENGES AND IMPLICATIONS FOR POLICY MAKERS 46 (2021) [hereinafter OECD].

connections[51] or there may be some amount of "drift" in either laws or consumer behaviors that causes the AI results to become increasingly less accurate.[52]

Due to AI's self-learning nature, it is generally accepted that giving the AI larger amounts of data leads to better results from the AI.[53] To take advantage of this , programmers who develop the AI algorithms "feed" increasing amounts of data into these AIs.[54] This need for such large amounts of data has had two notable effects: the increasing adoption of "alternative" data[55] and the development of algorithms that have become too complex for programmers to identify precisely what the algorithms are doing.[56]

In the lending context, alternative data[57] is nonfinancial data used to determine creditworthiness.[58] Examples of alternative data include social media activities, the college one attended, address history, and professional licensures, as well as more surprising data points such as whether one uses correct capitalization in an online application and how much (or little) time one spends looking at an online terms-and-conditions disclosure.[59] Compared to FICO's estimated fifty data points, the amount of data an AI algorithm might use to evaluate creditworthiness can be enormous, with at least one lender reportedly using more than 12,000 data points.[60] Further, the scope of information used by these algorithms is expected to continue to expand.[61]

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51. *See infra* Part IV.B for examples of such behavior.

52. *See* OECD, *supra* note 50, at 46–47 (explaining how drift may arise).

53. FINTECH AND INNOVATION, *supra* note 39, at 53.

54. Bruckner, *supra* note 5, at 15.

55. Rodriguez, *supra* note 40, at 1858–59.

56. Mihailis E. Diamantis, *The Extended Corporate Mind: When Corporations Use AI to Break the Law*, 98 N.C. L. REV. 893, 910 (2020).

57. The term "alternative data" has evolved over the past 10–20 years. Early discussions used the term "big data" to refer to the large amounts of data being collected, but this seems to have given way to "alternative data" to more clearly identify the non-traditional nature of this data. While there is likely a subtle distinction between the two terms, within the scope of this paper they can be considered largely synonymous. This note will primarily use the term "alternative data," but will refer to "big data" in situations where specific parties were using that term during a specific time period, such as *infra* Part V.

58. Rodriguez, *supra* note 40, at 1855.

59. *Id.* at 1858–59.

60. Bruckner, *supra* note 5, at 13–14.

61. *See* FINTECH AND INNOVATION, *supra* note 39, at 54 ("The sheer magnitude of data . . . and . . . the vast amounts of information . . . [are] only expected to accelerate in volume . . . .").

This extensive use of data leads to the second effect: the amount of information being processed can become too much for any person to interpret or even identify how the algorithm came to its conclusion.[62] The processes used by an AI as it analyzes and "trains" from the data it is fed while creating the algorithm may not use the same logic that a person would use in analyzing similar data.[63] After an AI has been trained, the algorithm can become so complex that it is impossible to reverse-engineer how it works.[64] This opacity in identifying exactly what happens between entering data into an AI algorithm and receiving data out has led to such programs being referred to as "black boxes."[65]

IV. HOW AI LENDING CAN HELP AND HARM

Given the complexity of AI, whether AI lending algorithms are, on balance, helpful or harmful is widely debated.[66] However, a fair consideration shows there are benefits and risks—both proven and hypothesized—inherent in AI algorithmic lending.

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62. Feldman, *supra* note 35, at 97. *But see* Gillis, *supra* note 21, at 474 (arguing that it's not that the algorithms are opaque and uninterpretable, but rather that the people trying to interpret how the algorithms came to their decisions are not asking the right questions).

63. *See* Kristin Johnson, Frank Pasquale, and Jennifer Chapman, *Artificial Intelligence, Machine Learning, and Bias in Finance: Toward Responsible Innovation*, 88 FORDHAM L. REV. 499, 507 (2019) ("[I]t is important to understand the term 'learning' here as a metaphor . . . . AI methods [are] vulnerable to pursuing forms of analysis that might be set aside as suspect by a seasoned financial professional.").

64. Diamantis, *supra* note 56, at 910; *see also* Rodriguez, *supra* note 40, at 1855 ("But what happens between input and output? Few really know why or how an algorithm comes to a certain decision . . . .").

65. Feldman, *supra* note 35, at 97. However, at least one commentator has argued that such algorithmic opacity is perhaps no worse than the inability to know exactly why *people* reach certain decisions. *See* Gillis, *supra* note 21, at 474 ("Unlike the human decision-making context in which many aspects of the decision remain highly opaque—sometimes even in the decisionmakers themselves— . . . we can observe many aspects of the decision and therefore scrutinize these decisions to a greater extent.").

66. *See, e.g.*, Hiller, *supra* note 40, at 925 ("It has been argued that the use of alternative data and AI automated credit decision systems could expand access to credit. On the other hand, it has been argued that alternative credit scoring is opaque and unfair."); Diamantis, *supra* note 56, at 896 ("Algorithms promise to make corporations more efficient and (perhaps) more objective, but they do not remove (or even reduce) the possibility that things will sometimes go awry.") (citations omitted).

A. AI Algorithmic Lending Can Offer Benefits to Both Lenders and Borrowers

AI lending algorithms may benefit lenders by increasing lender operational efficiency, improving the quality of products that lenders can offer, and providing a competitive advantage to lenders that adopt the technology.[67] It has been reported that AI can save lenders money during the process of making credit decisions.[68] For example, one would expect the use of automated AI lending processes to reduce the number of employees required to process credit applications, though at least one author has pointed out the possibility that such savings may be offset, at least in the short term, by a necessary increase in the number of technical positions required to manage the software.[69] Nevertheless, effective credit scoring systems can reduce costs to lenders by streamlining the process of making credit decisions.[70]

In addition to saving costs by reducing the time it takes to process credit applications, improved systems of credit assessment (such as those promised by AI algorithm developers) reduce costs to lenders by reducing the rate of default.[71] Studies have shown evidence that AI systems have been able to help lenders more accurately predict default risks.[72] For example, one algorithmic lender has claimed to decrease the rate of default by 12%.[73]

An improved ability to predict defaults can also benefit borrowers by allowing lenders to offer credit to a broader pool of credit applicants, including those unable to access credit under more traditional models.[74] Fundamentally, credit scoring systems are simply tools used to evaluate whether a lender may trust a borrower to pay a

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67. FINTECH AND INNOVATION, *supra* note 39, at 54–55.
68. Hiller, *supra* note 40, at 927.
69. Bruckner, *supra* note 5, at 21.
70. Hiller, *supra* note 40, at 920.
71. *See, e.g.*, Rodriguez, *supra* note 40, at 1852 (stating the FICO score was purportedly introduced to focus "solely on factors related to a person's ability to repay a loan."); Bruckner, *supra* note 5, at 21 ("One of the clearest potential cost savings for algorithmic lenders is that a more accurate credit-underwriting model should decrease the incidence of loan defaults.").
72. Johnson, supra note 63, at 506.
73. *See* Bruckner, *supra* note 5, at 21 (citing claim from Lenddo).
74. Talia B. Gillis, *The Input Fallacy*, 106 MINN. L. REV. 1175, 1180 (2022).

debt.[75] When a lender can more accurately predict default risk, it may find that certain applicants have a lower risk level than previously thought, allowing those applicants access to credit that would have previously been denied.[76]

Additionally, AI lending algorithms can open credit opportunities to applicants who are considered "credit invisible."[77] Under traditional credit scoring models, such as FICO scores, significant weight is given to the applicant's financial history.[78] In other words, an applicant's present access to credit is determined, at least in part, by the credit they had access to in the past. For underserved populations—such as minorities, youths, and low-income borrowers—the fact that they have never had the opportunity to develop these financial characteristics further reduces their access to affordable credit.[79] These applicants are penalized not because they have done anything negative but because there is not enough information for the credit model to assign them a score.[80] By integrating alternative data, AI lenders can give these borrowers credit opportunities they otherwise would not have.[81]

While the benefits of better predictability are significant, when considering the context and goals of the ECOA, perhaps the most significant benefit that AI lending algorithms offer is the potential to reduce bias in the lending process.[82] Before the advent of credit

75. *See* Regulation B, 12 C.F.R. § 1002.2(p)(1) (2022) (defining "credit scoring system" as "a system that evaluates an applicant's creditworthiness mechanically."); Jim Akin, *What Is Creditworthiness?*, EXPERIAN: REPORT ADVICE (July 3, 2020), https://www.experian.com/blogs/ask-experian/what-is-creditworthiness/ [https://perma.cc/F5NR-P7T7] (defining "creditworthiness" as "a lender's willingness to trust you to pay your debts.").

76. Gillis, *supra* note 74, at 1191.

77. Rodriguez, *supra* note 40, at 1859. For more on "credit invisible" applicants, see *infra* notes 116–17 and accompanying text.

78. *Id.* at 1852–53.

79. Bruckner, *supra* note 5, at 18.

80. *Id.*

81. FINTECH AND INNOVATION, *supra* note 39, at 12. *But see* Hiller, *supra* note 40, at 925 ("On the other hand, it has been argued that alternative credit scoring is opaque and unfair.").

82. *See, e.g.*, Jason R. Bent, *Is Algorithmic Affirmative Action Legal?*, 108 GEO. L.J. 803, 810 (2020) ("This automated process can remove some of the subjectivity and bias of human decisionmaking . . . ."); FINTECH AND INNOVATION, *supra* note 39, at 57 ("One advantage of machine learning and AI methods is that they can potentially help avoid discrimination based on human interactions by ceding aspects of such decision making to an algorithm.").

scoring, credit decisions were generally made by human loan officers in a process where bias and discrimination could easily arise.[83] Moreover, these biases could arise even without the realization of the decision-makers.[84] FICO scores were generally considered to be an improvement in avoiding discrimination,[85] though FICO scores' overall effectiveness in this regard has been questioned.[86] The promise made by proponents of AI lending algorithms is that because AI systems can find correlations in any data set,[87] biased decisions can be entirely avoided by simply removing biased data.[88]

B. *Risks of Harm from AI Lending Algorithms*

Despite claims that an AI algorithm's reliance on data makes it inherently reliable and unbiased, evidence shows that may not necessarily be true.[89] Even some of the largest technology companies have been faced with problematic results after deploying AI-powered systems. For example, after Amazon used an AI system that relied on concentrations of existing Amazon Prime customers to plan the rollout of Amazon's same-day delivery service, several majority-Black ZIP codes in several cities were excluded despite the fact they directly neighbored (or were surrounded by) majority-white ZIP codes where the service was offered.[90] In another instance, a machine learning program designed to rank Amazon employee applications relied on past hiring data, but, due to the prevalence of men in the tech industry, the algorithm penalized resumes that indicated that the applicants were

83. Rodriguez, *supra* note 40, at 1852.

84. *See* Gillis, *supra* note 21, at 463 n.16 ("[T]his opaqueness [in discriminatory human decisions] . . . is also a result of human decision-making often being opaque to the decisionmakers themselves.").

85. Hurley, *supra* note 21, at 155.

86. *See supra* note 40.

87. Hiller, *supra* note 40, at 923–24.

88. *See, e.g.*, Bruckner, *supra* note 5, at 23 (discussing promises of increased fairness through removing human biases).

89. *See* Ifeoma Ajunwa, *The Paradox of Automation as Anti-Bias Intervention*, 41 CARDOZO L. REV. 1671, 1685–86 (2020) ("[The] unquestioning belief in data objectivity . . . becomes a problematic feature of algorithmic systems . . . [and] often results in an uncritical acceptance of decisions derived from such algorithmic systems . . . . Biases can exist in big data as much as they do in the real world . . . .").

90. David Ingold & Spencer Soper, *Amazon Doesn't Consider the Race of Its Customers. Should It?*, BLOOMBERG (Apr. 21, 2016), https://www.bloomberg.com/graphics/2016-amazon-same-day/ [https://perma.cc/UJ23-QQS3].

women.[91] Microsoft had to rapidly shut down an AI Twitter chatbot that, within hours of going live, learned to tweet racist and obscene comments.[92] And a 2012 study found that Google's search algorithm began connecting names more common in Black communities with search results targeting potential criminals.[93]

While none of these examples are lending-specific, AI lending systems might create discriminatory results for similar reasons. For example, one of the most basic reasons that an AI algorithm may develop a bias is simply that the data pool used to train the algorithm was biased.[94] Like the Amazon hiring algorithm, there have been reports of AI hiring systems perpetuating pre-existing biases in the hiring process.[95] Historically, certain groups have faced significant discrimination regarding receiving credit, and traditional credit approaches have perpetuated this discrimination by relying on earlier credit availability.[96] While the use of alternative data ideally would allow an AI lending algorithm to avoid these biases, past discrimination may nevertheless become entrenched in the algorithm.[97]

The risk that an AI algorithm will perpetuate historical discrimination is compounded by AI's fundamental nature of taking in enormous amounts of data and putting out results in ways people cannot

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91. Jeffrey Dastin, *Amazon Scraps Secret AI Recruiting Tool that Showed Bias Against Women*, REUTERS (Oct. 10, 2018, 7:04 PM), 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/P8JG-KVHN].

92. Daniel Victor, *Microsoft Created a Twitter Bot to Learn From Users. It Quickly Became a Racist Jerk.*, N.Y. TIMES (Mar. 24, 2016) https://www.nytimes.com/2016/03/25/technology/microsoft-created-a-twitter-bot-to-learn-from-users-it-quickly-became-a-racist-jerk.html [https://perma.cc/M2DZ-K2GJ].

93. Bruckner, *supra* note 5, at 27 (citing Latanya Sweeney, Discrimination in Online Ad Delivery, ACM QUEUE, Apr. 2, 2013).

94. Bent, *supra* note 82, at 812.

95. *See, e.g.*, *id.* (2020) (discussing St. George's Hospital in the United Kingdom who used past data, including systemic discrimination against minorities and women, when developing a system for evaluating med school applications); *see also* Ajunwa, *supra* note 89, at 1676 ("That study concluded that while one purported *raison d'etre* . . . of automated hiring systems was to reduce hirer bias . . . the reality remained that 'algorithmic specification of "fit" can itself become a vehicle for bias.'") (citation omitted).

96. *See, e.g.*, Gillis, *supra* note 74, at 1179 ("[D]iscriminatory practices have prevented racial minorities from being equal participants in credit markets.").

97. *See* Hurley, *supra* note 21, at 193 ("[M]achine-learning tools may foment unintentional discrimination if they define target variables in a manner that encodes existing bias . . . .").

anticipate.[98] Because AIs create highly complex decision-making systems that incorporate a wide range of variables, they can identify endemic factors within the social structure and use those factors as proxies for protected characteristics.[99] It may be impossible to entirely exclude a protected characteristic (such as race) if other variables easily correlate with that characteristic.[100]

For example, some alternative data points used in AI lending algorithms are particularly vulnerable to being used as proxies for discrimination based on impermissible factors; for instance, ZIP codes are easily correlated with race.[101] Educational history can also, at times, be readily adopted as a proxy for race.[102] Such proxies can arise, and are particularly hard to identify or avoid, when the relationship between a factor and a decision is not actually based on a protected characteristic but nevertheless is particularly correlated with one such characteristic.[103] Finding and avoiding the use of such proxies is further complicated by the fact that determinations of what factors to exclude come down to the imprecise, intuitive judgments of programmers who may not recognize such factors' potential as proxies for protected characteristics.[104]

V. THE HISTORY OF FEDERAL GOVERNMENT RESPONSES TO AI

In recent years, a number of government entities have made clear that they consider these types of impacts from AI to be areas of concern. The statements and actions cataloged below are just a

98. For another example of unexpected results outside of the scope of potential discrimination, one report discussed the risk of AIs engaging in tacit collusion. In such a situation an AI would recognize the behavior of market participants—or even to other active AI models—and adapt in such a way as to create collusive outcomes even without any humans ever being aware of the collusion. OECD, *supra* note 50, at 40.

99. Rodriguez, *supra* note 40, at 1861.

100. Gillis, *supra* note 21, at 469.

101. Hurley, *supra* note 21, at 182.

102. *See, e.g.*, Bruckner, *supra* note 5, at 29 (using graduation from an HBCU as an example of a racial proxy); Hiller, *supra* note 40, at 933 ("[T]he known educational data points have been widely shown to reflect discrimination based on race.").

103. *See, e.g.*, Rodriguez, *supra* note 40, at 1857 (using, as an example, a correlation between listening to particular musical genres (here, hip-hop) with disparate impacts on a racial group).

104. Gillis, *supra* note 21, at 469.

selection of responses from the federal government, but they indicate an evolution in the government's approach to questions around AI.[105]

A. Presidential Responses to AI

Before looking at agency-specific statements and actions, it is perhaps helpful to acknowledge the context in which they were made—that is, the approach of the Chief Executives during these periods. Since at least 2014, the President has directed attention to the risks posed by what was then called "big data." In his January 17, 2014 address, President Obama announced a "comprehensive review of big data and privacy" that would look at how both public and private entities could balance the opportunities presented with concerns over privacy and security.[106] While the primary focus of this directive was privacy concerns, even the early reports noted that "big data" could contribute to both perpetuating and preventing discrimination in access to credit.[107] By 2016, the "Big Data" Reports from the Executive Office of the President discussed how big data is not inherently objective, how it might expand credit to underserved populations, and how unintentional proxies for protected characteristics might develop within an

105. In considering these actions, an evolution in the way these topics are referenced seems to appear. The earlier government statements focused on the data being collected, referring first to big data (i.e., the collection and use of large amounts of data) then to alternative data (i.e., data that is fundamentally different from traditional data sources). As technology (and, likely, the government's understanding of that technology) continued to develop, the techniques used to interpret that data using artificial intelligence and machine learning came more into focus. While it's plausible (maybe even likely) that not all of these actions *actually* involved AI, they nevertheless seem to be important steps in the sequence that brings us to current government actions.

106. Off. of the Press Sec'y, *Remarks by the President on Review of Signals Intelligence*, THE WHITE HOUSE: SPEECHES & REMARKS (Jan. 17, 2014), https://obamawhitehouse.archives.gov/the-press-office/2014/01/17/remarks-president-review-signals-intelligence [https://perma.cc/Z5DW-RXZZ].

107. *See* EXEC. OFF. OF THE PRESIDENT, BIG DATA AND PRIVACY: A TECHNOLOGICAL PERSPECTIVE 12 (2014) https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/PCAST/pcast_big_data_and_privacy_-_may_2014.pdf [https://perma.cc/8RBE-YY63] (citing LendUp's use of nontraditional data in credit determinations); PRESIDENT'S COUNCIL OF ADVISORS ON SCI. AND TECH., EXEC. OFF. OF THE PRESIDENT, BIG DATA AND PRIVACY: SEIZING OPPORTUNITIES, PRESERVING VALUES 7 (2015) https://obamawhitehouse.archives.gov/sites/default/files/docs/20150204_Big_Data_Seizing_Opportunities_Preserving_Values_Memo.pdf [https://perma.cc/72JR-95ZZ] ("[T]he new report will take a deeper dive into how big data interacts with . . . credit—considering both how the use of big data technologies can perpetuate discrimination and prevent it.").

algorithm.[108] Some reports included considerations of how the use of big data should impact public policy and government rulemaking.[109]

In contrast to the Obama Administration's attention to the risks from AI, the Trump Administration generally underplayed these risks in favor of a policy of driving breakthroughs in AI technology and reducing barriers to AI deployment.[110] This relaxing of regulatory oversight is notably apparent in an updated Policy on No-Action Letters[111] implemented in September 2019 that announced a significantly relaxed approach to the CFPB's granting of No-Action Letters.[112]

Under the Biden administration, a new focus on the concerns around AI has been apparent, including the release in October 2022 of the administration's "Blueprint for an AI Bill of Rights."[113] The Blueprint, not an actionable policy but rather a set of principles intended to guide the creation and use of AI systems, is intended to be applicable across all realms of AI use (not just its use in finance) and guard against the potential harms from AI.[114] The portion of the Blueprint dedicated to protecting the public from algorithmic discrimination includes expectations of automated systems including: showcasing proactive assessments of equity; including representative and robust data; guarding against proxies; ensuring accessibility during design, development, and deployment; assessing and mitigating disparities; ongoing monitoring for discrimination; and demonstrating protections

108. EXEC. OFF. OF THE PRESIDENT, BIG DATA: A REPORT ON ALGORITHMIC SYSTEMS, OPPORTUNITY, AND CIVIL RIGHTS 6–13 (2016) [hereinafter ALGORITHMIC SYSTEMS].

109. *Id.* at 24.

110. Exec. Order No. 13859, 84 Fed. Reg. 3967 (Feb. 14, 2019).

111. A No-Action Letter is granted by an administrative agency after request from an entity to evaluate whether a product, action, or service would violate the law. No-Action Letters say that the agency will not pursue enforcement against that entity for that cause but do not grant precedence for future non-enforcement. *See, e.g.*, U.S. Sec. & Exch. Comm'n, *No Action Letters*, INVESTOR.GOV: INTRODUCTION TO INVESTING (last visited Jan. 29, 2023), https://www.investor.gov/introduction-investing/investing-basics/glossary/no-action-letters [https://perma.cc/3PM8-MEHW] (explaining no-action letters).

112. *See* Policy on No-Action Letters, 84 Fed. Reg. 48229, 48229–30 (Sept. 13, 2019) (criticizing the existing no-action policy as limiting the CFPB's ability to "facilitat[e] innovation").

113. Off. of Sci. & Tech. Pol'y, *Blueprint for an AI Bill of Rights: Making Automated Systems Work for the American People*, THE WHITE HOUSE, https://www.whitehouse.gov/ostp/ai-bill-of-rights/ [https://perma.cc/WV6L-V8SL] (last visited Jan. 3, 2023).

114. *Id.*

against algorithmic discrimination that can be independently evaluated.[115]

B. Agency Responses to AI

In 2015, the CFPB released a report on the issue of "credit invisible" consumers.[116] It was estimated that as of 2010 there were approximately twenty-six million credit invisible consumers (defined as consumers without credit records from the nationwide credit reporting agencies) plus an additional nineteen million "unscorable" consumers (defined as consumers who have a credit record but not enough credit history to generate a credit score).[117] While the report was focused on the challenges that credit invisible and unscorable consumers face and did not specifically reference AI, it did refer to studies considering the use of alternative data as a way to extend credit to these consumers.[118]

A 2016 report from the FTC looked at the use of big data across various areas under the FTC's jurisdiction.[119] Many of the same considerations addressed in this note were present in that report, including the potential benefit of reaching underserved populations[120] and the challenge of unrecognized biases in the data used.[121] It also recognized that while algorithms can be highly effective at identifying correlations, such correlations may not equate to causations, potentially leading to inaccurate results and unintended consequences.[122] The report also explicitly pointed out potential violations of the ECOA that may arise from using big data.[123] Finally, its discussion was summarized by advising companies using big data to both (i) consider

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115. Off. of Sci. & Tech. Pol'y, *Blueprint for an AI Bill of Rights: Algorithmic Discrimination Protections*, THE WHITE HOUSE, https://www.whitehouse.gov/ostp/ai-bill-of-rights/algorithmic-discrimination-protections-2/ [https://perma.cc/V87F-6AXK] (last visited Jan. 3, 2023).

116. CONSUMER FIN. PROT. BUREAU, DATA POINT: CREDIT INVISIBLES (May 2015), https://files.consumerfinance.gov/f/201505_cfpb_data-point-credit-invisibles.pdf [https://perma.cc/JE2M-HFCU].

117. *Id.* at 6.

118. *Id.* at 5.

119. FED. TRADE COMM'N, BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION? I (Jan. 2016), https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf [https://perma.cc/KBC3-R6N6].

120. *Id.* at 6.

121. *Id.* at 8.

122. *Id.* at 9.

123. *Id.* at 19.

how complete and representative the data sets being used are for the populations being served and (ii) review the algorithms for hidden biases.[124]

In early 2017, the CFPB published a Request for Information ("RFI") to learn more about the potential uses and risks of alternative data and modeling techniques used by creditors.[125] The RFI discussed the problem of credit invisible and unscorable consumers and how the use of alternative data and scoring methods might extend credit to these underserved consumers; it also acknowledged risks including problems verifying the accuracy of such models, the lack of transparency and control that might arise, and the possibility of discriminatory outcomes or disadvantages to specific groups of consumers.[126] The RFI also explicitly mentioned AI techniques such as artificial neural networks, an indication of a shift in focus from just the data being collected to how that data was being processed.[127]

One of the CFPB's first significant actions involving alternative data and automated credit processing was its No-Action Letter granted to Upstart in 2017.[128] In 2017, Upstart described itself as providing an online lending platform that combined traditional and non-traditional factors to offer credit to those with limited credit histories.[129] In its request for a No-Action Letter, Upstart stated that the No-Action letter was necessary because, while it believed it was not creating a disparate impact through its lending methods, the "expected evolution of [its] automated underwriting model" presented a significant risk of unexpectedly violating the ECOA and Regulation B.[130] When the grant

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124. *Id.* at 32.

125. Request for Information Regarding Use of Alternative Data and Modeling Techniques in the Credit Process, 82 Fed. Reg. 11183 (Feb. 21, 2017).

126. *Id.* at 11184–85.

127. *Id.* at 11185.

128. *CFPB Announces First No-Action Letter to Upstart Network*, CONSUMER FIN. PROT. BUREAU: NEWSROOM (Sept. 14, 2017), https://www.consumerfinance.gov/about-us/newsroom/cfpb-announces-first-no-action-letter-upstart-network/ [https://perma.cc/89TN-RHXD].

129. Upstart, Request for a No-Action Letter at 4 (Sept. 2017), https://files.consumerfinance.gov/f/documents/201709_cfpb_upstart-no-action-letter-request.pdf [https://perma.cc/69HZ-EEK9]. As of January 2023, Upstart describes itself as "a leading artificial intelligence (AI) lending marketplace designed to improve access to affordable credit while reducing the risk and costs of lending for our bank partners." *About Us*, UPSTART https://www.upstart.com/i/about [https://perma.cc/VS8N-5TNY] (last visited Jan. 3, 2023).

130. Upstart, *supra* note 129, at 9.

of the No-Action Letter to Upstart was announced, the CFPB stated that it expected Upstart to be open about certain information surrounding the AI processes, including how it makes approval determinations, how it manages risk to consumers, and how it expands credit to underserved populations.[131] Additionally, the announcement stated that the CFPB expected that the information supplied by Upstart would further the CFPB's understanding of non-traditional automated credit underwriting and the use of alternative data in credit underwriting.[132]

The evolution of the CFPB's focus on alternative data and AI systems can be, to an extent, traced through the Bureau's annual Fair Lending Reports. While the CFPB's Fair Lending Report covering activities undertaken in 2017 did briefly acknowledge the Upstart No-Action Letter and the CFPB's exploration of alternative data,[133] the following year's report was the first to directly state that the expansion of credit through the use of alternative data and modeling techniques was an area of focus.[134] The report covering 2018 activities also mentioned reviews the CFPB was undertaking to assess the risks of such systems.[135] The CFPB's Fair Lending Report for 2019's actions was the first to directly discuss the use of AI in credit decisionmaking, but its discussion only extended to providing adverse action notices when using AI credit systems.[136] By the report for 2021, mentions of "artificial intelligence" outnumbered mentions of "alternative data," and the use of AI models was listed as a focus for the CFPB's fair lending supervision efforts.[137]

A 2018 speech by Lael Brainard from the Federal Reserve Board highlighted that while it was still early in the adoption of AI within financial services, questions surrounding the potential risks posed by AI must be considered in order to take advantage of its potential.[138] In December 2019, a joint statement from the Federal

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131. CFPB, *supra* note 128.
132. *Id.*
133. 2018 CONSUMER FIN. PROT. BUREAU FAIR LENDING REP. at 31.
134. 2019 CONSUMER FIN. PROT. BUREAU FAIR LENDING REP. at 11.
135. *Id.*
136. 2020 CONSUMER FIN. PROT. BUREAU FAIR LENDING REP. at 9.
137. 2022 CONSUMER FIN. PROT. BUREAU FAIR LENDING REP. at 4.
138. Lael Brainard, *What Are We Learning About Artificial Intelligence in Financial Services?*, FED. RSRV. BD.: SPEECH (Nov. 13, 2018),

Reserve Board, CFPB, FDIC, NCUA, and OCC promoted the potential benefits of alternative data usage and connected the use of such data to the requirements of the ECOA and the Fair Credit Reporting Act.[139]

After the CFPB's 2017 No-Action Letter to Upstart expired, a second No-Action Letter was granted to Upstart in 2020.[140] Notably, though, this second No-Action Letter was terminated by the CFPB in June 2022.[141] Officially, the termination came as a result of a request by Upstart to change the term of the No-Action Letter to expire immediately.[142] This request came in response to the CFPB telling Upstart that more time was needed to determine whether the addition of new variables to Upstart's algorithm complied with the terms of the 2020 No-Action Letter.[143] However, in the termination order, the CFPB went out of its way to refute suggestions that it had either assisted with the development of Upstart's credit model or concluded that the model complied with the ECOA.[144] It is hard not to speculate that at least some of the motivation behind this termination arose from the change in Presidential administrations and calls from senators to reexamine the No-Action Letter.[145]

In 2021, an FTC blog post highlighted the FTC's attention to the potential for AI systems to violate laws—including the ECOA—and provided guidance including to test algorithms for discriminatory outcomes, embrace transparency, and not exaggerate an algorithm's capability to provide fair or unbiased results.[146]

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https://www.federalreserve.gov/newsevents/speech/brainard20181113a.htm [https://perma.cc/B6NA-X58A].

139. *Interagency Statement on the Use of Alternative Data in Credit Underwriting*, FED. DEPOSIT INS. CORP. (Dec. 4, 2019), https://www.fdic.gov/news/speeches/2019/spdec0319.html [https://perma.cc/5JY6-6PSX].

140. *Consumer Financial Protection Bureau Issues No Action Letter to Facilitate the Use of Artificial Intelligence for Pricing and Underwriting Loans*, CONSUMER FIN. PROT. BUREAU: NEWSROOM (Nov. 30, 2020), https://www.consumerfinance.gov/about-us/newsroom/consumer-financial-protection-bureau-issues-no-action-letter-facilitate-use-artificial-intelligence-pricing-and-underwriting-loans/ [https://perma.cc/LMD8-KZJJ].

141. Upstart Network, Inc., In re November 20, 2020 No-Action Letter (June 8, 2022), https://files.consumerfinance.gov/f/documents/cfpb_upstart-no-action-letter-termination_order_2022-06.pdf [https://perma.cc/GN63-U7ZT].

142. *Id.* at 2.

143. *Id.* at 1.

144. *Id.* at 2.

145. *See infra* note 158 and accompanying text.

146. Elisa Jillson, *Aiming For Truth, Fairness, and Equity In Your Company's Use of AI*, FED. TRADE COMM'N: BUS. BLOG (Apr. 19, 2021), https://www.ftc.gov/business-

Also in 2021, a multi-agency Request for Information was published seeking comments regarding the use of AI by financial institutions and any risks posed by such systems.[147] The RFI included 17 questions, categorized into concerns surrounding the explainability of AI systems; risks arising from data quality, "overfitting" (where an algorithm incorrectly extrapolates a pattern from a smaller sample group to a broader population), cybersecurity, and dynamic updating; challenges faced by smaller lenders (e.g., community institutions); financial institutions' oversight of AI developed by third parties; and compliance with fair lending laws.[148]

Several agencies made statements in 2022 about how they were looking at AI. In March, the National Institute of Standards and Technology (a division of the Department of Commerce) put out a Special Publication highlighting the need to develop standards for managing the biases that arise in AIs.[149] While the publication was written to direct the attention of the parties that create and use AI systems to how these biases appear and not to promote a particular regulatory approach, it nevertheless acknowledged that such discussions could not be entirely separated from how laws and regulations approach questions of discrimination and fairness.[150] The publication may not offer specific regulatory insight, but it does illustrate the increasing focus of the government on issues surrounding biased AI systems.

In May 2022, the OCC's Deputy Comptroller for Operation Risk Policy made a statement before the House Task Force on Artificial Intelligence on the opportunities, benefits, and risks of banks' use of AI.[151] These comments stressed that effective governance processes

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guidance/blog/2021/04/aiming-truth-fairness-equity-your-companys-use-ai [https://perma.cc/63W7-EJ88].

147. Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, Including Machine Learning, 86 Fed. Reg. 16837 (Mar. 31, 2021) (hereinafter 2021 RFI). The RFI was put out jointly by the Board of Governors of the Federal Reserve System, CFPB, FDIC, NCUA, and OCC. *See infra* Part VI for a discussion regarding major categories of comments submitted.

148. *Id.* at 16840–41.

149. NAT'L INST. OF STANDARDS AND TECH., SPECIAL PUBL'N 1270, TOWARDS A STANDARD FOR IDENTIFYING AND MANAGING BIAS IN ARTIFICIAL INTELLIGENCE (Mar. 2022), https://nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.1270.pdf [https://perma.cc/2PTU-TMJX].

150. *Id.* at 4.

151. *Statement of Kevin Greenfield, Deputy Comptroller for Operational Risk Policy, Office of the Comptroller of the Currency before the Task Force on Artificial Intelligence, Committee on Financial Services, United States House of Representatives*, OFF. OF THE

and controls were essential to realizing the benefits while mitigating the risks.[152] Also in May, the CFPB put out a Circular affirming that using complex algorithms would not be a defense for failing to supply adverse action notifications as required by the ECOA.[153] Regarding that statement, CFPB Director Rohit Chopra explicitly stated that technology does not absolve companies of their legal obligations.[154]

C. Congressional Responses to AI

While there has been considerably less attention placed on AI and fair lending from Congress than from the Executive Branch, legislators have taken some actions in recent years. In 2019, a bill was introduced that would have directed the FTC to implement regulations requiring assessments of automated systems that pose a high risk of creating or contributing to discriminatory decisions impacting customers.[155] In 2020, Congress passed the National AI Initiative Act with the purpose of, among other things, "lead[ing] the world in the development and use of trustworthy artificial intelligence systems in the public and private sectors."[156] As of December 2022, a National Artificial Intelligence Research Resource (NAIRR) Task Force has been collecting comments surrounding the feasibility of establishing a NAIRR and what such a resource's goals, approaches, and composition should be in supporting government and private development of AI systems.[157]

COMPTROLLER OF THE CURRENCY (May 13, 2022), https://www.occ.gov/news-issuances/congressional-testimony/2022/ct-occ-2022-52-written.pdf [https://perma.cc/B6GN-JQA3].

152. *Id.* at 5.

153. CONSUMER FIN. PROT. BUREAU, CIRCULAR 2022-03: ADVERSE ACTION NOTIFICATION REQUIREMENTS IN CONNECTION WITH CREDIT DECISIONS BASED ON COMPLEX ALGORITHMS (May 26, 2022), https://files.consumerfinance.gov/f/documents/cfpb_2022-03_circular_2022-05.pdf [https://perma.cc/2FHF-2K95].

154. *CFPB Acts to Protect the Public from Black-Box Credit Models Using Complex Algorithms*, CONSUMER FIN. PROT. BUREAU: NEWSROOM (May 26, 2020), https://www.consumerfinance.gov/about-us/newsroom/cfpb-acts-to-protect-the-public-from-black-box-credit-models-using-complex-algorithms/ [https://perma.cc/8954-Z37E].

155. Algorithmic Accountability Act of 2019, S.1108, 116th Cong. (2019).

156. National Artificial Intelligence Initiative Act of 2020, Pub. L No. 116-283 § 5101(a)(2).

157. *The National Artificial Intelligence Research Resource Task Force: About the Task Force*, NAT'L A.I. INITIATIVE (last visited Jan. 3, 2023), https://www.ai.gov/nairrtf/#A_NATIONAL_AI_RESEARCH_RESOURCE [https://perma.cc/92KA-SGLP].

Also in 2020, a group of senators wrote a letter to the CFPB calling on the Bureau to look harder at financial technology ("fintech") lenders like Upstart due to the risk they pose of engaging in discriminatory practices.[158] In particular, the letter pointed out potential violations arising from lenders' use of educational data including both the school the applicant attended and the applicant's college major in making credit decisions.[159] In support of their stance, the senators cited studies and research papers showing that using either data point can result in discrimination against minority borrowers.[160] In their report, the senators also recommended the CFPB take specific actions, including reexamining the lenders' use of such data, looking further into whether academic majors can serve as proxies for protected classes, conducting fair lending examinations of lenders relying on educational criteria, and issuing additional guidelines for student lenders.[161]

VI. CONSIDERING HOW TO PROCEED WITH AI

Across all of the commentators and policymakers discussed above who are considering the use of AI within the financial industry, there seem to be none who take an all-or-nothing view. Instead, the consensus seems to be that AI lending holds great promise by allowing lenders to more effectively manage their risks and offer better financial services to a broader pool of applicants, including those who have historically been underserved. However, there are also undeniable risks arising from using AI in the credit underwriting process. Even under the best of situations, there seems to always be a risk that biases will appear in the AI algorithms. In the worst situations, it is easy to imagine ways to coopt an algorithm to exploit vulnerable consumers.

Where the ideal balance between mitigating risks and realizing maximum benefit might lie will almost certainly vary depending on the

158. Letter from Sen. Sherrod Brown, Sen., Elizabeth Warren, Sen., and Kamala D. Harris, Sen., to Kathleen Kraninger, Dir., Consumer Fin. Prot. Bureau (July 30, 2020), https://www.warren.senate.gov/imo/media/doc/2020-07-30_Letter%20to%20CFPB%20re%20use%20of%20educational%20data.pdf [https://perma.cc/PRR9-T2KA].

159. *Id.*

160. *Id.*

161. COMM. ON BANKING, HOUS., AND URB. AFFS, 116TH CONG., USE OF EDUCATIONAL DATA TO MAKE CREDIT DETERMINATIONS (2020), https://www.banking.senate.gov/imo/media/doc/Review%20-%20Use%20of%20Educational%20Data.pdf [https://perma.cc/2A52-5CPK].

underlying agenda of the person asked. Some will be willing to accept less benefit if it means being more protective, while others will want to take full advantage of AI's capabilities even if there is an increased risk of disparate outcomes. There likely is no "correct" answer here. How, then, should regulators and the financial industry proceed?

In looking at responses to the 2021 Request for Information, specific categories of concern were common. For example, the explainability of algorithms (which was explicitly asked about) was a common area of discussion, as were considerations of biases, fairness, and algorithmic drift. There were also a number of comments discussing regulatory standards and creating a level playing field across different classes of lenders. These comments can give insight into what one might expect to be areas of focus for regulators and, in turn, how lenders might prepare.

A. How Might Regulators Approach AI?

If regulators are going to work towards ensuring that AI lending systems comply with fair lending laws, one broad challenge is that different categories of lenders face different hurdles. Such differences will need to be addressed for any regulatory scheme to be effective.

Several significant challenges arise from the sheer complexity of creating and maintaining an AI system. While it seems likely that there will be an increasing adoption of AI tools across the financial industry, the level of skill, expertise, and resources necessary to develop these systems is still relatively uncommon within the financial industry.[162] These needs are unlikely to be within the capabilities of smaller financial institutions such as community banks and small credit unions. Many of these sorts of institutions not only have limited resources but also limited customer bases; because AI systems are more powerful as they are fed more data, such small institutions are unlikely ever to be able to develop effective AI systems.[163]

To overcome these challenges, smaller financial institutions will likely be entirely reliant on third-party vendors who can supply and

162. Model Risk Managers Int'l Ass'n, Comment Letter on 2021 RFI at 13 (May 25, 2021), https://www.regulations.gov/comment/OCC-2020-0049-0008 [https://perma.cc/SCV2-5TVG] [hereinafter MRMIA].

163. *Id.* at 12–13.

maintain AI systems.[164] However, this reliance on third-party vendors creates further challenges. How can a small financial institution ensure that a vendor they choose is developing reliable algorithms? Where does legal liability fall if there is a flaw in the algorithm that makes it non-compliant with fair lending laws? A third-party vendor will often not share its underlying code or give in-depth details of how its algorithm works to allow a financial institution to thoroughly verify whether fair lending laws are being complied with.[165] Even if a financial institution can get in-depth access to see how a third-party AI works, it is unlikely to have the expertise to adequately interpret the algorithm or evaluate its compliance with fair lending laws.[166]

For any regulatory solution to this challenge, there must be clear and easily interpretable standards for both first- and third-party algorithms that would allow for some degree of assurance that a particular algorithm was compliant with fair lending laws. For example, there will likely always be questions about what is considered fair.[167] Under the ECOA's disparate impact analysis, such impacts are only a violation if a "less discriminatory alternative" exists, but this can give rise to questions such as which model is genuinely better or whether

164. OakNorth Credit Intel., Comment Letter on 2021 RFI at 5 (June 24, 2021), https://www.regulations.gov/comment/OCC-2020-0049-0017 [https://perma.cc/VSQ8-QFBB].

165. *See, e.g.*, NContracts, Comment Letter on 2021 RFI at 2 (June 29, 2021), https://www.regulations.gov/comment/OCC-2020-0049-0026 [https://perma.cc/JV62-MHUL] ("The [Financial Institution] doesn't entirely know how decisions are made because the third-party vendors that own the technology may not want to share proprietary data on how the AI draws its conclusions."); Bank Pol'y Inst., Comment Letter on 2021 RFT at 19 (June 29, 2021), https://www.regulations.gov/comment/OCC-2020-0049-0020 [https://perma.cc/3ZWQ-NAQN] ("Banks may not be exposed to underlying algorithms or source codes, making it difficult to investigate 'under the hood' . . . ."); TruEra, Comment Letter on 2021 RFI at 9 (June 29, 2021), https://www.regulations.gov/comment/OCC-2020-0049-0024 [https://perma.cc/BGC3-7MET] ("The third party will often be unwilling to share their 'secret sauce' . . . leav[ing] the FI exposed to not knowing how one of the inputs into *their* automated decision making is calculated.").

166. NContracts, *supra* note 165, at 4.

167. *See, e.g.*, OakNorth, *supra* note 164, at 6 ("While fairness is a very important objective . . . , it is extremely challenging . . . given that there isn't a consensus about what fairness means and satisfying certain definitions of fairness breaks others."); TruEra, *supra* note 165, at 12 ("There are two main camps of fairness: group fairness and individual fairness."); *id.* at 14 ("[T]here needs to be a consensus on appropriate measures of fairness and how to quantify fairness for specific financial applications.").

potential models would prove to be unreasonable to implement.[168] Furthermore, as already discussed, the standards for approaching these questions should be easily understandable and applicable by smaller financial institutions with more limited capabilities.

One potential solution would be creating a federal certification-type program for AI lending systems.[169] One commenter pointed out that every financial institution is essentially "having to reinvent the wheel" when creating an AI system.[170] By creating a certification program, the challenge that small financial institutions face in having the skills to assess an algorithm could be largely eliminated; if a third-party lending algorithm is certified, a financial institution that licenses that algorithm can be assured that it complies with all relevant laws. Such a certification would not necessarily have to be *required* of all lenders using AI systems. For example, larger institutions with enough experience and resources might be allowed to develop their own systems to achieve greater effectiveness or more closely tailor the system to their unique needs. But by creating a certification—and, perhaps most importantly, the underlying standards for evaluating certification requests—any financial institution or fintech creating an AI would have clear guidelines to comply with while entities unable to build their own system would have access to tools that they could have some degree of confidence in.

Another challenge lenders currently face arises from the ECOA's prohibitions on identifying protected characteristics.[171] Without being able to identify protected characteristics, lenders are less able to identify when disparate impacts arise. While the prohibition on identifying these characteristics may help reduce human biases in lending decisions, they do not necessarily protect against biases arising

168. Zest AI, Comment Letter on 2021 RFI at 7 (June 24, 2021), https://www.regulations.gov/comment/OCC-2020-0049-0016 [https://perma.cc/8852-YRSM].

169. U.C. Irvine A.I. Pol'y Lab, Comment Letter on 2021 RFI at 4–5 (June 29, 2021), https://www.regulations.gov/comment/OCC-2020-0049-0025 [https://perma.cc/CZ33-EM7B].

170. Operartis, Comment Letter on 2021 RFI (May 24, 2021), https://www.regulations.gov/comment/OCC-2020-0049-0006 [https://perma.cc/2833-NVCG].

171. *See* MRMIA, *supra* note 162, at 14 (stating that the general prohibition on capturing protected class data causes lenders to be unable to prove unbiased models or find causes when models become biased).

within AI models.[172] Despite claims otherwise, data and AI models are not inherently unbiased,[173] and simply removing the brightest signals for biases will not necessarily eliminate the underlying biases.[174] Effective verification of algorithmic compliance will likely involve comparing real-world results against theoretically "fair" results and looking for deviations that correlate with protected classes. Currently, evaluations of disparate impacts require trying to identify protected characteristics through "clever ways," a practice that is questionable from both an accuracy and a compliance standpoint.[175] To better address the potential problems with AI lending, regulators should look into ways to permit the collection of protected characteristics while ensuring such data is used for verification and not decisionmaking.

B. How Might Lenders Approach AI?

Lenders who are (or are considering) using AI-powered algorithms should recognize how complex the regulatory landscape surrounding these algorithms can be. The ECOA is firmly established with the express purpose to "promote the availability of credit to all creditworthy applicants."[176] This purpose is pursued by prohibiting discrimination (both in treatment and impact) and requiring lenders to provide notifications whenever they take adverse actions. A new technology now exists that seems likely to be "the future for many corporations."[177] This technology (1) offers lenders the opportunity to increase efficiency, reduce costs, and provide better services, and (2) promises to benefit consumers by expanding the availability of credit, offering credit at lower costs, and (purportedly) reducing biases in the lending process. But this technology also carries a high risk of perpetuating existing (or introducing new) discriminatory biases, and,

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172. MITRE Corporation, Comment Letter on 2021 RFI at 8 (June 29, 2021), https://www.regulations.gov/comment/OCC-2020-0049-0018 [https://perma.cc/326G-2CSK].

173. One such claim came from the comment from the Online Lenders Alliance, Comment Letter on 2021 RFI at 7 (July 2, 2021), https://www.regulations.gov/comment/OCC-2020-0049-0074 [https://perma.cc/8DPR-LRP5] ("AI/ML models are inherently free of bias . . . . Data cannot see color, gender, or race . . . .").

174. MRMIA, *supra* note 162, at 15.

175. *Id.*

176. Regulation B, 12 C.F.R. § 1002.1(b) (2022).

177. Diamantis, *supra* note 56, at 930.

because of its black-box nature, there can be difficulty in identifying *why* it makes certain decisions.

There has been a growing focus from the government to evaluate and protect against the risks from AI, including a desire to crack down on violations of the ECOA by AI processes, but it is unclear how regulatory policy may evolve. There will likely be a strong correlation between which political party is in the White House and how assertively new regulations are put forward, as was seen between the Obama–Trump–Biden transitions. It seems likely that an increasing focus will continue being placed on AI's implementation, and it is possible that the regulators overseeing compliance with the ECOA (and other fair lending laws) might make significant new regulations. On the other hand, it is plausible that if the financial industry demonstrates that they are effectively policing themselves then the regulators may take a more relaxed approach.

For a lender considering how to approach adopting AI processes against this background, the first, and perhaps best, guidance is the fundamental purpose of the ECOA: to promote the availability of credit to *all* creditworthy applicants. Whether a lender is developing an AI system in-house or working with a fintech vendor, this goal of expanding credit means working to eliminate processes that lead to discrimination. The widespread assumption that AI processes are inherently unbiased interpretations of large amounts of data is, unfortunately, not necessarily true.[178] An AI that is not fed high-quality data—either during the training process or after going live—will give flawed results, a situation sometimes referred to as "garbage in, garbage out."[179]

To combat the potential flaws in AI, developers of AI lending systems should be focused on ensuring that the results from the algorithms are explainable, verifiable, and transparent. While many have expressed skepticism about how explainable an AI system can be, some companies already claim that their algorithms are fully explainable.[180] That said, explainability is another concept that means

178. ALGORITHMIC SYSTEMS, *supra* note 108, at 6 (2016).

179. OECD, *supra* note 50, at 40 (2021).

180. *See* Equifax, Comment Letter on 2021 RFI at 3 (July 2, 2021), https://www.regulations.gov/comment/OCC-2020-0049-0070 [https://perma.cc/85R3-P3GJ] ("Equifax recognizes the importance of explainability and has addressed this challenge by developing explainable machine learning models.").

different things to different people.[181] But explainable AI is being actively researched, and various methods to explain AI results have been developed.[182] Lenders should ensure that their AI lending tools were built to be explainable before deploying those tools.

To ensure that an AI is working as intended, AI verifications should be consistent and ongoing, both before and after the AI goes live, to confirm that the results coming from the algorithm are accurate and unbiased.[183] While it is unsurprising that AI developers want to keep secret the details of how their algorithms work, such black box models do not lead to trust in the fairness or methods of those algorithms.[184] Adequate verifiability will likely only exist when parties who did not develop the AI (e.g., regulators, the financial institutions themselves, or outside neutral organizations) can thoroughly examine the algorithm.

In addition to the general trust that explainability and verification can engender, ensuring those characteristics are present will also help ensure compliance with the second provision of the ECOA—providing explanations for adverse actions.[185] Something that perhaps should be acknowledged here is that there already exists two different levels of focus on such explainability. Bank lenders have long been required to explain their actions and take care to ensure that their products meet strict regulatory oversight standards; nonbank lenders, particularly new fintech companies, have a more limited history of such

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181. *See, e.g.*, MRMIA, *supra* note 162, at 5 (discussing the difference between explaining all aspects of how an algorithm works compared to understanding how an algorithm makes a specific decision about a specific applicant); Bank Policy Institute, *supra* note 165, at 8 (discussing that explainability also varies depending on the perspective of the person considering an AI's explainability).

182. *See, e.g.*, MRMIA, *supra* note 162, at 4–5 (considering different emerging explainability standards).

183. Anna Hrushka, *Bank Regulators' Heightened Scrutiny of AI Highlights Third-Party Risk*, BANKING DIVE (June 29, 2022), https://www.bankingdive.com/news/bank-regulators-heightened-scrutiny-of-ai-highlights-third-party-risk/626301 [https://perma.cc/835L-VGC2]; *see also* Robin Nunn, *Discrimination and Algorithms in Financial Services: Unintended Consequences of AI*, DAVIS WRIGHT TREMAINE, LLP: FIN. SERVS. L. ADVISOR (MAR. 6, 2018), https://www.dwt.com/blogs/financial-services-law-advisor/2018/03/discrimination-and-algorithms-in-financial-service [https://perma.cc/Y2WY-D9K4] ("[T]he best approach would be to utilize . . . counsel . . . who . . . can continuously monitor and test the outcomes of algorithmic programs to identify any problems.").

184. NContracts, *supra* note 165, at 2.

185. *See* OECD, *supra* note 50, at 44 (2021) (stating that being unable to explain why an algorithm came to its decision makes it "difficult, if not impossible" to sufficiently audit the results the algorithm is generating).

careful oversight.[186] It seems likely that these two categories of lenders may be taking substantially different approaches, with bank lenders taking more care to ensure compliance than some nonbank lenders. This is one area where the financial industry may want to proactively consider industry-driven measures to ensure that all lenders are held to the same standards in order to avoid regulators taking such actions for them.

Lenders should also be cognizant of moderating their enthusiasm for new AI technologies. Part of the great promise of AI is being able to take much of the human labor out of the lending process, but keeping some degree of manual control could help mitigate the risks posed by AI. For example, an AI algorithm may be treated as simply one step in the underwriting process, with a human combining the AI's output with other variables to manually make a final determination.[187] Processes like dynamic updating, where the AI automatically integrates new data into the AI model, can keep the AI continually updated, but it can also lead to unexpected changes in how the AI works.[188] While dynamic updating may seem efficient, a better approach may be to have a non-live, test version of the algorithm that is dynamically updated but not deployed until testing and validation can ensure that the updates offer actual improvements and do not introduce new biases into the AI. Lenders should also temper their presentations of the AI systems they are using and not make claims about their effectiveness or safety that cannot be supported.[189]

VII. CONCLUSION

When lender practices align with the goals of the ECOA, the results are a win–win situation: lenders can expand their customer base to include customers who might otherwise be denied credit while also

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186. *See, e.g.*, Bank Pol'y Inst., *supra* note 165, at 29 ("While banks face intense scrutiny from regulators in complying with the Model Risk Management Guidance, nonbank lenders may utilize AI credit underwriting models with no obligation to follow the Model Risk Management Guidance or answer to regulators through supervisory examinations."); Hrushka, *supra* note 183 (warning banks partnering with fintechs to be wary of the limited experience most fintechs have with financial regulators).

187. OakNorth, *supra* note 164, at 2.

188. MITRE Corporation, *supra* note 172, at 6.

189. This is essentially the same guidance already provided by the FTC. See *supra* note 146 and accompanying text.

lowering the risk of defaults, and consumers can access credit that is, and has long been recognized as, an essential part of life.[190] Modern computer technology, through algorithms created by artificial intelligence processes, has made possible the ability to analyze data in ways that no person can do, opening new possibilities to reach groups that were once "credit-invisible." But this technology is not without its dangers. Without careful programming, monitoring, and implementation, AI lending programs can both perpetuate existing discrimination and autonomously discover new patterns that lead to discriminatory results. Nevertheless, the benefits promised by AI algorithms—to both lenders and consumers—are significant enough that widespread adoption of this technology is largely inevitable.

While increasing regulatory oversight seems likely, lenders should proactively strive to ensure that any AI tools they deploy are designed to mitigate discriminatory risks, comply with the ECOA, and realize the true potential of AI lending. Laying out rigid standards and constantly monitoring the algorithm will open new commercial opportunities to lenders and grant new opportunities to those who have historically been left behind.

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190. *See, e.g.*, COMM. ON BANKING, HOUS., AND URB. AFFS, EQUAL CREDIT OPPORTUNITY ACT AMENDMENTS OF 1976, S. REP. NO. 94-589, at 3 (1976) ("Credit has ceased to be a luxury item, either for consumers or for business entrepreneurs."); ALGORITHMIC SYSTEMS, *supra* note 108, at 11 ("Access to fairly-priced and affordable credit is an important factor in enabling Americans to thrive economically, especially those working to enter the middle class.").

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