

Problem Solved?: Is the Fintech Era Uprooting Decades Long Discriminatory Lending Practices?

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I. INTRODUCTION

Artificial intelligence (AI) technology is at the forefront of our daily lives. This technology works by “combining large amounts of data with fast, iterative processing and intelligent algorithms, allowing the software

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to learn automatically from patterns or features in the data.”¹ Artificial intelligence describes a variety of methods and subsets, from machine learning to cognitive computing.² Consumers interact directly with this transformative technology when we perform tasks as simple as using a smartphone or watching our favorite shows and movies on Netflix. Apple, Samsung, and Huawei have created smartphones that rely on artificial intelligence technology to provide features from Face ID to augmented reality.³ Additionally, smartphones come equipped with voice assistants that are capable of understanding user commands and performing a variety of tasks.⁴ Netflix uses machine learning technology to provide personalized recommendations to its viewers based on films that they’ve watched previously.⁵ However, despite the multitude of technology readily available to consumers, artificial intelligence technology is not exclusively used by consumers.

Artificial intelligence technology is being tasked with making seminal decisions, allowing it to play an important gatekeeping role in our daily lives. This technology is transforming numerous industries and is increasingly being implemented as a screening mechanism in the fields of healthcare, law enforcement, housing, and credit-based lending. Proponents of these applications of artificial intelligence technology argue that “artificial intelligence is enabling businesses to work smarter and faster, [and to] do[] more with significantly less.”⁶ Due to the desire for convenience, speed, and accuracy, algorithms, rather than humans, have been tasked with making important decisions that have significant exclusionary impacts on millions of Americans. While the use of this technology is believed to be a progression towards fairness, in practice, there are numerous examples of race and gender related biases resulting from the ubiquitous use of artificial intelligence technology in the decision-making process.

1. *Artificial Intelligence—What it Is and Why it Matters*, SAS, http://www.sas.com/en_us/insights/analytics/what-is-artificial-intelligence.html (last visited Feb. 1, 2020).

2. *Id.*

3. Udi Jacobi, *AI: Increasing the Intelligence on Smartphones*, AI THORITY (Apr. 21, 2020), <http://www.aithority.com/guest-authors/ai-increasing-the-intelligence-on-smartphones/>.

4. Anita George, *Mobile Technology: AI in Phones*, LIFE WIRE (Mar. 9, 2020), <http://www.lifewire.com/mobile-technology-ai-in-phones-4584792>.

5. Allen Yu, *How Netflix Uses AI, Data Science, and Machine Learning—From a Product Perspective*, MEDIUM (Feb. 27, 2019), <http://becominghuman.ai/how-netflix-uses-ai-and-machine-learning-a087614630fe>.

6. Katrina Wakefield, *Artificial Intelligence in Business*, SAS, http://www.sas.com/en_gb/insights/articles/analytics/applications-of-artificial-intelligence.html (last visited Feb. 1, 2020).

A. *Examples of Racial Bias in Algorithmic Data*

In the healthcare industry, algorithms are increasingly being used to determine the care provided to patients.⁷ Recent research showed that software influencing the care provided to patients favored White patients over sicker, Black patients.⁸ Analysis of 50,000 records of a major U.S. hospital highlights the disparities in healthcare offered to Black and White patients based solely on the recommendations of an algorithm.⁹ The algorithm effectively let White patients have priority for special programs for patients with complex, chronic conditions, over Black patients with more severe illnesses.¹⁰ The skewed results produced by the algorithm reduced the number of Black patients receiving similar care by [50%].¹¹ Although the algorithm was not supplied with patients' racial data when assessing a person's health risk, the results highlight the discriminatory effect that algorithms can have when supplied with data that is representative of existing societal inequalities.¹² This seemingly race-neutral algorithm has consistently barred Black patients from accessing adequate healthcare to treat chronic illnesses. This highlights just how dangerous it can be when human agents are removed from the decision-making process and biased algorithmic outputs are the sole mechanism upon which decisions are based.

Artificial intelligence technology is revolutionizing more than the healthcare industry. Law enforcement officials around the world utilize facial recognition technology to identify persons of interest. Recently, law enforcement's use of facial recognition technology has received widespread criticism.¹³ Tests conducted by the Massachusetts ACLU revealed that when set to the default confidence setting, Amazon's facial recognition software falsely matched twenty-seven professional athletes to mugshots in a law enforcement database.¹⁴ After being misidentified by

7. Tom Simonite, *A Health Care Algorithm Offered Less Care to Black Patients*, WIRED (Oct. 24, 2019, 2:00 PM), <http://www.wired.com/story/how-algorithm-favored-whites-over-blacks-health-care/>.

8. *Id.*

9. *Id.*

10. *Id.*

11. *Id.*

12. *Id.*

13. See Aaron Holmes, *Patriots Player Duron Harmon is Speaking Out After Amazon's Facial-Recognition Tech Falsely Matched Him to a Mugshot*, BUS. INSIDER (Oct. 23, 2019, 10:39 AM), <http://www.businessinsider.com/amazon-facial-recognition-falsely-matched-nfl-players-duron-harmon-mugshots-2019-10>.

14. *Id.*

the software, New England Patriots safety Duron Harmon advocated for a moratorium on the use of this software by law enforcement, stating that if it misidentified him, his teammates, and other professional athletes in an experiment, law enforcement should consider the real-life impact of false matches.¹⁵ While the impact of algorithmic decision-making on the healthcare and law enforcement sectors is not the focus of this Comment, these examples highlight the consequences that overreliance on potentially biased algorithmic outputs have on people's lives.

B. How Artificial Intelligence Is Revolutionizing the Financial Services Industry

In addition to being widely used in the healthcare and criminal justice sectors, artificial intelligence is also reforming the financial services industry. Many financial institutions rely on machine learning algorithms and big data in the credit underwriting process.¹⁶ Sophisticated algorithms are responsible for rendering decisions about consumer risk and creditworthiness.¹⁷ These algorithms decide who has access to credit at fair terms, an essential tool for financial planning and wealth building.¹⁸ Access to fair credit opportunities enables many people an opportunity to buy a home, attend college, and ultimately, achieve financial stability. Because credit access is critical to ensuring economic stability, algorithms and big data have the ability to have a profound impact on our lives and economy.

This Comment focuses on the increasingly important role that artificial intelligence plays in the financial services sector. First, it explains possible concerns that result from an overreliance on algorithms, primarily focusing on algorithmic bias and how it arises in seemingly race-neutral data. Next, this Comment highlights the need for algorithmic accountability by first addressing historically unfair credit-lending practices and evaluating whether using artificial intelligence technology in the credit lending industry is a sufficient remedy for race-based economic injustice. Finally, this Comment addresses why businesses using artificial intelligence technology should be subject to regulations to

15. *Id.*

16. Alex Woodie, *Alternative Data Goes Mainstream in Financial Services*, DATANAMI (Nov. 21, 2019), <http://www.datanami.com/2019/11/21/alternative-data-goes-mainstream-in-financial-services/>.

17. *Id.*

18. *Id.*

prevent potential discrimination, civil rights violations, and to ensure the use of artificial intelligence technology achieves equitable results.

II. THE NEW AGE OF DECISION-MAKING: MACHINE LEARNING ALGORITHMS IN THE DECISION-MAKING PROCESS

Before the extensive use of artificial intelligence technology in business, humans were tasked with making momentous decisions that had significant impacts on people's lives. In the decision-making process, human agents decided whether or not individuals had access to credit-based lending, housing, and employment opportunities. These human agents were regulated to ensure that they were not violating civil liberties and to prevent discrimination against marginalized individuals. Federal, state, and local laws sought to shield consumers from discrimination based on race, gender, nationality, and socioeconomic status. While existing anti-discrimination laws did not completely eliminate human bias from the decision-making process, these laws function as a means of holding organizations accountable if they implemented discriminatory practices in the decision-making process.

However, in the digital age, businesses are growing increasingly reliant on artificial intelligence technology and machine learning algorithms to automate decision-making, thus stripping the responsibility away from human agents.¹⁹ Machine learning describes a “computer’s ability to learn without being explicitly programmed.”²⁰ Machine learning uses “programmed algorithms that receive and analyze input data to predict output values.”²¹ In machine learning, developers supply algorithms with a multitude of data sets that signal to the algorithm what the correct output values are.²² Using the data, the algorithm then “learns a model which can be applied to other people or objects and make predictions about what the correct outputs should be for them.”²³ As developers input new data, the algorithms develop human-like

19. Nicol Turner Lee et al., *Algorithmic Bias Detection and Mitigation: Best Practices and Policies to Reduce Consumer Harms*, BROOKINGS (May 22, 2019), <http://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms>.

20. Katrina Wakefield, *A Guide to Machine Learning Algorithms and Their Applications*, SAS, http://www.sas.com/en_us/insights/articles/analytics/machine-learning-algorithms-guide.html (last visited Feb. 1, 2020).

21. *Id.*

22. Lee et al., *supra* note 19.

23. *Id.*

intelligence, allowing them to make complex decisions based on patterns in the inputted information.²⁴ Based on patterns identified in the provided data, these algorithms learn to make inferences about people’s “identities, [] demographic attributes, [] preferences, and [] likely future behaviors, as well as the objects related to them.”²⁵ Because of the sophisticated capability of machine learning algorithms, these algorithms are now tasked with making a wide variety of decisions that have far-reaching implications.²⁶

A. What Is “Algorithmic Bias”?

While businesses hoped that machine learning algorithms would give more equitable outputs due to their use of mathematics and data analysis to draw conclusions, these algorithms have repeatedly been found to produce biased results. Algorithmic bias occurs when the algorithmic outcomes are “systematically less favorable to individuals within a particular group and where there is no relevant difference between groups that justifies such harms.”²⁷ According to technology innovation experts, this bias can result from “unrepresentative or incomplete [data inputs] or reliance on flawed information that [mirrors existing societal] inequities.”²⁸

1. How Do Algorithms “Learn” Biases?

Because data scientists are training machine learning algorithms using data reflective of society, these algorithms develop human-like biases by learning to make inferences about people and objects based on historical data that reflects race and gender biases.²⁹ In a 2017 study, data scientists taught a computer how to “understand” English using machine learning software and performed an implicit association test to uncover how algorithms developed human-like biases.³⁰ The results revealed that applying machine learning to ordinary human language resulted in the

24. Wakefield, *supra* note 20.

25. Lee et al., *supra* note 19.

26. *See id.*

27. *Id.*

28. *Id.*

29. Brian Resnick, *Yes, Artificial Intelligence Can Be Racist*, VOX (Jan. 24, 2019, 8:31 AM), <http://www.vox.com/science-and-health/2019/1/23/18194717/alexandria-ocasio-cortez-ai-bias>.

30. Aylin Caliskan et al., *Semantics Derived Automatically from Language Corpora Contain Human-Like Biases*, 356 SCI. 183 (2017), <http://science.sciencemag.org/content/sci/356/6334/183.full.pdf>.

algorithm developing biases against African Americans and women.³¹ In this study, “they used a common machine learning program to [search] the Internet, look at 840 billion words, and teach itself the definitions of those words.”³² To learn English, the machine learning software studied “how often certain words appear[ed] in the same sentence.”³³ After developing an extensive English vocabulary, the machine learning software was subjected to an implicit association test, conducted by scientists, to evaluate how closely the computer thought two words were related.³⁴ The results revealed that the computer learned that African-American sounding names were more associated with unpleasantness, while White names were closely associated with the word “pleasant.”³⁵ The computer also learned that female names were more associated with words relating to family than male names.³⁶

Additionally, algorithmic bias was exposed after Amazon attempted to build a résumé screening tool that relied on a machine learning algorithm. The screening algorithm was built in an attempt to increase efficiency and used data from résumés the company collected for a decade.³⁷ However, those résumés were typically from men.³⁸ As a result, the system had implicitly learned to discriminate against female applicants.³⁹ Despite being provided with gender neutral data, the software learned to discriminate against female applicants on the basis of certain “proxies associated with being female,” such as attending a women’s college.⁴⁰

2. Why We Should Care About Algorithmic Bias

The digitization of decision-making allows artificial intelligence technology to play an overly important role in the lives of millions of people. Businesses, intending to gain fast, fair, and accurate results, are

31. *Id.*

32. Resnick, *supra* note 29.

33. *Id.*

34. *Id.*

35. *Id.*

36. *Id.*

37. Rebecca Heilweil, *Artificial Intelligence Will Help Determine if You Get Your Next Job*, VOX: RECODE (Dec. 12, 2019, 8:00 AM), <http://www.vox.com/recode/2019/12/12/20993665/artificial-intelligence-ai-job-screen>.

38. *Id.*

39. *Id.*

40. *Id.*

becoming increasingly reliant on machine learning algorithms in the decision-making process. This technology is often used to determine who has access to necessities like credit-based lending, employment, and housing opportunities.⁴¹ The reliance on algorithmic outputs based on biased data has enabled this technology to play a gatekeeping role, resulting in exclusionary effects for historically marginalized groups. Relying on decisions made by machine-learning algorithms without regulation or safeguards to ensure accurate and equitable results does not remedy existing human biases, it merely allows machines to digitize and perpetuate them.

III. THE ECONOMIC EFFECTS OF RACIAL BIAS IN CREDIT LENDING

A. *The History of Lending Discrimination and the Racial Wealth Gap*

Evidence of the socioeconomic disparities between White people and people of color is apparent when examining the credit scoring and lending processes. Credit scores are three-digit numbers that have considerable ramifications on an individual's social and economic opportunities. An individual's credit rating can determine their access to housing, employment, insurance, and loans. A favorable credit score allows consumers to receive affordable rates on loans, enabling them to purchase homes, automobiles, and even to access lucrative career opportunities, all of which are essential to economic advancement. While people tend to believe that credit scores are race-neutral, the credit scoring process has an extensive history of prejudice, relying heavily on racial inequalities in the computing process.⁴² Since its origin in the 1800s, White, middle-class men were tasked with evaluating an individual's creditworthiness and creating credit reports.⁴³ In these reports, credit evaluators put their biases on full display, cautioning financial institutions against lending to minority borrowers.⁴⁴ As a result, financial institutions, believing that minority borrowers were not creditworthy, redlined communities of color.⁴⁵ Redlining describes "a systematic refusal by banks to make loans or

41. Nizan Geslevich Packin, *Social Credit: Much More Than Your Traditional Financial Credit Score Data*, FORBES (Dec. 13, 2019, 12:54 PM), <http://www.forbes.com/sites/nizangpackin/2019/12/13/social-credit-much-more-than-your-traditional-financial-credit-score-data/#92e12d15a824>.

42. Rose Eveleth, *Credit Scores Could Soon Get Even Creepier and More Biased*, VICE (June 13, 2019, 8:00 AM), http://www.vice.com/en_us/article/zmpgp9/credit-scores-could-soon-get-even-creepier-and-more-biased.

43. *Id.*

44. *Id.*

45. *Id.*

[open] branches in ‘hazardous’ areas” occupied almost exclusively by minorities.⁴⁶ Financial institutions labeled redlined areas as ‘credit risks’ largely due to residents’ racial and ethnic backgrounds.⁴⁷ In these communities, loans were either overpriced or unavailable, thus barring people of color from fair credit opportunities that their White counterparts could easily access.⁴⁸

The Home Owners’ Loan Corporation, a government-sponsored entity, drew red lines around communities predominantly occupied by people of color, flagging them as hazardous places to underwrite mortgages based on the belief that the presence of minorities would undermine property values.⁴⁹ The designation of these neighborhoods as “hazardous” and “declining” systematically resulted in race based discrimination and inequities in the lending process.⁵⁰ Based on an analysis of redlined maps, researchers found that people living in poorly rated neighborhoods had trouble obtaining mortgages for homes, regardless of their individual creditworthiness.⁵¹ Consequently, those who could not obtain loans with favorable terms relied on predatory loans with significantly higher interest rates to achieve the goal of owning a home.⁵² Due to the higher intrinsic risks of these predatory mortgages, lenders frequently repossessed these homes, resulting in more population instability compared to areas that received adequate financial investment.⁵³ Additionally, slumlords infiltrated these neighborhoods, exploiting the plight of these residents by acquiring “value from subdivided rental homes that otherwise might have been owned by families.”⁵⁴ While slumlords purchased these properties with little investment into their maintenance and upkeep to turn profits, commercial investors shied away from redlined areas.⁵⁵ Additionally, existing

46. *Id.*

47. Tracy Jan, *Redlining Was Banned 50 Years Ago. It’s Still Hurting Minorities Today.*, WASH. POST (Mar. 28, 2018, 5:00 AM), <http://www.washingtonpost.com/news/wonk/wp/2018/03/28/redlining-was-banned-50-years-ago-its-still-hurting-minorities-today/>.

48. *Id.*

49. Emily Badger, *How Redlining’s Racist Effects Lasted for Decades*, N.Y. TIMES (Aug. 24, 2017), <http://www.nytimes.com/2017/08/24/upshot/how-redlinings-racist-effects-lasting-for-decades.html>.

50. *Id.*

51. *Id.*

52. *Id.*

53. *Id.*

54. *Id.*

55. *Id.*

homeowners in redlined areas struggled to obtain credit to finance the necessary repair and maintenance of these properties.⁵⁶ As a result of credit inaccessibility and economic injustice, the perceived undesirability of these neighborhoods became reality and the wealth gap between people of color and their White counterparts widened.⁵⁷

Congress enacted multiple laws in an attempt to remedy economic inequities, such as the Equal Credit Opportunity Act and the Fair Housing Act. Under the Equal Credit Opportunity Act of 1974, Congress made it unlawful for any creditor to discriminate on the basis of race, religion, national origin, sex, marital status, age, or receipt of public assistance income.⁵⁸ Under the Fair Housing Act, discrimination in the sale, rental, and financing of dwellings, and other housing-related transactions, based on race, color, religion, sex, familial status, national origin, and disability is prohibited.⁵⁹ However, the Fair Housing Act failed to remedy the adverse effects of lending discrimination.⁶⁰ The provision forbidding lending discrimination was difficult to enforce because it was difficult for borrowers to prove that lenders were, in fact, making decisions based on discriminatory practices.⁶¹ As a consequence, discriminatory mortgage lending practices persisted, barring many people of color from homeownership and solidifying the racial segregation of communities for decades to come.⁶²

In an attempt to uproot the lingering effects of redlining, the Community Reinvestment Act was enacted to address the Fair Housing Act's shortcomings. The Community Reinvestment Act requires financial institutions to describe their service area and divulge how they are affirmatively serving their customers.⁶³

B. Modern Day Impacts of Discriminatory Lending Practices

Discriminatory credit lending practices have stifled marginalized individuals' opportunities for upward mobility. The availability of credit has a significant impact on a person's livelihood, enabling access to higher

56. *Id.*

57. *Id.*

58. 15 U.S.C. § 1691.

59. 42 U.S.C. § 3604.

60. Kriston Capps, *How the Fair Housing Act Failed Black Homeowners*, BLOOMBERG CITYLAB (Apr. 18, 2018, 9:54 AM), <http://www.citylab.com/equity/2018/04/how-the-fair-housing-act-failed-black-homeowners/557576/>.

61. *Id.*

62. *Id.*

63. 12 U.S.C. § 2901.

education, homeownership, and other embodiments of the American Dream. Research has shown that the lack of access to mainstream financial services hinders economic mobility.⁶⁴ The government practice of redlining dealt devastating blows to communities of color, preventing Black and Brown residents in these communities from accessing financial investment, and thus, limiting their ability for socioeconomic success.⁶⁵

People of color in historically redlined communities continue to struggle economically, even decades after Congress banned the racist practice. According to the Federal Reserve, White families today have nearly ten times the net worth of Black families and more than eight times that of Hispanic families, a direct consequence of inaccessibility to affordable loans and mortgages.⁶⁶ Economists at the Federal Reserve Bank of Chicago analyzed redlined maps and found that as recently as 2010, there were still stark racial differences in homeownership rates, home values, and credit scores.⁶⁷ Although Congress has outlawed discriminatory mortgage lending practices, African Americans and Latinos are still being denied conventional mortgage loans at a higher rate than their White counterparts.⁶⁸ According to Home Mortgage Disclosure Act records, modern-day redlining occurred heavily in sixty-one metro areas such as Atlanta, Detroit, and Philadelphia, even when accounting for applicants' income, loan amount, and neighborhood.⁶⁹ Researchers who analyzed these records found that people of color were consistently denied mortgage loans.⁷⁰ Specifically, Black applicants were denied mortgage loans at significantly higher rates than White applicants in forty-eight cities, Latino applicants in twenty-five cities, Asian applicants in nine cities, and Native American applicants in three cities.⁷¹ In Washington D.C., all four groups were significantly more likely to be denied a home

64. Charles Davidson, *Lack of Access to Financial Services Impedes Economic Mobility*, FED. RSRV. BANK OF ATLANTA (Oct. 16, 2018), <http://www.frbatlanta.org/economy-matters/community-and-economic-development/2018/10/16/lack-of-access-to-financial-services-impedes-economic-mobility>.

65. Badger, *supra* note 49.

66. Jan, *supra* note 47.

67. Badger, *supra* note 49.

68. Aaron Glantz & Emmanuel Martinez, *Modern-Day Redlining: How Banks Block People of Color from Homeownership*, CHI. TRIB. (Feb. 17, 2018, 2:30PM), <http://www.chicagotribune.com/business/ct-biz-modern-day-redlining-20180215-story.html>.

69. *Id.*

70. *Id.*

71. *Id.*

loan than their White counterparts.⁷² Mortgage lenders claim that these denials are based on borrowers' credit history and debt-to-income ratio, rather than race.⁷³ However, because people of color were historically targeted by predatory lending schemes, it is a direct consequence that they are more likely to have lower credit scores or blemishes in their credit history than White people. Furthermore, this research highlights the role that redlining and other discriminatory lending practices have played in creating economic disparities by denying people of color the opportunity to access credit, housing, and ultimately, wealth accumulation.⁷⁴

Although Congress outlawed predatory lending practices, disparities in loan interest rates offered to people of color and White people persist.⁷⁵ A study conducted by UC Berkeley in 2018 discovered that in traditional face-to-face interactions, lenders charged Latino and African American borrowers interest rates that were six to nine basis points higher than their White counterparts.⁷⁶ Banks have also targeted historically redlined communities with predatory mortgages and loans, threatening the financial stability of Black and Latino residents of those communities.⁷⁷ These predatory practices include targeting Black and Latino communities with high interest rates and intrinsically risky financial products, resulting in higher delinquency and default rates.⁷⁸ Experts estimate that the higher rates of foreclosure on predatory mortgages devastated communities of color by wiping out nearly 400 billion dollars in these communities between 2009 and 2012, long after discriminatory laws had been outlawed.⁷⁹ In a move that further degrades minorities' financial stability, companies that purchase debts and sue to recover judgments have targeted people of color more than any other group.⁸⁰ Furthermore, missed payments and judgments are blemishes on a consumer's credit history that remain for seven years. As a result of these practices, Blacks and Latino people are more likely than their White counterparts to have damaged

72. *Id.*

73. *Id.*

74. Badger, *supra* note 49.

75. Sally Ward-Foxton, *Reducing Bias in AI Models for Credit and Loan Decisions*, EE TIMES (Apr. 30, 2019), <http://www.eetimes.com/reducing-bias-in-ai-models-for-credit-and-loan-decisions/>.

76. *Id.*

77. Eveleth, *supra* note 42.

78. Sarah Ludwig, *Credit Scores in America Perpetuate Racial Injustice. Here's How*, THE GUARDIAN (Oct. 13, 2015, 10:14 AM), <http://www.theguardian.com/commentisfree/2015/oct/13/your-credit-score-is-racist-heres-why>.

79. Eveleth, *supra* note 42.

80. *Id.*

credit and poor credit scores.⁸¹ Numerous studies have shown that credit scores in communities predominantly occupied by people of color are far lower than the credit scores of communities nearby that are occupied by White people.⁸² As these consumers' credit scores decrease, their access to social and economic advances also decreases.

C. Is Artificial Intelligence Technology a Remedy for Bias in Lending?

Financial institutions have sought to remedy credit inaccessibility by adding machine learning algorithms and big data to the credit scoring and underwriting processes.⁸³ Many market lenders and large financial institutions use big data and machine learning technology to evaluate consumer risk and creditworthiness.⁸⁴ Big data describes “extensive datasets—primarily in the characteristics of volume, velocity, and/or variability—that require a scalable architecture for efficient storage, manipulation, and analysis.”⁸⁵ This data can be extremely valuable for lenders, allowing them an opportunity to gain a holistic view of their consumers.⁸⁶ The use of big data is transforming the credit lending industry, allowing financial institutions the ability to consider alternative information in the scoring and underwriting processes.⁸⁷ By inputting large datasets into machine learning algorithms, the technology is able to analyze thousands of data points to find empirical relationships between consumer behavior and creditworthiness.⁸⁸

Alternative data broadly describes “[i]nformation not typically found in the consumer’s credit files of the nationwide consumer reporting agencies or customarily provided by consumers as part of applications for credit.”⁸⁹ This data may include information regarding consumers’ telecommunications, utilities, or residential rental payment history.⁹⁰

81. *Id.*

82. *Id.*

83. Aaron Klein, *Credit Denial in the Age of AI*, BROOKINGS (Apr. 11, 2019), <http://www.brookings.edu/research/credit-denial-in-the-age-of-ai>.

84. Steve Cocheo, *Nontraditional Credit Data Could Bring Loans to More Consumers*, THE FIN. BRAND, <http://thefinancialbrand.com/91849/personal-loan-alternative-credit-data-consumer-borrowing/> (last visited Feb. 1, 2020).

85. *What Is Big Data?*, UNIV. OF WIS. DATA SCI., <http://datasciencedegree.wisconsin.edu/data-science/what-is-big-data/> (last visited Feb. 1, 2020).

86. Cocheo, *supra* note 84.

87. *Id.*

88. Klein, *supra* note 83.

89. Cocheo, *supra* note 84.

90. *Id.*

Financial institutions may also consider a consumer's social media and web behavior, employment history, education, and even restaurant reviews or business check-ins in the credit scoring process.⁹¹ Many financial institutions use these non-traditional factors in conjunction with the existing FICO data model to develop alternative credit scores that they believe are more reflective of consumers' creditworthiness and financial habits.⁹²

This alternative consumer data is acquired from a multitude of sources such as streaming technology, social media interactions, cloud data sources, a consumer's "digital footprint," and public records.⁹³ Financial technology firms then input this alternative data into machine learning algorithms, or other forms of artificial intelligence technology, to generate predictive outputs about consumers' creditworthiness and credit performance.⁹⁴ Fintech firms believe that the use of non-traditional data such as behavioral and social information reveals pertinent information about consumers' financial habits and allows them to reach out to a broader range of consumers, particularly those who have historically struggled to acquire credit.⁹⁵ The Consumer Financial Protection Bureau estimates that 26 million Americans have no credit history, while another 18 million Americans are not scorable.⁹⁶ The Bureau's report revealed that 27% of Black and Latino adults are credit invisible, while only 16% of White adults are credit invisible.⁹⁷ A lack of credit history exposes economically vulnerable consumers to higher borrowing costs and barriers to housing and employment.⁹⁸ The use of alternative data in the credit scoring process has allowed many lenders to offer "credit invisibles" access to credit opportunities at favorable interest rates.⁹⁹

While lenders highlight the benefits of the use of alternative data in credit evaluations, it is imperative to consider the potential risks the use of this data poses for consumers. First, the use of data that is not traditionally

91. Eveleth, *supra* note 42.

92. Cocheo, *supra* note 84.

93. "Digital footprint" refers to a trail of data that an individual creates while accessing the Internet. *Big Data: What it Is and Why it Matters*, SAS, http://www.sas.com/en_us/insights/big-data/what-is-big-data.html (last visited Feb. 1, 2020).

94. Cocheo, *supra* note 84.

95. *Id.*

96. *Id.*

97. Eveleth, *supra* note 42.

98. *Expanding Access to Credit*, CONSUMER FIN. PROT. BUREAU, <http://www.consumerfinance.gov/practitioner-resources/economically-vulnerable/expanding-credit-access/> (last visited Feb. 1, 2020).

99. Cocheo, *supra* note 84.

reported by credit reporting agencies raises significant concerns regarding accuracy. The Fair Credit Reporting Act requires that credit reporting agencies adopt fair procedures for reporting and utilizing accurate consumer information.¹⁰⁰ Financial institutions rely on this information in evaluating consumer creditworthiness. Ensuring accuracy allows consumers the opportunity to gain access to credit, and ultimately, financial stability. However, since alternative data involves factors that are not reported to the credit bureaus, there are potential issues regarding the accuracy of the information that lenders are relying on. Regulatory agencies have broadly articulated the meaning of “alternative data,” leaving open the possibility of endless information used by lenders in their analysis of consumers, none of which is required to be reported to credit bureaus or checked for accuracy. As a result, lenders may be relying on inaccurate information that fails to accurately convey an individual’s creditworthiness.

The use of alternative data in the credit scoring process also raises privacy and fairness concerns. Critics argue that allowing lenders access to information such as a consumer’s spending habits, social media usage, browsing history, sexual orientation, and a multitude of other types of non-conventional information means giving up privacy in exchange for credit access.¹⁰¹ Additionally, the algorithms evaluate this information to identify patterns that consumers may be unaware of.¹⁰² Fintech companies believe that a consumer’s posts, pictures, shares, likes, social media friends, and even typing habits and writing styles can play a role in gauging a person’s financial trustworthiness.¹⁰³ According to financial lenders, a lot of information can be learned simply by knowing the type of computer a person uses, the type of device they use, the time of day they applied for credit, and even if their name is used in their e-mail domain.¹⁰⁴ A study that used a consumer’s “digital footprint” to develop alternative credit scores suggested that iPhone users were more likely to pay back loans than Android users.¹⁰⁵ When evaluating social media behavior, fintech firms evaluate consumers based on their network, rather than evaluating

100. 15 U.S.C. § 1681.

101. See Cocheo, *supra* note 84.

102. Eveleth, *supra* note 42.

103. *Id.*

104. Klein, *supra* note 83.

105. Eveleth, *supra* note 42.

consumers as an individual.¹⁰⁶ Therefore, having the “wrong friend” or engaging with the “wrong posts” on social media could be the difference between being approved or denied access to fair credit opportunities.

Finally, algorithms could use information acquired from alternative data to reinforce existing disparities, resulting in exclusionary effects for certain groups. Because machine learning algorithms identify patterns in the data, they could potentially learn to use certain factors as a proxy to discriminate against protected classes.¹⁰⁷ Data such as a consumer’s zip code could lead the algorithm to infer that a borrower is a person of color.¹⁰⁸ Furthermore, data could be biased against an applicant in the screening process if the applicant attended a historically Black college.¹⁰⁹ Proxy discrimination is a phenomenon that occurs when “the predictive power of a facially-neutral characteristic is at least partially attributable to its correlation with a suspect classifier.”¹¹⁰ Critics argue that

when AI uncovers a statistical correlation between a certain behavior of an individual and their likelihood to repay a loan, that correlation is actually being driven by two distinct phenomena: the actual informative change signaled by this behavior and an underlying correlation that exists in a protected class.¹¹¹

Algorithms produce outputs without explaining how they came to the result, making proxy discrimination hard to detect and exposing minorities to a risk of lending discrimination with no remedy. For example, participants in a recent study on big data raised concerns that big data can lead to decision-making based on the actions of others with whom consumers share some characteristics.¹¹² Several participants in the study explained that “some credit card companies ha[d] lowered [their] credit limit, not based on [their] payment history, but rather based on analysis of other customers with a poor repayment history that had shopped at the same establishments where the customer had shopped.”¹¹³ Reliance on biased data that reflects existing inequalities will cause these sophisticated machine learning algorithms to produce outputs reflective of that bias.

106. Packin, *supra* note 41.

107. Klein, *supra* note 83.

108. Eveleth, *supra* note 42.

109. *Id.*

110. Klein, *supra* note 83.

111. *Id.*

112. FED. TRADE COMM’N, BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION? 9 (2016), <http://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf>.

113. *Id.*

When machine learning was first implemented, many people thought that removing humans from the lending process was a progression towards fairness in lending.¹¹⁴ Although financial institutions have sought to remedy unfair lending practices by removing humans, studies show that these algorithms can, and oftentimes do, exhibit human-like bias. For example, a study conducted by Stanford found that the transition from face-to-face interactions to machine learning algorithms produced the same results.¹¹⁵ Despite stripping potentially biased human agents from the credit underwriting process, Black and Latino borrowers are still charged rates six to nine basis points higher than similarly situated White borrowers when evaluated solely by machine learning algorithms.¹¹⁶

III. CONCLUSION

Fintech firms are confident that the use of alternative data in the underwriting process is a means of achieving fairness in lending by reaching out to consumers who have difficulty accessing mainstream credit opportunities.¹¹⁷ However, as the use of artificial intelligence technology and big data becomes normative in the financial services sector, it is important for regulation of financial technology to become normative as well.¹¹⁸ The use of financial technology presents significant challenges when combined with antiquated anti-discrimination laws that are not reflective of today's society.¹¹⁹ Regulatory bodies must protect consumers by promulgating modern day solutions that eradicate unfair lending practices.¹²⁰

First, it is important to ensure that the non-traditional information that financial institutions use in the underwriting process is accurate. Ensuring accuracy allows applicants to be evaluated holistically based on information that is truly reflective of their financial habits. Lawmakers must put consumers first, rather than financial institutions, by articulating clear standards for reporting alternative data. Financial institutions should be required to be transparent with consumers. This transparency includes

114. Eveleth, *supra* note 42.

115. *Id.*

116. *Id.*

117. Cocheo, *supra* note 84.

118. Klein, *supra* note 83.

119. Aaron Klein, *Up for Debate: Should Mac Users Get Better Rates on Loans*, MEDIUM (May 23, 2017), <http://medium.com/@Brookings/up-for-debate-should-mac-users-get-better-rates-on-loans-20c45357622c>.

120. *Id.*

communicating the specific factors it considers in the underwriting process and providing consumers the opportunity to self-correct any inaccuracies. Ensuring transparency would ensure that the alternative information used in the underwriting process is an accurate description of a borrower's financial habits and creditworthiness.

It is also critical that the information used in the underwriting process is fairly representative of a consumer's creditworthiness and that the use of this information does not violate a consumer's privacy. Big data leaves room for entities to use any information they can recover about a person and feed that information to an algorithm to predict creditworthiness. While there may be patterns in this information, much of this information is inappropriate to use in a credit evaluation. Some of this information, like social media data, has no place in the underwriting process. Using a consumer's likes, shares, and posts to search for patterns in their financial habits seems inappropriate and could potentially harm individuals. A person's use of social media for entertainment and to connect with personal friends does not seem relevant or useful in a credit inquiry and could potentially result in someone's harmless online behavior having negative impacts on their real lives. Furthermore, the use of this data risks perpetuating existing biases by rewarding users who are the "right" race, who are doing the "right" things, and who are friends with the "right" people on social media. The problematic effects of social-based scoring become apparent when evaluating China's social based credit system.¹²¹ Under this system, individuals are ranked based on their social interactions and habits.¹²² This ranking is based on many factors such as a person's online behavior, how often they consume fast food, or whether they clean up after their pets.¹²³ An unfavorable ranking impacts an individual's consumption, home rental, employment prospects, and encourages social segregation.¹²⁴ "Digital footprint" data also presents issues. While this data is not discriminatory itself, is it fair for lenders to treat Mac users differently than PC users, even if Mac users are less risky borrowers?¹²⁵ Consider whether the answer would change if it were true that Mac users were disproportionately White or male.¹²⁶ If this were true, would it be fair for lenders to use this information, especially if machine learning

121. Packin, *supra* note 41.

122. *Id.*

123. *Id.*

124. *Id.*

125. Klein, *supra* note 83.

126. *Id.*

algorithms used it as a proxy for race, gender, or socioeconomic status?¹²⁷ If the inclusion of non-traditional data is meant to expand credit opportunities to those who are financially underserved, the data must be relevant to that person's financial spending habits. If financial institutions are limited to only using data that is closely related to financial habits, like utilities payments, financial institutions can provide a more accurate means of evaluating consumers' creditworthiness without infringing on their civil rights.

Finally, lawmakers must ensure that financial institutions work to curb algorithmic bias.¹²⁸ The proper regulation of the use of artificial intelligence technology can help reduce discrimination.¹²⁹ Regulations should be put in place to ensure that the information put into these algorithms can be stored and studied by highly skilled data analysts who can check the inputs for over or under representative data to ensure that the algorithms aren't learning patterns based on biased data.¹³⁰ When these algorithms that businesses heavily rely on are being fed data based on existing human biases, these inequities remain prevalent.¹³¹ Once artificial intelligence technology is properly regulated, better algorithms can help ensure fairer outputs, thus allowing marginalized groups to have access to equal opportunities.¹³² If regulated, this technology can be a means of leveling the playing field for communities who have been disenfranchised under the mainstream credit underwriting model. However, if left unregulated, biases will continue to be pervasive in a wide range of industries.

127. *Id.*

128. See FED. TRADE COMM'N, *supra* note 112.

129. Sendhil Mullainathan, *Biased Algorithms Are Easier to Fix Than Biased People*, N.Y. TIMES (Dec. 6, 2019), <http://www.nytimes.com/2019/12/06/business/algorithm-bias-fix.html>.

130. *Id.*

131. Resnick, *supra* note 29.

132. Mullainathan, *supra* note 129.