National Consumer Law Center

NATIONAL HEADQUARTERS
7 Winthrop Square, Boston, MA 02110
(617) 542-8010

WASHINGTON OFFICE
Spanogle Institute for Consumer Advocacy
1001 Connecticut Avenue, NW, Suite 510
Washington, DC 20036
(202) 452-6252

NCLC.ORG

July 1, 2021

Board of Governors of the Federal Reserve System
Consumer Financial Protection Bureau
Federal Deposit Insurance Corporation
National Credit Union Administration
Office of the Comptroller of the Currency
(Collectively, the "Agencies")

Re: Request for Information and Comment on the Financial Institutions' Use of Artificial Intelligence, Including Machine Learning

To the Agencies:

The National Consumer Law Center (NCLC)[1] submits these comments on behalf of its low-income clients in response to the Agencies' *Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, Including Machine Learning*. The widespread adoption of artificial intelligence (AI), machine learning (ML), and related technologies by financial institutions raises fair lending and consumer protection concerns. Use of this technology by financial institutions has the potential to reduce costs, increase efficiency in the underwriting process, and provide other operational benefits. However, the use of complex, opaque algorithmic models in consumer credit transactions also heightens the risk of unlawful discrimination, and unfair, deceptive, and abusive practices.

We welcome the Agencies' focus on financial institutions' use of this technology. AI and ML pose a systemic risk to consumers. Poor implementation or monitoring of how financial institutions use AI and ML may amplify discriminatory patterns in the credit market, increase costs to consumers, or create barriers to access. The risk to consumers is enhanced because these algorithmic models are proprietary

---

[1] The **National Consumer Law Center, Inc. (NCLC)** is a non-profit Massachusetts Corporation, founded in 1969, specializing in low-income consumer issues, with an emphasis on consumer credit. On a daily basis, NCLC provides legal and technical consulting and assistance on consumer law issues to legal services, government, and private attorneys representing low-income consumers across the country. NCLC publishes a series of practice treatises on consumer credit laws and unfair and deceptive practices. NCLC attorneys have written and advocated extensively on all aspects of consumer law affecting low-income people, conducted trainings for tens of thousands of legal services and private attorneys, and provided extensive oral and written testimony to numerous Congressional committees on various topics. In addition NCLC attorneys regularly provide comprehensive comments to federal agencies on the regulations under consumer laws that affect low-income consumers. These comments were written by NCLC attorneys Odette Williamson, Jeremiah Battle, Chi Chi Wu, Ariel Nelson, Kyra Taylor, and Andrew Pizor.

and often closely guarded by the companies that develop them. This lack of transparency makes it difficult for fair lending advocates, researchers, and others to assess the impact models have on protected classes. We urge the Agencies to provide more guidance and adopt a robust process for analyzing the fair lending and consumer protection risks posed by these models.

I. Introduction

A. What is artificial intelligence?

The RFI did not address a basic but important level-setting question: "What do we mean by the term 'artificial intelligence?'" The RFI does not include an explanation of the term nor does it ask commenters for a definition. This is understandable given that, as noted by the White House National Science and Technology Council (NSTC), there does not appear to be a universally agreed upon definition.[2]

An NSTC report described how AI has been "defined loosely as a computerized system that exhibits behavior that is commonly thought of as requiring intelligence."[3] Similar definitions involve the concept of getting computers to do things requiring "intelligence."[4] But that begs the question of what does it mean to engage in a task or behavior with intelligence?

The difficulty in defining what is AI is compounded by:

- The lack of transparency as to what exactly is being used by different actors—we can't define something if we don't have enough information about it.
- The fact that the terms "artificial intelligence," "machine learning," and "algorithms" are often used interchangeably for all sorts of different applications.
- There are different "levels" of artificial intelligence—from simple chatbots that can only provide information in response to simple queries all the way to software guiding robots that will adapt to dynamic real-world environments.
- There is also a tendency to conflate alternative data, which is the actual pieces of information being used, with AI, which involves the method of analyzing and using the information.

The lack of a definition for AI is understandable, but it is also problematic. There may be incorrect assumptions that the use of AI necessarily makes a system more accurate or predictive, or that it is

---

[2] *See* National Science and Technology Council, Preparing for the Future of Artificial Intelligence, October 2016, p. 6 ("There is no single definition of AI that is universally accepted by practitioners").

[3] *Id.*

[4] The consulting firm Deloitte has described AI as "concerned with getting computers to do tasks that would normally require human intelligence." https://www2.deloitte.com/se/sv/pages/technology/articles/part1-artificial-intelligence-defined.htm.
Deloitte also notes a similar description from Alan Turing, considered the father of the modern computer: "AI is the science and engineering of making intelligent machines, especially intelligent computer programs"

unbiased and unquestionably fair. Public perception of what constitutes AI has been heavily influenced by popular entertainment culture (e.g., 2001: A Space Odyssey or Terminator) and many think of AI as incredibly human-like and sentient, which is very far from current reality. AI Blindspot has noted how the fluidity of the term intersects with the assumption that AI is more powerful than its reality:

> [a]rtificial intelligence has become a catch-all category of systems that derive patterns, insights, and predictions from big datasets. While they might aspire to emulate and automate intelligent human-like judgment, most algorithms referred to as AI are in fact simple, imperfect models susceptible to making erroneous inferences.[5]

The lack of a definition for AI, combined with the lack of transparency, may create consumer protection issues. Since we don't know what companies actually use when they claim to employ AI, we don't know if they are making exaggerated claims to create an impression of accuracy and sophistication. For example, many consumers have experienced chatbots supposedly using AI that make nonsensical responses.

This leads to some fundamental questions about the use of AI in financial services: How do we evaluate if the AI is actually an improvement or effective for the purpose for which it is being used? Who is evaluating if an AI model is predictive or even functional? For regulated financial institutions, it would be the prudential regulator's role to examine AI used for credit underwriting and risk management—we certainly hope that the examiners will be focused on this. But we urge that examinations not be limited to those areas, and that the Agencies examine the use of AI for other purposes such as customer service, servicing, and collections. The CFPB should examine the use of AI by other non-bank supervised entities (such as mortgage and student loan servicers and debt collectors) to assess the impact on consumers—especially for racial disparities.

Outside of financial services, there is a complete lack of supervision for businesses claiming to use AI, where their systems are not actually predictive or accurate. Tenant screening, discussed below, is a prime example of this problem, with possibly huge negative impacts for consumers. Consumers should be able to seek redress for such "faux" inaccurate or unpredictive AI models under, *inter alia*, the Fair Credit Reporting Act or state UDAP laws, and the Agencies should take action under applicable laws they enforce.

B. **AI and machine learning models have the potential to accelerate existing discriminatory patterns, and create systemic risks for consumers in credit and housing markets.**

Discrimination in the credit and housing markets has led to disparities in wealth, homeownership, and economic opportuniy for consumers of color and a widening racial wealth gap.[6] Creditors discriminate at every stage of the credit transaction, including which customers they solicit for business, to whom

[5] AI Blindspot available at https://aiblindspot.media.mit.edu/.

[6] See Thomas Shapiro, Tatjana Meschede & Sam Osoro, Institute on Assets and Social Policy, *The Roots of the Widening Racial Wealth Gap: Explaining the Black-White Economic Divide* (2013), *available at* https://drum.lib.umd.edu/bitstream/handle/1903/24590/racialwealthgapbrief.pdf; Rakesh Kochhar & Anthony Cilluffo, Pew Research Ctr., *How wealth inequality has changed in the U.S. since the Great Recession, by race, ethnicity and income*, Fact Tank (Nov. 1, 2017), https://www.pewresearch.org/fact-tank/2017/11/01/how-wealth-inequality-has-changed-in-the-u-s-since-the-great-recession-by-race-ethnicity-and-income/.

they grant credit, the terms and conditions on which credit is extended, and how customers are treated in subsequent stages of the credit transaction, such as loan servicing and debt collection.

These practices are built on a foundation of government policies and programs that redlined communities, sanctioned racially exclusionary housing practices, codified discriminatory appraisal and underwriting guidelines, and otherwise denied African Americans and other consumers of color access to affordable mortgages.[7] Weak government regulation created dual credit markets where high-cost fringe lenders like payday lenders, auto title lenders, check cashers, and the like are heavily concentrated in Black and Latinx communities underserved by mainstream lenders.[8] One study in North Carolina, for example, noted that Black neighborhoods have three times as many payday loan stores per capita as white neighborhoods, a concentration that increased as the proportion of Black people in the neighborhood increased.[9] The use of AI by the financial industry has the potential to provide equitable access to credit for consumers of color or perpetuate and calcify historical patterns.

This history is baked into the training data used by AI models. The inclusion of alternative data, including data not typically found in credit reports issued by the nationwide consumer reporting agencies, or provided as part of a credit application, raises heightened fair lending concerns.[10] The industry promises that use of this data in credit underwriting will expand credit for consumers who are "credit invisible" due to a lack of history or a thin file with the traditional credit bureaus.[11] Leveraging new types of data and analytical techniques could potentially benefit consumers.

However, both traditional and alternative data reflect deeply ingrained structural inequalities in education, employment, housing and access to credit. Some forms of alternative data also raise additional concerns regarding accuracy, relevance and predictability, and how data used in these models could potentially worsen existing disparities. Non-financial Big Data, for example, including web browsing history, social media profile, and friends and family data may not be accurate or predictive of credit quality. An NCLC report on Big Data highlighted that information collected on consumers by four data brokers was riddled with errors.[12] The information was often inaccurate and incomplete and primarily gathered without the consumer's knowledge. There was no easy mechanism for consumers to dispute the accuracy of the information.

---

[7] See Richard Rothstein, *The Color of Law: A Forgotten History of How Our Government Segregated America*, 2017.

[8] Delvin Davis et al, Race Matters: *The Concentration of Payday Lenders in African American Communities in North Carolina*, Center for Responsible Lending (March 2005); Assaf Oron, *Easy Prey: Evidence for Race and Military Related Targeting in the Distribution of Payday Loan Branches in Washington State*, Department of Statistics, University of Washington (March 2006).

[9] Uriah King et al., *Race Matters: The Concentration of Payday Lenders in African American Neighborhoods in North Carolina*, Center for Responsible Lending (2005). See also Brandon Coleman and Delvin Davis, *Perfect Storm: Payday Lenders Harm Florida Consumers Despite State Law*, Center for Responsible Lending (March 2016); Li, et al., *Predatory Profiling: The Role of Race and Ethnicity in the Location of Payday Lenders in California*, Center for Responsible Lending, 2009.

[10] See Consumer Financial Protection Bureau, Request for Information Regarding Use of Alternative Data and Modeling Techniques in the Credit Process, 82 Fed. Reg. 11183 (May 17, 2017).

[11] See Consumer Financial Protection Bureau, *Blog: Report on the Bureau's Building Bridge to Credit Visibility Symposium*, available at https://www.consumerfinance.gov/about-us/blog/report-credit-visibility-symposium/.

[12] National Consumer Law Center, *Big Data: A Big Disappointment for Scoring Consumer Credit Risk*, at 18 (March 2014).

Data used for credit decisions must comply with the requirements of the Equal Credit Opportunity Act (ECOA) and the Fair Credit Reporting Act (FCRA) to be accurate and predictive of creditworthiness.[13] Unlike traditional credit scores, which also display racial disparities but under a business necessity analysis may be used to predict credit quality, with Big Data it is unclear how data gathered from social media, online behavior, and by other means measures creditworthiness.[14] Moreover, the newer AI models may not be a less discriminatory alternative to traditional credit scores, especially if the model is not tested or validated.

As these models evolve, and newer sources of data are mined, more scrutiny is needed to ensure that AI models do not replicate existing biases and perpetuate discrimination. As a Federal Reserve article noted, "statistical models have the potential to increase consistency in decision making and to ensure that the results are empirically sound, depending on the data analyzed and the underlying assumptions, models may reflect and perpetuate existing social inequalities . . . . [T]he fact that an algorithm is data driven does not ensure that it is fair or objective."[15] The Agencies should use their supervision authority to ensure that creditors routinely evaluate data sources including those relied on by vendors or third party providers as part of the larger fair lending evaluation of the outputs generated by the models.

C. Fair lending and civil rights laws provide a framework for addressing the systemic risks posed to consumers by AI and machine learning models.

Federal credit discrimination laws have been used for decades to challenge unfair and discriminatory credit practices. Financial institutions are evaluated for compliance with fair lending laws. The framework developed by regulators for supervision and enforcement of fair lending laws, particularly disparate impact, should be used to evaluate the risks to consumers posed by this newest technology. The Agencies should issue additional detailed guidance on how the current framework can be adapted to assess financial institutions' use of AI and machine learning models.

The Equal Credit Opportunity Act (ECOA) prohibits discrimination on the basis of race, color, religion, national origin, sex, marital status, age, receipt of income from public benefits, or exercise of rights under consumer credit protection statutes.[16] The Act makes it unlawful to discriminate in any aspect of a credit transaction. Under Regulation B this prohibition includes making any oral or written statement in advertisement or otherwise that would discourage a reasonable person from making or pursuing a credit application.[17] The Fair Housing Act (FHA) prohibits discrimination on the basis of race, color, religion, national origin, sex, familial status, or disability in residential real-estate related loans.[18] Discrimination in advertising regarding the sale or rental of a dwelling, including related to mortgage credit, is prohibited.[19]

---

[13] ECOA, 15 U.S.C. §§1691 et seq.; FCRA, 15 USC §§ 1681 et seq.

[14] See National Consumer Law Center, *Past Imperfect: How Credit Scores and Other Analytics "Bake In" Past Discrimination and Perpetuate It*, May 2016 (African American, Latinx, and Asian consumers have lower credit scores as a group than whites).

[15] Carol Evans, Board of Governors of the Federal Reserve System, *Keeping Fintech Fair: Thinking about Fair Lending and UDAP Risks*, Consumer Compliance Outlook (Second Issue 2017) at 4.

[16] 15 U.S.C. §§ 1691 et seq. See also 12 C.F.R. § 1002.2(z).

[17] See 12 C.F.R. § 1002.4(b).

[18] 42 U.S.C. §§ 3601 et seq.

[19] 42 U.S.C. § 3604(c); 24 C.F.R. 100.75(c)(3).

The ECOA and FHA prohibit discrimination that is intentional and overt. This disparate treatment occurs when the creditor treats the consumer differently because of a protected characteristic, though the practice need not be motivated by prejudice or specific intent to harm a member of a protected group. The statutes also prohibit discrimination based upon disparate impact, which occurs when a lender's policy or practice is neutral on its face but adversely impacts a protected class. The three-step framework for determining whether a policy has an unlawful disparate impact first considers whether a policy or practice disproportionately disadvantages a protected class; and if so, the second step determines whether there is a legitimate business interest served by the policy or practice; and third, if the policy or practice serves a legitimate business interest, whether there is an reasonable alternate practice that would serve the same end while reducing the negative impact on protected class members.

Advocates have used credit discrimination statutes, and disparate impact in particular, to challenge the unlawful policies and practices of financial institutions. The laws have been used to challenge lenders that refuse to extend credit, extend credit on different terms, including variances in the interest rate, amount or term of a loan, or otherwise treat similarly situated consumers differently on the basis of a protected characteristic. For example, NCLC and other consumer and civil rights advocates brought disparate impact claims under the ECOA and other civil rights statutes to challenge creditor policies permitting car dealers to "mark-up" interest rates on loans based on subjective criteria unrelated to creditworthiness;[20] mortgage lenders whose policies resulted in more expensive loans to protected classes than similarly situated white borrowers;[21] and predatory home financing schemes using contracts that result in consumers being evicted from the home and losing all of their investment in the property.[22] Many of these policies and practices had a disparate impact on African American, Latinx, and other consumers who paid more for credit than whites with similar credit ratings.

Federal agencies investigating lending discrimination have long recognized and applied disparate impact in supervision and enforcement.[23] The CFPB, in Bulletin 2012-04 on lending discrimination, affirmed its adherence to the fair lending principles outlined in the ECOA and Regulation B and expressly concurred with the *Policy Statement on Fair Lending* issued by federal agencies in 1994.[24] Thus, financial institutions are well aware of fair lending and disparate impact risks with respect to their credit practices, and should expect such fair lending examinations of their newest technology. Financial institutions should also have fair lending testing, compliance and monitoring regimens in place to decrease such risks. Fair lending evaluation of AI and machine learning models is a continuation of the assessment of risk undertaken with respect to more traditional models.

---

[20] National Consumer Law Center, Credit Discrimination, §8.6.2. (7th ed. 2018). See also NCLC, *Racial Disparities in Auto Loan Mark-Ups: State by State Data*, available at https://www.nclc.org/images/pdf/car_sales/ib-auto-dealers-racial_disparites.p

[21] See e.g., Ramirez v. GreenPoint Mortg. Funding, Inc., 268 F.R.D. 627 (N.D. Cal. 2010); Guerra v. GMAC, L.L.C., 2009 WL 449153 (E.D. Pa. Feb. 20, 2009); Taylor v. Accredited Home Lenders, Inc., 580 F. Supp. 2d 1062 (S.D. Cal. 2008); Miller v. Countrywide Bank, 571 F. Supp. 2d 251 (D. Mass. 2008); Ware v. Indymac Bank, 534 F. Supp. 2d 835 (N.D.Ill. 2008); Garcia v. Countrywide Fin. Corp. [12], No. 07-1161 (C.D. Cal. Jan. 15, 2008).

[22] Henderson v. Vision Property Management, LLC, complaint and other material available at https://www.nclc.org/litigation/nclc-sues-company-over-racially-targeted-home-scheme.html.

[23] See *Policy Statement on Discrimination in Lending*, 59 Fed. Reg. 18266, Apr. 15, 1994.

[24] CFPB Bulletin 2012-04 (Fair Lending)," Consumer Financial Protection Bureau. April 2012. Available at: https://files.consumerfinance.gov/f/201404_cfpb_bulletin_lending_discrimination.pdf.

The disparate impact standard is flexible enough to respond to the latest innovations in the credit market, as it has in the past. Under the three-step analysis, if testing of an AI model used in underwriting reveals that it disproportionately disadvantages a protected class, and produces inaccurate results that are not predictive of credit quality, there is not a legitimate business justification for using such a model. Moreover, even if the AI model were accurate and predictive, it could be that a more traditional credit assessment is a less discriminatory alternative.

The Agencies should require financial institutions to test AI models used in underwriting and other parts of the credit transaction to ensure the outputs are empirically derived, statistically sound and accurately predict risk or achieve other valid objectives. AI-based underwriting models should also be subject to routine monitoring for discrimination to account for drift or changes in the model. The potential of this technology to increase access to credit does not call on the Agencies to abandon a rigorous fair lending evaluation or water down long-held and workable standards.

D. Current regulatory efforts fall short of protecting consumers from unlawful discrimination due to financial institutions' use of AI and machine learning models in credit underwriting and disclosures.

We urge the Agencies to put a robust regulatory process in place to monitor the use of AI and machine learning models by financial institutions. Companies should not be exempt from supervision or enforcement actions if their credit models produce discriminatory results. Instead the Agencies should learn from past actions that eased regulatory oversight increases the risk to consumers. Specifically:

No Action Letter to Upstart Network. The CFPB issued No Action Letters to Upstart Network ("Upstart"). Upstart makes consumer loans, including private student loans, and sells its underwriting technology to other banks. It bills itself as "a leading artificial intelligence (AI) lending platform designed to improve access to affordable credit while reducing the risk and costs of lending for our bank partners."[25] It uses a "machine learning model that uses over 1,500 variables to make credit and pricing decisions."[26] Although Upstart's algorithms are proprietary, it advertises its ability to "leverage 1000+ data points" when making credit decisions.[27] Educational data—such as standardized test scores, degree attainment, and school attended—are some of those datapoints.[28]

In 2017, Upstart applied to the CFPB's No-Action Letter program so that it could continue lending without fear that the CFPB would bring an enforcement action against it for ECOA and Regulation B violations. Upstart claimed it needed a No Action Letter to "address regulatory uncertainty surrounding the sufficiency of its efforts to ensure compliance with ECOA and Regulation B, with respect to a model for underwriting applicants for unsecured non-revolving credit who would otherwise not receive such credit on as favorable terms."[29] The application detailed testing Upstart had done to demonstrate the expanded access to credit consumers would receive under the Upstart model as compared to the traditional credit model. It also stated that Upstart had done disparate impact testing and had not found unlawful disparate impact. Upstart confidentially provided the results of that testing to the CFPB.

---

[25] *Upstart: Investor Relations,* Upstart (last viewed July 1, 2021) https://ir.upstart.com/.

[26] Letter from Dave Girouard, Upstart, to Senators Brown, Warren, Menendez et al, attachment at 4 (Feb. 28, 2020) https://www.banking.senate.gov/imo/media/doc/Review%20-%20Use%20of%20Educational%20Data.pdf.

[27] *Credit Decision API*, Upstart (last viewed July 1, 2021) https://www.upstart.com/for-banks/credit-decision-api/

[28] Girouard Letter, supra n. 26, attachment at 4-5.

[29] Upstart No-Action application to the CFPB (Sept. 2017) https://files.consumerfinance.gov/f/documents/201709_cfpb_upstart-no-action-letter-request.pdf

The CFPB granted Upstart's application in 2017 and then renewed it in 2020, potentially giving it a free pass on ECOA and Regulation B violation.

Despite Upstart's claims that there was no unlawful discriminatory impact in Upstart's systems, the Student Borrower Protection Center (SBPC) identified in February 2020 that Upstart's AI model charged higher interest rates to hypothetical students who attended community colleges, historically black colleges and universities (HBCUs), and Hispanic serving institutions (HSIs).[30] SBPC used hypothetical applicants, identical in every way except for their higher education institution, to ascertain that the interest rates increased based on what type of school the borrower attended. As SBPC warned in that report, "[B]y considering the college or university attended by the consumer, a lender may capture disparate patterns in college attendance across class and race, thereby introducing bias in the underwriting process." That bias had infected Upstart's AI.

Upstart failed to adequately police its own technology for discriminatory impact. And, as SBPC's report illustrated, despite Upstart's claims that its AI model yielded higher acceptance rates for borrowers of color than traditional models, those same borrowers were charged more than similarly situated white borrowers which still resulted in a discriminatory impact. The CFPB failed to independently test Upstart's assertions, instead relying on the representations of the company rather than conducting its own analysis.

By December 1, 2020, Upstart, SBPC, and NAACP Legal Defense and Educational Fund, Inc. (LDF) entered an agreement where Relman Colfax, a civil rights law firm, would evaluate and monitor Upstart for fair lending.[31] Independent of monitoring, Upstart has already made changes. It created a "normalization" process for Minority Serving Institutions and eliminated the use of average incoming SAT and ACT scores to group educational institutions in its model.[32]

However, it remains to be seen what third party monitoring will reveal. Perhaps the most significant outstanding question is whether educational data can be used in a way that does not discriminatorily impact borrowers from protected classes.[33] Additionally, it is unclear whether monitoring will identify whether AI is using protected characteristics or proxies for protected characteristics in its decisionmaking. As Relman Colfax explained in its initial report, "It is difficult to understand how learning algorithms reach the results they do, including how AI/ML models process variables, which adds to concerns that they may rely on or contribute to protected class disparities in subtle ways, or that they may otherwise unnecessarily perpetuate disparate impacts." But without policing the algorithm and only policing the results, consumers cannot be fully protected against impermissible bias or predatory behavior on the part of the machine.

Tech Sprint regarding Adverse Action Notices. The CFPB's Tech Sprint initiative on adverse action notices in October 2020, for which one of our colleagues served on the judging panel, did include projects that attempted to improve the explainability of algorithmic credit decisions. However, it was

---

30 *Educational Redlining*, Student Borrower Protection Center, Feb. 2020, available at https://protectborrowers.org/wp-content/uploads/2020/02/Education-Redlining-Report.pdf

31 *Fair Lending Monitorship of Upstart Network's Lending Model,* Relman Colfax (April 14, 2021) https://www.relmanlaw.com/cases-406

32 *Fair Lending Monitorship of Upstart Network's Lending Model: Initial Report of the Independent Monitor* at 23-24(Apr. 14) https://www.relmanlaw.com/media/cases/1088_Upstart%20Initial%20Report%20-%20Final.pdf.

33 *Id*. at 17.

unclear whether the projects would truly be able to successfully explain the real, underlying reasons specifically for a decision made by an AI/machine learning model. Nor is it clear whether the CFPB will hold creditors responsible for providing such an explanation as required by the ECOA. While a Tech Sprint is an innovative approach, it does not replace regulation. More guidance and oversight is necessary to ensure that creditors adhere to the spirit and intent of the adverse action notice requirement under the ECOA.

II. Fair Lending Concerns Regarding the Use of AI and Machine Learning by Financial Institutions

Financial institutions use AI and machine learning models in credit transactions—from marketing to underwriting, servicing, and collection. We highlight a few of the issues that have come to our attention. Given the lack of transparency regarding whether this technology is used, and how it is used in credit underwriting and marketing, it is hard to catalog all the different ways AI and machine learning models impact the financial products and services offered to consumers.

A. The targeted marketing and solicitation of credit may steer vulnerable consumers to high-cost, predatory financial products.

The use of AI models to solicit customers for credit raises concerns regarding redlining and steering. Data-driven AI models have made it easier for creditors to finely target the audience for their online marketing campaigns. This may benefit some consumers who receive advertisements tailored to their interests. But other consumers are at a disadvantage if, instead of being shown a wide array of competitively priced credit options, they are steered to high-cost, subprime products.[34] Data collected and used in the models, including social media data, can be harmful to financially vulnerable consumers by identifying their emotional state,[35] medical characteristics,[36] or a propensity for substance or gambling addiction.[37] At its most extreme, an FTC study noted that unethical companies targeted consumers whom they knew to be vulnerable based on age, disability, or other factors to offer subprime credit.[38]

---

[34] See Carol Evans, Board of Governors of the Federal Reserve System, *From Catalog to Clicks, The Fair Lending Implications of Targeted, Internet Marketing*, Consumer Compliance Outlook (Second Issue 2017) at 4; Amit Datta et al. *Automated Experiments on Ad Privacy Settings: A Tale of Opacity, Choice, and Discrimination*, Cornell Univ., (2015) available at https://arxiv.org/abs/1408.6491.

[35] Robbie Gonzalez, *Your Facebook Posts Can Reveal If You're* Depressed, Wired (Oct. 16, 2018) https://www.wired.com/story/your-facebook-posts-can-reveal-if-youre-depressed/

[36] Charles Duhigg, *How Companies Learn Your Secrets*, NY Times (Feb. 16, 2012) https://www.nytimes.com/2012/02/19/magazine/shopping-habits.html; Colin Lecher, *How Big Pharma Finds Sick Users on Facebook,* The Markup (May 6, 2021) https://themarkup.org/citizen-browser/2021/05/06/how-big-pharma-finds-sick-users-on-facebook; *Facebook posts better at predicting diabetes, mental health, than demographic info,* U. of Penn School of Medicine (June 17, 2019)https://www.sciencedaily.com/releases/2019/06/190617175555.htm ;

[37] Tao Ding, Warren K Bickel, Shimei Pan, *Social Media-based Substance Use Prediction*, (revised May 31, 2017) https://arxiv.org/abs/1705.05633; *'If you have an addiction, you're screwed' – How Facebook and social casinos target the vulnerable*, Reveal (Aug. 4, 2019) https://revealnews.org/article/if-you-have-an-addiction-youre-screwed-how-facebook-and-social-casinos-target-the-vulnerable/

[38] See Nathan Newman, *How Big Data Enables Economic Harm to Consumers, Especially to Low-Income and Other Vulnerable Sectors of the Population*, at 6, available at https://www.ftc.gov/system/files/documents/public_comments/2014/08/00015-92370.pdf.

Digital redlining may also occur if creditors do not provide equal access to credit or provide credit on unequal terms based on race, color, national origin, or neighborhood.[39] Targeting consumers based on detailed information about their online habits, preferences and financial patterns, geolocation, and other data may result in both digital redlining and steering of protected class members to high-cost credit.

Civil rights organizations, lawmakers, and journalists have called out Facebook for both discriminatory ad targeting and ad delivery.[40] In 2016, ProPublica reported that Facebook not only allowed advertisers to target users based on their interests or background but also to exclude specific groups based on their race or ethnicity.[41] Following ProPublica's investigation, the National Fair Housing Alliance (NFHA) and other civil rights organizations sued, claiming that Facebook's advertising platform violated the Fair Housing Act. According to the complaint, "the stealth nature of Facebook's technology hides housing ads from entire groups of people," and "Facebook's algorithms can ensure exclusion and deny access to housing."[42] Facebook settled that case as well as other lawsuits alleging that its advertising platform enabled discrimination in 2019, agreeing that it would no longer permit advertisers to target ads based on protected classes or close proxies for protected classes.[43]

But Facebook's changes did not address yet another form of discrimination related to its use of AI. Later in 2019, researchers released a study finding that "previously unknown mechanisms" on the Facebook platform "can lead to potentially discriminatory ad *delivery*, even when advertisers set their targeting parameters to be highly inclusive."[44]

The 2019 research observed significant skew in ad delivery for housing opportunities along gender and racial lines.[45] HUD also determined Facebook continued engaging in discrimination in violation of the

---

[39] See Carol Evans, Board of Governors of the Federal Reserve System, *From Catalog to Clicks, The Fair Lending Implications of Targeted, Internet Marketing*, Consumer Compliance Outlook (Second Issue 2017) at 4.

[40] Louise Matsakis, *Facebook's Ad System Might be Hard-Coded for Discrimination*, Wired (Apr. 6, 2019), https://www.wired.com/story/facebooks-ad-system-discrimination/; Muhammad Ali, et al., *Discrimination through Optimization: How Facebook's Ad Delivery Can Lead to Biased Outcomes*, 3 Proceedings of the ACM on Human-Computer Interaction, Nov. 2019, at 199:2, https://www.ccs.neu.edu/~amislove/publications/FacebookDelivery-CSCW.pdf.

[41] Julia Angwin & Terry Parris Jr., *Facebook Lets Advertisers Exclude Users by Race*, ProPublica (Oct. 28, 2016), https://www.propublica.org/article/facebook-lets-advertisers-exclude-users-by-race.

[42] Complaint ¶ 5, Nat'l Fair Hous. All. v. Facebook, Inc., No. 1:18-CV-02689 (S.D.N.Y. Mar. 27, 2018), ECF No. 1; *see also* Valerie Schneider, *Locked Out by Big Data: How Big Data, Algorithms and Machine Learning May Undermine Housing Justice*, 52 Colum. Hum. Rts. L. Rev. 251, 287–88 (2020).

[43] Valerie Schneider, *Locked Out by Big Data: How Big Data, Algorithms and Machine Learning May Undermine Housing Justice*, 52 Colum. Hum. Rts. L. Rev. 251, 288–89 (2020).

[44] Muhammad Ali, et al., *Discrimination through Optimization: How Facebook's Ad Delivery Can Lead to Biased Outcomes*, 3 Proceedings of the ACM on Human-Computer Interaction, Nov. 2019, at 199:1, https://www.ccs.neu.edu/~amislove/publications/FacebookDelivery-CSCW.pdf (emphasis added); *see also* Louise Matsakis, *Facebook's Ad System Might be Hard-Coded for Discrimination*, Wired (Apr. 6, 2019), https://www.wired.com/story/facebooks-ad-system-discrimination/.

[45] Muhammad Ali, et al., *Discrimination through Optimization: How Facebook's Ad Delivery Can Lead to Biased Outcomes*, 3 Proceedings of the ACM on Human-Computer Interaction, Nov. 2019, at 199:1, https://www.ccs.neu.edu/~amislove/publications/FacebookDelivery-CSCW.pdf.

Fair Housing Act.[46] In its lawsuit against Facebook, HUD alleged that, even if an advertiser did not try to exclude members of a protected class, Facebook's artificial intelligence systems "may systematically do so in an effort to maximize its own profits."[47] According to HUD's Charge of Discrimination, Facebook's "ad delivery system will not show the ad to a diverse audience if the system considers users with particular characteristics most likely to engage with the ad."[48] Facebook "uses machine learning and other prediction techniques to classify and group users so as to project each user's likely response to a given ad" and, in doing so, "inevitably recreates groupings defined by their protected class."[49]

The Washington Post has reported that HUD is also reviewing Twitter's and Google's practices for similar violations, suggesting that housing discrimination by AI-powered advertising platforms is not limited to Facebook and could be widespread.[50] And the problem extends beyond housing as an affiliate marketer peddling rip-off products and misleading ads explained to a reporter, "Affiliates once had to guess what kind of person might fall for their unsophisticated cons, targeting ads by age, geography, or interests. Now Facebook does that work for them."[51]

Targeted online marketing of financial products poses many of the same risks identified by HUD in its housing action against Facebook, namely steering and digital redlining. The Agencies should provide guidance on how financial institutions can monitor the marketing of credit products online. As mentioned above, both the ECOA and FHA apply to advertising. Creditors engaging online advertising platforms that use AI should be charged with understanding which audiences are reached by their advertisement, such that the solicitations are not targeted based on prohibited characteristics or proxies for these characteristics, even if not what the creditor intended. Regulatory supervision should involve a fair lending review of online marketing strategies to ensure consumers are offered credit on the best term they qualify for regardless of the nature of the solicitation.

---

[46] Tracy Jan & Elizabeth Dwoskin, *HUD Is Reviewing Twitter's and Google's Ad Practices as Part of Housing Discrimination Probe*, Washington Post (Mar. 28, 2019), https://www.washingtonpost.com/business/2019/03/28/hud-charges-facebook-with-housing-discrimination/.
[47] Valerie Schneider, *Locked Out by Big Data: How Big Data, Algorithms and Machine Learning May Undermine Housing Justice*, 52 Colum. Hum. Rts. L. Rev. 251, 289 (2020).
[48] Charge of Discrimination ¶ 19, Facebook Inc., No. 018-0323-8 (Dep't of Hous. & Urban Dev. Mar. 28, 2019), https://www.hud.gov/sites/dfiles/Main/documents/HUD_v_Facebook.pdf.
[49] *Id.* ¶ 20.
[50] Tracy Jan & Elizabeth Dwoskin, *HUD Is Reviewing Twitter's and Google's Ad Practices as Part of Housing Discrimination Probe*, Washington Post (Mar. 28, 2019), https://www.washingtonpost.com/business/2019/03/28/hud-charges-facebook-with-housing-discrimination/.
[51] Zeke Faux, *How Facebook Helps Shady Advertisers Pollute the Internet*, Bloomberg (Mar. 27, 2018) https://www.bloomberg.com/news/features/2018-03-27/ad-scammers-need-suckers-and-facebook-helps-find-them

B. Agencies should monitor the use of AI and machine learning models in credit underwriting to guard against price discrimination and inequitable access to credit.

The use of algorithmic models in credit underwriting and decision-making is growing. Developers have been marketing their software to a diverse array of credit providers.[52] Zest, for example, has been working with companies and industries as diverse as Freddie Mac[53] and auto dealers.[54]

The use of AI models allow creditors to consider additional data points, beyond the traditional credit score, to enable risk-based pricing.[55] While denial of credit is still an issue, automated underwriting may reduce denials for protected classes.[56] For many consumers the primary risk posed by AI is now discriminatory pricing. One recent study found that even though AI reduced racial disparities in loan application rejection, it increased disparities in interest rates, especially for Black and Hispanic borrowers:

> Panel B makes evident that the winners from the new technology are disproportionately White non-Hispanic and Asian—the share of the borrowers in these groups that benefit from the new technology is roughly 10 percentage points higher than for the Black and White Hispanic populations, within which there are roughly equal fractions of winners and losers. As we have seen earlier, the Random Forest model is a more accurate predictor of defaults. Moreover, it generates higher acceptance rates on average. However, it penalizes some minority race groups significantly more than the previous technology, by giving them higher and more disperse interest rates.[57]

Another study found that Fintech lenders reduced but did not erase discriminatory lending patterns with respect to the pricing of loans.[58] Latinx and African American borrowers paid 7.9 and 3.6 basis points more in interest for home purchase and refinance mortgages respectively because of discrimination. These magnitudes represent 11.5% of lenders' average profit per loan.[59]

Stricter scrutiny is required regarding the pricing of financial products. Models used in credit underwriting should be routinely tested for price discrimination. There is room for error in how models are developed, and the data entered may be inaccurate or incomplete. These errors may change the

---

52 Penny Crossman, *The Banks are Warming to AI Based Lending*, American Banker, October 25, 2019.

53 Bonnie Sinnock, Nat'l Mortg. News, *Zest, Freddie Mac officially testing AI use in underwriting,* Nov. 19, 2020, available at https://www.nationalmortgagenews.com/news/zest-freddie-mac-officially-testing-ai-use-in-underwriting.

54 Becky Yerak, Wall St. J. (Online), *AI Helps Auto-Loan Company Handle Industry's Trickiest Turn*, Jan. 3, 2019, available at https://www.proquest.com/newspapers/ai-helps-auto-loan-company-handle-industrys/docview/2162731656/se-2?accountid=46320.

55 *See* National Consumer Law Center, *Mortgage Lending* § 6.2.2.2

56 Kenneth Harney, *Computerized underwriting appears fairer to minorities*, Balt. Sun, Dec. 8, 2002 ("Freddie Mac's current electronic system outperformed human underwriters in predicting later defaults, and produced net gains of 29 percent in loan approvals for minority groups . . . .").

57 Andreas Fuster, Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walther, *Predictably Unequal? The Effects of Machine Learning on Credit Markets* at 36 (Oct. 2020), available at https://ssrn.com/abstract=3072038

58 Robert Bartlett, Adair Morse, et al., *Consumer Lending Discrimination in the Fintech Era, National Bureau of Economic Research*, Working Paper 25943, June 2019.

59 Id.

model's calculation of risk and the credit decision, and may be hard to uncover.[60] With machine learning models developers may not uncover errors in the data, or know how the variables are combined or considered, or how the combinations are weighted or factored into the model's output.[61]

Moreover, even with accurate data, seemingly neutral variables when used alone or in combination can correlate with race, ethnicity, and other prohibited factors. Machine learning models process large volumes of information, including a diverse set of variables not traditionally used for credit underwriting. These models will likely pick up subtle but statistically significant patterns that correlate with race and other protected characteristics.[62] Given enough data almost any input can be correlated to a protected characteristic.[63] In other words many inputs, when recycled through powerful and sophisticated models, can become substitutes or proxies for protected classes.

Given this risk, the Agencies should step up their oversight of financial institutions using these models. Lack of transparency in these "black box" models allows patterns of discrimination to go unrecognized and unchallenged. Creditors should not benefit from this feature. The Agencies should require creditors to test their models for bias, adopt less discriminatory alternatives to models that negatively impact protected classes, and use its supervision and enforcement authority to identify and root out digital discrimination.

C. More research is needed to understand the disparate impact of automated valuation models (AVMs) in real estate financing.

Real estate finance depends on reliable appraisals. Property valuation is done with computer software, either exclusively or in conjunction with a visit to the property. The software, called an automated valuation model or AVM,[64] is based on data from traditional appraisals, public records, and private

---

[60] See Fannie Mae Selling Guide, B3-2-01, General Information on DU (8/7/2018); B3-2-10: Accuracy of DU Data, DU Tolerances, and Errors in the Credit Report (08/07/2019).

[61] See Cary Coglianese et al., *Regulating by Robot, Administrative Decision Making in the Machine Learning Era*, 105 Geo. L.J. 1147, 1159 (2017).

[62] See Moritz Hardt, *How Big Data is Unfair, Understanding Unintended Sources of Unfairness in Data Driven Decision Making*, (Sept. 2014); Andrew Selbst, *A New HUD Rule Would Effectively Encourage Discrimination by Algorithm*, Slate (August 19, 2019).

[63] See Claire Miller, *When Algorithms Discriminate*, New York Times (July 9, 2015); Moritz Hardt, *How Big Data is Unfair, Understanding Unintended Sources of Unfairness in Data Driven Decision Making* (Sept. 2014); Andrew Selbst, *A New HUD Rule Would Effectively Encourage Discrimination by Algorithm*, Slate (August 19, 2019). See also National Consumer Law Center, *Big Data: A Big Disappointment for Scoring Consumer Credit Risk*, at 18, (March 2014).

[64] The International Association of Assessing Officers defines an AVM as "A mathematically based computer software program that market analysts use to produce an estimate of market value based on market analysis of location, market conditions, and real estate characteristics from information that was previously and separately collected. The distinguishing feature of an AVM is that it is a market appraisal produced through mathematical modeling." Available at https://www.iaao.org/media/standards/AVM_STANDARD_2018.pdf

vendors.[65] Federal law requires lenders to use a state licensed or certified human appraiser,[66] but an exception to that law covers over 80% of home sales by aggregate dollar volume.[67]

Consumers depend on accurate valuations. An inaccurate AVM can overvalue or undervalue a property, creating serious, practical consequences for homeowners and buyers. As the Federal Housing Finance Administration observed, "[i]naccurate data may lead to an appraisal waiver on an overvalued property leading a borrower to have higher LTVs than anticipated and with less equity in the property."[68] If an appraisal undervalues a home so that lenders refuse to finance it, the buyer may be driven to a more expensive and risky land-installment or rent-to-own contract.[69] Additionally, applicants may be offered a rate that is too high or charged unnecessary PMI because the lender mistakenly believes the loan will have an LTV over 80%.

According to a 2011 report by the Government Accountability Office, "AVMs are generally not used as the primary source of information on property value for first-lien mortgage originations, due in part to potential limitations with the quality and completeness of the data AVMs use."[70] In the ten years since that report, the first half of the statement has become less true—AVMs *are* becoming the primary source of information on property value for first-lien mortgages. But it is less clear that the second half of the statement has changed as much. As late as September 2019, Fitch Ratings said "[d]espite improvements in accuracy, use of Automated Valuation Models . . . still requires a guarded view . . . ."[71]

Problems with the data fed into AVMs makes them less accurate. The history of housing and residential mortgage lending in the United States is riddled with racial discrimination. Some argue that AVMs will be free of bias if the data points do not include race.[72] But that ignores the fact that AVMs are trained on data that has, itself, been shaped by race.[73]

---

[65] CoreLogic, AVM FAQs (11-avm-faq-va-0804-00), https://www.corelogic.com/downloadable-docs/avm-faqs.pdf (2014).

[66] 12 U.S. Code §§ 3342, 3343

[67] 83 Fed. Reg. 63119 (Dec. 7, 2018).

[68] FHFA, Request for Information on Appraisal-Related Policies, Practices, and Processes 17-18 (Dec. 28, 2020), available at https://www.fhfa.gov/Media/PublicAffairs/PublicAffairsDocuments/RFI-Appraisal-Related-Policies.pdf.

[69] *See* National Consumer Law Center, *Toxic Transactions: How Land Installment Contracts Once Again Threaten Communities of Color* (2016), *available at* https://www.nclc.org/issues/toxic-transactions-threaten-communities-of-color.html; Sarah Mancini & Margot Saunders, *Land Installment Contracts: The Newest Wave of Predatory Home Lending Threatening Communities of Color*, Fed. Reserve Bank of Boston Communities and Banking (Apr. 2017).

[70] Government Accountability Office, Report No. GAO-11-653, *Residential Appraisals: Opportunities to Enhance Oversight of an Evolving Industry* at 16 (July 2011), *available at* https://www.gao.gov/products/GAO-11-653.

[71] Fitch Ratings, Conservatism Still the Best Path for AVMs in U.S. RMBS (Sept. 27, 2019), https://www.fitchratings.com/research/structured-finance/conservatism-still-best-path-for-avms-in-us-rmbs-27-09-2019.

[72] Edward Pinto & Tobias Peter, American Enterprise Institute, *How Common is Appraiser Bias* (Jan. 4, 2021), available at https://www.aei.org/how-common-is-appraiser-racial-bias/.

[73] Michael Neal, Sarah Strochak, Linna Zhu,and Caitlin Young, *How Automated Valuation Models Can Disproportionately Affect Majority-Black Neighborhoods* (Dec. 2020), available at

Currently the majority of the academic research on AVMs has focused on "accuracy."[74] But few researchers consider the impact of race on AVM results. The Agencies should fill this gap by working with the software industry and academics to develop metrics and standards to make sure AVMs are free of bias or disparate impact. In 2010 Congress directed the federal banking agencies and the CFPB to promulgate quality control standards for AVMs. This effort could be a part of that larger initiative.

III. Impact of AI and Machine Learning Models on Consumers' Ability to Access Housing

Financial institutions, the real estate industry, and housing providers have long used algorithmic models to buy, sell, rent, finance, and manage real estate. As large financial institutions move into the rental market, including for single-family housing, more information is emerging regarding how AI models impact consumers' ability to access housing. As discussed above, AI models are used to determine which consumers see ads for housing and which applicants are selected for housing. Although these uses of AI may make advertising and tenant selection more efficient for housing providers, they may also unfairly exclude people from rental housing and even result in housing discrimination.

Most rental housing providers now rely on allegedly AI-based tools to screen and assess applicants. Around 90% of landlords run credit and criminal background checks on all applicants and 85% run an eviction report on all applicants.[75] To run these checks, many landlords turn to third-party tenant screening companies, which are specialty consumer reporting agencies under the Fair Credit Reporting Act. Many of these companies do not simply provide a credit report and public record information, such as criminal and eviction records, to landlords and leave them to reach their own conclusions about which applicants to accept or reject. Instead, screening companies commonly offer products that "adjudicate" or "score" the applicant and provide a recommendation about whether to accept them.[76]

These automated decision-making products are designed to eliminate the need for a housing provider to consider an applicant's specific circumstances and make judgment calls. Tenant screening companies and others often assert that relying on these tools instead of human decision makers helps eliminate bias,[77] but research indicates that AI may instead worsen discrimination in housing.[78] One background

---

(https://www.urban.org/sites/default/files/publication/103429/how-automated-valuation-models-can-disproportionately-affect-majority-black-neighborhoods_1.pdf)

[74] *See, e.g.,* Miriam Steurer & Robert Hill, 2019. "Metrics for Evaluating the Performance of Automated Valuation Models," Graz Economics Papers 2019-02, University of Graz, Department of Economics, available at https://ideas.repec.org/p/grz/wpaper/2019-02.html)

[75] TransUnion Independent Landlord Survey Insights, TransUnion SmartMove (Aug. 7, 2017), https://www.mysmartmove.com/SmartMove/blog/landlord-rental-market-survey-insights-infographic.page.

[76] *See, e.g.*, SafeRent™ Score, MyRental, https://www.myrental.com/tenant-screening-products/saferent-score (last visited June 10, 2021); ResidentScore, TransUnion SmartMove, https://www.mysmartmove.com/SmartMove/landlord-credit-check-service.page (last visited June 10, 2021); *see also* Ariel Nelson, National Consumer Law Center, Broken Records Redux: How Errors by Criminal Background Check Companies Continue to Harm Consumers Seeking Jobs and Housing 12–13 (2019), https://www.nclc.org/images/pdf/criminal-justice/report-broken-records-redux.pdf.

[77] *See, e.g.*, Resident Screening, CoreLogic Rental Property Solutions, https://www.corelogic.com/products/resident-screening.aspx (last visited June 10, 2021) ("Our advanced technology models are statistically validated based on facts, not intuition or rules . . . . Whatever decision or information service you use, you'll find the same simple data entry process, rapid turnaround and clear concise results that eliminate the need for judgment calls by your leasing professionals.").

[78] Valerie Schneider, *Locked Out by Big Data: How Big Data, Algorithms and Machine Learning May Undermine Housing Justice*, 52 Colum. Hum. Rts. L. Rev. 251, 254 (2020); *see also* Cyrus Farivar, *Tenant screening software*

screening company has seemingly agreed, concluding that "today's [AI-driven background check tools] lack the nuance that is necessary to conduct fair, compliant, and compassionate vetting for . . . tenants."[79]

Whether or not a particular background screening company's automated decision-making product or other screening tools are AI-based is not always clear. A company's website may not explicitly say they use AI, and even when faced with a lawsuit, companies typically argue that information about their technologies should be kept confidential and filed under seal because it is proprietary business information or a confidential trade secret.[80] As a result of this lack of transparency, it is very difficult for the public to fully understand and evaluate the technologies that background screening companies use.

Nonetheless, some companies explicitly claim to use AI in at least two ways: to generate tenant screening scores or recommendations and to identify, categorize, and filter criminal records. For example, the tenant screening company RealPage claims that its "AI-based screening algorithm," along with "behavioral data," predicts an applicant's capability as well as willingness to pay rent.[81] Similarly, in 2019, TransUnion launched ResidentScore 3.0, a "rental housing-specific score" that "leverag[es] artificial intelligence enabled machine learning . . . to offer property managers greater insight into predicting the likelihood a renter will be evicted or 'skip' out of their rental unit without paying within 12 months."[82] One employment screening company, Checkr, also states that its background check platform "leverages artificial intelligence to improve turnaround time, and make background checks faster and fairer for all."[83] Checkr specifically describes how it uses AI to process criminal records, boasting that its "Charge Classifier uses machine learning to quickly categorize criminal charges from jurisdictions across the U.S." and that "[p]rocessing over 1.5 million background checks per month, Checkr's platform is

faces national reckoning, NBC News (Mar. 14, 2021), https://www.nbcnews.com/tech/tech-news/tenant-screening-software-faces-national-reckoning-n1260975.

[79] *See* backgroundchecks.com, Artificial Intelligence and Background Checks 4, https://www.backgroundchecks.com/hubfs/imported_docs/AI%20and%20Background%20Checks%20White%20Paper.pdf.

[80] *See, e.g.*, Def. CoreLogic Rental Property Solutions, LLC's Motion to Seal Documents Filed in Support of Pl.'s Motion to Compel, Connecticut Fair Housing Ctr. v. CoreLogic Rental Property Sols., LLC, No. 3:18-cv-00705 (D. Conn. Aug. 30, 2019), ECF No. 83; *see also* Mikella Hurley & Julius Adebayo, *Credit Scoring in the Era of Big Data*, 18 Yale J.L. & Tech. 148, 158 (2016) (discussing how companies creating alternative credit scoring models through "proprietary 'machine-learning' algorithms" treat "their machine-learning tools as closely guarded trade secrets, making it impossible to offer a comprehensive picture of the industry).

[81] RealPage, Artificial Intelligence Screening (last visited June 11, 2021), https://www.realpage.com/apartment-marketing/ai-screening/ ("RealPage AI Screening . . . [l]everages the power of AI and machine learning to deliver a predictive scoring model built to meet the needs of the multifamily industry.").

[82] *Property Managers Gain Greater Predictive Power to Help Further Decrease Future Evictions*, TransUnion (Sept. 18, 2019), https://newsroom.transunion.com/property-managers-gain-greater-predictive-power-to-help-further-decrease-future-evictions/; *see also* Katy McLaughlin, *Robots Are Taking Over (the Rental Screening Process)*, Wall Street Journal (Nov. 21, 2019), https://www.wsj.com/articles/robots-are-taking-over-the-rental-screening-process-11574332200.

[83] Technology, Checkr (last visited June 11, 2021), https://checkr.com/solutions/industries/technology.

constantly learning, giving [its] customers greater clarity and control."[84] It is possible that companies specializing in tenant screening also use AI-based systems to classify criminal records.[85]

Many problems arise when housing providers rely on these automated, AI-based processes to decide whether to accept rental housing applicants. First, no common standard exists for predicting whether an individual will be a "good tenant." In this sense, tenant screening scores differ from credit scores. With respect to credit scores, the implementing regulation of the ECOA requires a credit scoring system to be an "empirically derived, demonstrably and statistically sound, credit scoring system."[86] Further, federal regulators that supervise banks and credit unions review credit scoring models to ensure that they meet the standard of being predictive and statistically sound.[87] There is no equivalent regulatory supervision to ensure that the score that the tenant screening company provides is similarly predictive or statistically sound.

Second, these tenant screening products often eliminate the chance for humans to individually assess applicants, which in turn may exclude applicants who otherwise could have been eligible for housing or could be a successful tenant. Automated, AI-based screening tools collapse a consumer's particular story into machine-verified variables. A tenant screening report could recommend rejection based on a prior eviction case record, but that case could have been resolved in the applicant's favor.[88] And even an eviction case record actually related to wrongdoing by the tenant may not be reasonably predictive of the success of a future tenancy.[89] The same may be true of a potential tenant's criminal records.[90]

Third, AI-based decisions may give applicants and users of tenant screening products little insight into why the applicant was rejected, particularly in situations where the housing provider or leasing agent receives only a notification about the applicant's eligibility or a score.[91] This lack of information may mask errors in the report—which are common[92]—and limit an applicant's ability to explain to the

---

[84] AI Powered Core, Checkr (last visited June 11, 2021), https://checkr.com/platform/foundation/ai-powered.

[85] *See* backgroundchecks.com, Artificial Intelligence and Background Checks 2, https://www.backgroundchecks.com/hubfs/imported_docs/AI%20and%20Background%20Checks%20White%20Paper.pdf (suggesting CoreLogic's background check tools use AI, including their system of classifying criminal history information).

[86] Reg. B., 12 C.F.R. pt. 1002.2(p)(1); *see also* National Consumer Law Center, Fair Credit Reporting § 16.2.3.2 (9th ed. 2017), *updated at* www.nclc.org/library.

[87] National Consumer Law Center, *Fair Credit Reporting* § 16.2.3.2 & n.73 (9th ed. 2017), *updated at* www.nclc.org/library.

[88] *See generally*, National Consumer Law Center, *Salt in the Wound* (Aug. 2020), https://www.nclc.org/images/pdf/special_projects/covid-19/IB_Salt_in_the_Wound.pdf (discussing how landlords often automatically reject applications with eviction case records, regardless of the outcome, context, or how long ago the case was filed).

[89] Valerie Schneider, *Locked Out by Big Data: How Big Data, Algorithms and Machine Learning May Undermine Housing Justice*, 52 Colum. Hum. Rts. L. Rev. 251, 271 (2020).

[90] *Id.* at 273 (discussing how court records and "rap sheets" used by tenant screening companies provide "little or no data that would be predictive of success as a tenant").

[91] *See, e.g.*, *Connecticut Fair Hous. Ctr. v. CoreLogic Rental Prop. Sols., LLC*, 478 F. Supp. 3d 259, 275 (D. Conn. 2020) (describing how CoreLogic Rental Property Solutions tenant screening product allows users to suppress full reports from on-site staff and only provide them with an automated decision report).

[92] Ariel Nelson, National Consumer Law Center, *Broken Records Redux: How Errors by Criminal Background Check Companies Continue to Harm Consumers Seeking Jobs and Housing* 15–17 (2019), https://www.nclc.org/images/pdf/criminal-justice/report-broken-records-redux.pdf.

housing provider why the tenant screening report is wrong or why, if the report is correct, it should not bar them from housing.

Fourth, AI-based decision making tends to undermine consumers' rights to even see the reports made about them. Consumers who request disclosure of their files from the tenant screening company under the Fair Credit Reporting Act may receive the underlying records used to generate the recommendation but not information about how the company's scoring system classified public records or filtered them through the housing provider's acceptance criteria. As a result, if a housing denial resulted from an arrest record being erroneously filtered, categorized, or aged by the AI model, the tenant may have no way to discover the error.

Fifth, the decisions based on these AI-based tools may result in discrimination against members of protected classes. As discussed further elsewhere, algorithms "use historical data as input to produce a rule that is applied to a current situation," and therefore,

> [t]o the extent that historical data reflects the results of de jure segregation, Jim Crow laws, redlining, restrictive covenants, white flights, and other explicitly and implicitly racist, laws, policies, and actions, any given algorithmic 'rule' is likely to produce racist results, including when those patterns reflect past discrimination."[93] An AI system "learns" from past data, "refining algorithms to more accurately draw from patterns.[94]

Although this can lead to more predictive models, it also means that machines can perpetuate patterns of discrimination.

In the tenant screening context, the public records and other information—including criminal records, eviction records, address history, and credit information—that are fed into the algorithm or AI-based tool that recommends acceptance or rejection reflect racial disparities.[95] With respect to criminal records, African Americans are more than twice as likely to be arrested as whites, and bias by decision makers throughout the criminal justice process disadvantages African Americans. Studies have found, for instance, that African Americans are more likely to be stopped by the police, detained, charged with more serious crimes, and sentenced more harshly than whites.[96] Black tenants are also more likely to have an eviction record than white tenants.[97] An ACLU study from 2020 revealed that in at least 17

---

[93] Valerie Schneider, *Locked Out by Big Data: How Big Data, Algorithms and Machine Learning May Undermine Housing Justice*, 52 Colum. Hum. Rts. L. Rev. 251, 274–75 (2020).

[94] *Id.* at 275.

[95] *See id.* at 281 ("Algorithms . . . are particularly likely to create a disparate impact based on a protected class because of what researchers call 'redundant encodings'—i.e., when 'membership in a protected class happens to be encoded in other data.' . . . For example, if a tenant-screening algorithm gives lower scores to people with eviction or criminal records and such records are disproportionately prevalent in a protected class, then the algorithm will have a disparate impact on the protected class . . . .").

[96] Ariel Nelson, National Consumer Law Center, *Broken Records Redux: How Errors by Criminal Background Check Companies Continue to Harm Consumers Seeking Jobs and Housing* 8–9 (2019), https://www.nclc.org/images/pdf/criminal-justice/report-broken-records-redux.pdf (citing sources); *see also* Valerie Schneider, *Locked Out by Big Data: How Big Data, Algorithms and Machine Learning May Undermine Housing Justice*, 52 Colum. Hum. Rts. L. Rev. 251, 274 (2020); Connecticut Fair Hous. Ctr. v. CoreLogic Rental Prop. Sols., LLC, 478 F. Supp. 3d 259, 276–77 (D. Conn. 2020) (citing data and research on racial disparities in the criminal justice process).

[97] *See* Valerie Schneider, *Locked Out by Big Data: How Big Data, Algorithms and Machine Learning May Undermine Housing Justice*, 52 Colum. Hum. Rts. L. Rev. 251, 278–79 (2020).

states, landlords filed eviction cases against Black tenants at double the rate or higher as white tenants.[98] Black consumers also have lower credit scores as a group than whites due to historical and current discrimination and the racial wealth gap.[99]

One ongoing lawsuit illustrates how these tenant screening tools can result in discrimination. The Connecticut Fair Housing Center and individual plaintiff Carmen Arroyo sued CoreLogic Rental Property Solutions, arguing that one of its tenant screening products, called CrimSAFE, discriminates on the basis of race, national origin, and disability in violation of the Fair Housing Act. In 2016, Ms. Arroyo sought to have her disabled son, for whom she was conservator and primary caregiver, move into her apartment complex. However, his application was rejected after CoreLogic provided the apartment complex with a tenant screening report that included a "Crim Decision" stating that unspecified "disqualifying records" were found.[100] The sole criminal record that CoreLogic relied upon in making its "Crim Decision" was a charge for retail theft from 2014 that was withdrawn and had occurred before the son had become disabled due to an accident.[101] The leasing agents could not see this underlying record, which the CrimSAFE product had categorized into offense type and then into whether the record was disqualifying according to the housing provider's choices.

As the district court determined, the tenant screening company "transforms the criminal records review process into a yes/no switch," eliminating the possibility that the housing provider can fully assess the suitability of an applicant and enabling the denial of housing to people whose records do not suggest they posed any risk.[102] Moreover, CoreLogic had continued to allow its clients to rely on its automated CrimSAFE product to screen for arrest records even though HUD's Office of General Counsel had issued guidance in 2016 that "Nationally, racial and ethnic minorities face disproportionately high rates of arrest and incarceration" and that "the fact of an arrest is not a reliable basis upon which to assess the potential risk to resident safety or property posed by a particular individual."[103]

The Agencies should issue guidance regarding the use of AI-based tenant screening tools and engage in enforcement actions to ensure compliance with the applicable laws they enforce, including the Fair Credit Reporting Act. To the extent that the CFPB has supervisory authority over certain companies offering tenant screening products,[104] it should also exercise that authority.

---

[98] Sophie Beiers, Sandra Park, & Linda Morris, *Clearing the Record: How Eviction Sealing Laws Can Advance Housing Access for Women of Color*, ACLU (Jan. 10, 2020).

[99] National Consumer Law Center, *Past Imperfect: How Credit Scores and Other Analytics "Bake In" and Perpetuate Past Discrimination* 1, 5–7 (2016), https://www.nclc.org/images/pdf/credit_discrimination/Past_Imperfect050616.pdf.

[100] *Connecticut Fair Hous. Ctr. v. CoreLogic Rental Prop. Sols., LLC*, 478 F. Supp. 3d 259, 273, 279 (D. Conn. 2020).

[101] *Id.* at 279–80.

[102] *Id. at* 289.

[103] *Id.* at 304 (quoting HUD OGC 4/4/2016 Guidance at 3–5).

[104] All three of the nationwide consumer reporting agencies, which are certainly subject to CFPB supervision, offer tenant screening products. SmartMove, TransUnion (last visited July 1, 2021), https://www.mysmartmove.com/; Tenant Screening Services, Experian (last visited July 1, 2021), https://www.experian.com/screening-services/tenant-screening-services/; Resident and Tenant Screening, Equifax (last visited July 1, 2021), https://www.equifax.com/business/resident-and-tenant-screening/. And TransUnion has specifically advertised its use of an AI-based tenant screening score. *Property Managers Gain Greater Predictive Power to Help Further Decrease Future Evictions*, TransUnion (Sept. 18, 2019), https://newsroom.transunion.com/property-managers-gain-greater-predictive-power-to-help-further-decrease-future-evictions/.

IV. Question Regarding Equal Credit Opportunity Act

Question 15: The Equal Credit Opportunity Act (ECOA), which is implemented by Regulation B, requires creditors to notify an applicant of the principal reasons for taking adverse action for credit or to provide an applicant a disclosure of the right to request those reasons. What approaches can be used to identify the reasons for taking adverse action on a credit application, when AI is employed? Does Regulation B provide sufficient clarity for the statement of reasons for adverse action when AI is used? If not, please describe in detail any opportunities for clarity.

The Agencies Should Ensure that Financial Institutions that Use Complex AI or Machine Learning Models Comply with the ECOA and Regulation B by Providing Adverse Action Notices that Accurately Describe the Factors Considered in Credit Decisions.

Under the ECOA's notice requirements, creditors who take adverse action on credit applications are required to provide applicants with either a written statement of reasons for such action or a written notification of the right to such a statement [105] Regulation B and its official interpretations follow the statutory mandate and make clear that general statements that simply say an adverse action was based on the creditor's internal standards or policies or that the applicant failed to achieve a qualifying score on the creditor's credit scoring system, are insufficient.[106] Instead, specificity and accuracy is required. The notice must state the *specific* reason for the adverse action.[107] Also, the reasons disclosed *must relate to and accurately describe those factors actually reviewed, considered, or scored*.[108] No factor that was a principal reason for the adverse decision may be excluded, even if the relationship of that factor to creditworthiness may not be clear to the applicant.[109] The Regulation B requirements are clear and no further clarity is needed regarding the statement of reasons for adverse actions when AI or machine learning is used.

The notice requirement fulfills the ECOA's dual goal of education and consumer protection.[110] First, as described in the legislative history, consumers denied credit will learn how their credit application fell short and this information provides an educational benefit.[111] Consumers need to understand this information so they can make a successful application for credit that is critical and consequential for life outcomes. Beyond being told only that they do not meet a particular creditor's standards, consumers will benefit from knowing the specific factors reviewed and the specific reason for the denial of credit. If the creditor acted in error based on misinformation or inadequate information, the statement of reasons also gives the applicant a chance to correct the mistake.[112]

Second, the notices may uncover whether the creditor's decision was discriminatory. Discrimination is hidden; it is difficult for consumers to detect whether they are being treated worse than other similarly

---

[105] 15 U.S.C. 1691(d)(1)

[106] Reg. B, 12 C.F.R. § 1002.9(b)(2).

[107] Reg. B., 12 C.F. R. pt. 1002 app. C.

[108] Official Interpretations of Reg. B, 12 C.F.R. pt. 1002, supp. I, § 1002.9(b) (1)-2.

[109] Official Interpretations of Reg. B, 12 C.F.R. § 1002.9(b) (2)-4.

[110] Fischl v. Gen. Motors Acceptance Corp., 708 F.2d 143, 146 (5th Cir. 1983).

[111] See S. Rep. No. 94-589 (1976), reprinted in 1976 U.S.C.A.A.N. 403, 406.

[112] See id.

situated applicants with different personal features tied to race, sex, or other characteristics protected under the ECOA. A pattern of denial or other adverse action taken against consumers with certain characteristics for specific reasons may, taken together, signal the need for further investigation. This may assist Fair Housing/Lending organizations in determining whether and how to bring test cases. Moreover, the act of disclosing specific identifiable reasons for an adverse action may discourage discriminatory conduct. The Senate report for the ECOA amendments stated that a strict notice provision was "[a] strong and necessary adjunct to the antidiscrimination purpose of the legislation, for only if creditors know they must explain their decisions will they effectively be discouraged from discriminatory practices." [113]

The adverse action notice required by ECOA highlights key issues regarding the use of alternative models that rely upon AI or machine learning—transparency and explainability. Artificial intelligence or machine learning models must be transparent and explainable to be effective. Consumers are entitled to know what information is being used in credit determinations to evaluate them and how that information is being used. Consumers should be able to review the information for inaccuracies so they can dispute errors. Creditors who adopt AI or machine learning models must use approaches which adhere to ECOA by providing adverse action notices that disclose, with specificity and accuracy, the principle reason or reasons for the action taken.[114] Opaque AI or machine learning models which fail to meet this standard must be reengineered. Anything less undermines a core intent of ECOA and may lead to discriminatory conduct by creditors.

V. Summary of Recommendations

Financial institutions' use of AI and machine learning models may lead to unlawful discrimination and abusive practices in the credit process, including in underwriting, pricing, and credit decisions. Machine learning, the most powerful form of artificial intelligence, heightens this risk because it makes non-intuitive connections using large volumes of data that result in decisions that may not be readily understandable or explainable in an adverse action notice. Discriminatory credit practices will go unrecognized and unchallenged. To ensure consumers have nondiscriminatory and equitable access to credit the Agencies should:

- Conduct in-depth reviews of financial institutions' use of AI, including assessments of compliance with fair lending and consumer protection laws.
- Issue detailed guidance regarding the application of fair lending laws to AI and machine learning models.
- Require that financial institutions routinely test their models to ensure the outputs are fair, empirically derived, and statistically sound and accurately predict risk or achieve other valid objectives.
- Ensure that financial institutions produce models that are explainable, non-discriminatory, and comply with fair lending and consumer protection laws.

---

[113] S. Rep. No. 94-589 (1976), *reprinted in* 1976 U.S.C.A.A.N. 403, 406.

[114] Reg B, 12 C.F. R. pt 1002, app C

- Engage a diverse group of stakeholders, including consumer advocates, civil rights organizations, and impacted communities to provide input and feedback while Agencies' build the regulatory framework to evaluate the risk posed by AI and machine learning models.

- Ensure transparency by requiring financial institutions to share with their regulators and the public as much information as possible on how their models work to allow for research and independent assessment of discriminatory impact.

Conclusion

Discrimination in the credit market strips wealth and economic opportunity from individuals and vulnerable communities. Much more is needed to ensure that every consumer has equitable and nondiscriminatory access to credit. The Agencies should use their full supervision, enforcement, and rulemaking authority to ensure that financial markets work for everyone.