

**DEPARTMENT OF TREASURY**  
**Washington, D.C. 20220**

**Comments of**  
**National Consumer Law Center**  
**on behalf of its low-income clients**

**Re: Request for Information on Uses, Opportunities, and**  
**Risks of Artificial intelligence in the Financial Services Sector**

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## COMMENTS

The National Consumer Law Center (NCLC)<sup>1</sup> submits these comments on behalf of its low-income clients in response to the U.S. Department of Treasury's (Treasury) *Request for Information on Uses, Opportunities, and Risks of Artificial Intelligence in the Financial Services Sector*.<sup>2</sup> The widespread adoption of artificial intelligence, including machine learning and generative technology (collectively AI/ML), is transforming the financial services industry. Use of this technology by financial institutions has the potential to reduce costs, increase efficiency in the underwriting process, detect fraud, and improve customer relations. However, the use of complex, opaque algorithmic models in consumer credit and banking transactions also heightens the risk of unlawful discrimination, and unfair, deceptive, and abusive practices.

Despite AI's promise to democratize credit and financial services, concerns remain about all aspects of the use of this technology by the financial services industry in marketing, underwriting and pricing of credit, and other consumer-facing functions, including fraud detection, servicing and debt collection. Concerns arise regarding the lack of transparency and explainability of the more complicated models, the unrestrained surveillance and collection of consumer data, and the potential for bias and discrimination.

The speed and power of this technology, and its wide-scale adoption with little regulatory oversight, puts consumers at systemic risk of harm. Treasury needs to act now to put a robust slate of safeguards in place to protect consumers' rights under fair lending and consumer protection laws.

### **I. Financial institutions' widespread use of AI/ML in consumer credit, banking and financial services poses a systemic risk to consumers which calls for a robust regulatory response.**

AI/ML systems with the capacity to make decisions regarding credit, housing, banking, insurance and finance are high-risk systems that should receive the highest level of regulatory scrutiny. This technology can cut consumers off from housing and economic opportunity at the speed of light in violation of consumer protection laws, fair lending and civil rights. Treasury and other federal agencies should develop a regulatory framework which requires robust evaluation

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<sup>1</sup> 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. This comment was written by Carla Sanchez-Adams, Jerry Battle, April Kuehnhoff, Andrew Pizor, Steve Sharpe and Odette Williamson.

<sup>2</sup> 89 Fed. Reg. 50048 (June 12, 2024).

of AI/ML at every stage of development and deployment to determine whether AI systems are safe and effective. Regulators should exercise enforcement authority to the fullest extent possible for AI/ML that violate individual rights and consumer protection.

Along with other federal regulators, Treasury should pursue a rights-based approach which protects consumers from harm and preserves their rights. This framework looks at the potential harm to consumers, and does not seek to simply mitigate the risk AI/ML poses to financial institutions. This approach was pursued by the Administration in its blueprint for the AI Bill of Rights, and is the basis for a robust regulatory scheme that protects consumers.<sup>3</sup> An approach that prioritizes the risks to financial institutions can result in an unacceptable infringement of civil rights, constitutional rights, privacy rights, and statutory consumer protections.

### **A. Definition of Artificial Intelligence**

For the purpose of responding to this RFI we will use the definition adopted by Executive Order 14110 on the *Safe, Secure and Trustworthy Development and Use of Artificial Intelligence*, which defines artificial intelligence (AI) as

“a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. Artificial intelligence systems use machine- and human-based inputs to perceive real and virtual environments; abstract such perceptions into models through analysis in an automated manner; and use model inference to formulate options for information or action.”<sup>4</sup>

These comments will reference concerns regarding a wide range of AI-branded technology but will focus on the more complicated machine learning and generative models to the extent we can discern that this technology is being used by the financial services industry, or a financial institution touts its use.

Though we adopt the definition outlined in the Executive Order for the purpose of this comment, it is difficult to discern when and how companies are using this technology even when they disclose the use of AI in their marketing material and in statements to regulators, investors and the like. The industry has not adopted a uniform or set definition of AI, and in fact some models previously described as simple automated systems are now being rebranded as AI. To the extent a company touts its use of AI there is often no insight into the complexity of the model being deployed.

The lack of an industry-wide definition for AI, combined with the complete lack of transparency, heightens 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

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<sup>3</sup> White House, Blueprint for an AI Bill of Rights, available at <https://www.whitehouse.gov/ostp/ai-bill-of-rights/>.

<sup>4</sup> White House, *Executive Order 14110 Safe, Secure and Trustworthy Development and Use of Artificial Intelligence* (October 30, 2023) available at <https://www.whitehouse.gov/briefing-room/presidential-actions/2023/10/30/executive-order-on-the-safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence/>. This definition is also referenced in the RFI. 89 Fed. Reg. at 50049.

impression of accuracy and sophistication for consumers, regulators, outside investors and others.

This leads to fundamental questions about the use of AI in financial services: how do we evaluate if AI is actually an improvement or effective for the purpose for which it is being used? Who is evaluating whether an AI model is predictive or even functional? Regulators need to step up their examination and oversight of these models, especially those used to provide credit, banking and other financial services.

## **B. AI/ML has the potential to amplify discrimination and bias in credit, banking and financial services.**

Access to credit, insurance, banking and other financial products and services define life opportunities in the United States. Consumers looking for housing or vehicles, or to build wealth through homeownership, business creation, or education, seek sustainable and fairly priced financing. Yet the well-documented history of discrimination in these markets has fueled disparities in wealth creation and stifled economic opportunity for consumers of color.<sup>5</sup>

Creditors discriminate at every stage of a credit transaction and in providing financial products and services. This includes whom they market to or solicit as customers, to whom they grant credit, the price and other terms and conditions on which credit is extended, and how customers are treated in subsequent stages of the transaction, such as extension of credit to existing customers, fraud monitoring and account closure, loan servicing, and debt collection.

The history of discrimination in the credit, insurance, banking and housing markets includes predatory and high-cost lending, redlining, appraisal bias and other racially exclusionary housing practices. These practices created credit deserts, cutting some communities off from affordable credit, including mortgages, all the while inundating these same communities with high-risk destructive credit.<sup>6</sup> High-cost fringe lenders like payday lenders, auto title lenders, check cashers, and the like are heavily concentrated in Black and Latino/ Hispanic communities underserved by mainstream lenders.<sup>7</sup> Some Black neighborhoods have three times as many payday loan stores per capita as white neighborhoods, a concentration that increased as the

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<sup>5</sup> 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/>.

<sup>6</sup> See Richard Rothstein, *The Color of Law: A Forgotten History of How Our Government Segregated America*, 2017.

<sup>7</sup> 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).

proportion of Black people in the neighborhood increased.<sup>8</sup> So too were subprime mortgage lenders heavily concentrated in communities of color in the years leading up to the foreclosure crisis and Great Recession.<sup>9</sup> During this era a large number of cases were brought against mortgage lenders, many alleging that creditors' policies resulted in Black and Latino borrowers receiving more expensive loans than similarly situated white borrowers.<sup>10</sup> Predatory practices combined with weak government regulation created this dual credit market; some communities have access to competitively priced mainstream credit and others are ringed by wealth-draining financiers.

Discrimination in credit and financial services results in a persistent and enduring racial wealth gap. According to the Fed's research, in 2022 the typical white family had \$285,000 in wealth compared to \$44,900 for the typical Black family—about 15 percent of the wealth of the typical white family. The typical Hispanic family held only about 20 percent of the wealth of the typical white family (about \$61,600). The remaining families, a diverse group that includes those identifying as American Indian, Alaska Native, Native Hawaiian, Pacific Islander, or other race, and those of more than one racial identification, had median wealth similar to the typical Black or Hispanic family.<sup>11</sup>

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. Already there is acknowledgment that some AI/ML produce biased results. Ongoing efforts to debias the models may bear fruit but given the deep-rooted history of credit discrimination in the United States and wide scale adoption of this technology by financial firms more must be done to protect consumers.

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<sup>8</sup> See 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.

<sup>9</sup> See e.g., a series of reports by The Woodstock Institute, et al, *The Subprime Shakeout and Its Impact on Lower-Income and Minority Communities*, mapping subprime lending across eight communities, available at <https://woodstockinst.org/research/reports/paying-more-american-dream-subprime-shakeout-and-its-impact-lower-income-and-minority-communities>.

<sup>10</sup> See *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), available at [www.nclc.org/unreported](http://www.nclc.org/unreported); *Newman v. Apex Fin. Grp.*, 2008 WL 130924 (N.D. Ill. Jan. 11, 2008); *Martinez v. Freedom Mortg. Team*, 527 F. Supp. 2d 827 (N.D. Ill. 2007); *Jackson v. Novastar Mortg., Inc.*, 2007 WL 4568976 (W.D. Tenn. Dec. 20, 2007).

<sup>11</sup> Aditya Aladangady, Andrew C. Chang et al, *Fed Notes: Greater Wealth, Greater Uncertainty: Changes in Racial Inequality in the Survey of Consumer Finances*, October 2023 available at <https://www.federalreserve.gov/econres/notes/feds-notes/greater-wealth-greater-uncertainty-changes-in-racial-inequality-in-the-survey-of-consumer-finances-20231018.html>.

### **C. Bias is encoded in AI/ML, starting with the data used to train the models.**

The data used to train AI/ML models can be biased, unrepresentative, and inaccurate. Historical and ongoing discrimination in credit and financial services markets discussed above is reflected in the raw data. Feeding data with racial disparities into AI/ML can replicate and amplify the disparities. The Federal Reserve noted,

“while 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 also reflect and perpetuate existing social inequalities. . . . [T]he fact that an algorithm is data driven does not ensure that it is fair or objective.”<sup>12</sup>

While we acknowledge that there are ongoing efforts by some firms to scrub the data used in AI/ML to remove bias, that practice may not be widespread or effective and more protections are needed at every stage of the development and deployment process to ensure a more equitable outcome for consumers on the back end. This includes strict scrutiny of the type of consumer data used, how it is used, and whether it is used with permission.

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.<sup>13</sup> 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.<sup>14</sup> 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, educational background, 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.<sup>15</sup> The information was often inaccurate and incomplete and primarily gathered without

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<sup>12</sup> 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.

<sup>13</sup> See Consumer Financial Protection Bureau, *Request for Information Regarding Use of Alternative Data and Modeling Techniques in the Credit Process*, 82 Fed. Reg. 11183 (Feb. 21, 2017) (defining alternative data as information not typically found in consumers’ credit files at nationwide consumer reporting agencies).

<sup>14</sup> 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/>.

<sup>15</sup> National Consumer Law Center, *Big Data: A Big Disappointment for Scoring Consumer Credit Risk*, at 18 (March 2014).



the consumer’s knowledge. There was no easy mechanism for consumers to dispute the accuracy of the information.

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.<sup>16</sup> 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.<sup>17</sup> The newer AI/ML 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. Even models trained on more conventional forms of alternative data may produce adverse results. This data (e.g., rent and utility payments, bank account transactions) comes with its own set of risks depending on how it is supplied and used. Using rental payment data, for example, may put financially struggling consumers at risk of homelessness if negative information is shared. The use of negative utility data, for gas and electric bill payment, may dissuade consumers from taking advantage of state protections against shutoffs. Bank account transaction and cashflow information holds greater promise as a form of alternative data. But even this data contains very sensitive and revealing information about consumers (e.g. where they shop, get health care) that financial firms should be mindful of using.

Regulators should use their supervision authority to ensure that financial institutions routinely and rigorously evaluate data sources including data provided by vendors or third-party party organizations. Regulators should ensure the collection of data is voluntary – that is, the consumer knowingly consents to the collection and use of the data. The data should be used for the purpose for which the consumer granted permission. Consumers who choose to safeguard their data and privacy should not be penalized (financially or otherwise) for withholding their consent. As part of the larger fair lending evaluation of the outputs generated by AI/ML, regulators should be mindful of exclusion, unfair treatment or higher pricing of consumers of color.

#### **D. Industry self-monitoring will not work - consumers need a robust regulatory scheme to address the threat of discrimination and bias.**

Industry self-monitoring and self-policing will not work. Treasury can learn from past actions that eased regulatory oversight of financial services firms using AI/ML but increased the risk of harm to consumers. The CFPB’s issuance of No Action Letters to Upstart Network (“Upstart”) in 2017 and 2020 is a case study in failed regulatory oversight.

Upstart received No Action Letters to continue its lending program without fear that the Bureau would bring an enforcement action against it for violations of the ECOA and Regulation B.

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<sup>16</sup> ECOA, 15 U.S.C. §§1691 et seq.; FCRA, 15 USC §§ 1681 et seq.

<sup>17</sup> See National Consumer Law Center, *Past Imperfect: How Credit Scores “Bake In” and Perpetuate Past Discrimination*, Updated May 2024 (African American, Latino, and Asian consumers have lower credit scores as a group than whites).

Upstart makes consumer loans, including private student loans, and sells its underwriting technology to other banks. Upstart claimed it used a “machine learning model that uses over 1,500 variables to make credit and pricing decisions.”<sup>18</sup> It advertised its ability to “leverage 1000+ data points” including educational data to make its credit decisions.<sup>19</sup> In its application the company 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.”<sup>20</sup>

Though Upstart’s application to the CFPB stated that the company had done disparate impact testing and had not found unlawful disparate impact, 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).<sup>21</sup> As SBPC warned in its 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 had 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 under which Relman Colfax, a civil rights law firm, would evaluate and monitor Upstart for fair lending.<sup>22</sup> Upstart subsequently made changes to normalize the use of educational data in its model.<sup>23</sup> As Relman Colfax explained in its initial report, “It is difficult to

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<sup>18</sup> 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>.

<sup>19</sup> *Credit Decision API*, Upstart (last viewed July 1, 2021) <https://www.upstart.com/for-banks/credit-decision-api/>.

<sup>20</sup> Upstart No-Action application to the CFPB (Sept. 2017) [https://files.consumerfinance.gov/f/documents/201709\\_cfpb\\_upstart-no-action-letter-request.pdf](https://files.consumerfinance.gov/f/documents/201709_cfpb_upstart-no-action-letter-request.pdf).

<sup>21</sup> *Educational Redlining*, Student Borrower Protection Center, Feb. 2020, available at <https://protectborrowers.org/wp-content/uploads/2020/02/Education-Redlining-Report.pdf>.

<sup>22</sup> *Fair Lending Monitorship of Upstart Network’s Lending Model*, Relman Colfax (April 14, 2021) <https://www.relmanlaw.com/cases-406>.

<sup>23</sup> See *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](https://www.relmanlaw.com/media/cases/1088_Upstart%20Initial%20Report%20-%20Final.pdf).

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.

As the Upstart case study exemplifies, poor supervision of financial institutions’ use of AI/ML amplifies discriminatory behavior in the credit and financial markets, increases costs to consumers, and creates barriers to access. The risk to consumers is enhanced because AI/ML models are proprietary and the details of the model are 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 of AI/ML on consumers of color and other protected classes. We urge Treasury and other federal agencies to provide more guidance and adopt a robust process for analyzing the fair lending and consumer protection risks posed by these models.

## **II. Fair lending and consumer protection concerns arise in a wide variety of AI/ML uses in consumer-facing financial products and services.**

Financial institutions use AI/ML in a wide range of business uses, from compliance to fraud detection.<sup>24</sup> Consumer-facing uses include marketing and advertising, underwriting and pricing of credit, evaluation of collateral, customer service, servicing and collections. Non-credit uses include fraud detection and the monitoring and closure of bank accounts.

The widespread use of these models in the financial services market raises concerns regarding fair lending, equity and transparency. We highlight a few of the issues that have come to our attention. Given the lack of transparency regarding whether and how this technology is used, it is difficult to catalog all the different ways AI/ML impacts the financial products and services offered to consumers. Below we discuss a sampling of the uses and the systemic risks posed to consumers.

### **A. Hyper targeted marketing and advertising steers consumers to higher priced credit, and predatory financial products.**

The financial services industry makes aggressive use of AI-driven models to target consumers online with highly personalized offers of credit and other financial products and services. This customization may lead to steering and digital redlining of vulnerable consumers. While a customized offer may benefit some consumers who receive advertisements tailored to their interests, other consumers are at a disadvantage if, instead of being shown a wide array of competitively priced credit options and financial products, they are steered to high-cost,

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<sup>24</sup> OCC, *Comptroller’s Handbook, Safety and Soundness, Model Risk Management*, Ver. 1.0, August 2021. Examples of AI uses in banks include fraud detection and prevention, marketing, chatbots, credit underwriting, credit and fair lending risk management, robo-advising (i.e., an automated digital investment advisory service), trading algorithms and automation, financial marketing analysis, cybersecurity, Bank Secrecy Act/anti-money laundering (BSA/AML) suspicious activity monitoring and customer due diligence, robotic process automation, and audit and independent risk management.

subprime products.<sup>25</sup> This is a distinct risk as consumers are often not able to do an apples-to-apples price comparison with such customized offers.

This hyper targeted solicitation is made possible by the online surveillance of consumers which tracks their behavior or activity across multiple platforms and makes inferences about their interests, demographics, and other characteristics, from information collected and sold by brokers.<sup>26</sup> Data collected and used in the models, including social media data, can be harmful to financially vulnerable consumers by identifying their emotional state,<sup>27</sup> medical characteristics,<sup>28</sup> or a propensity for substance or gambling addiction.<sup>29</sup> 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.<sup>30</sup>

Digital redlining can occur if creditors do not provide equal access to credit or provide credit on unequal terms based on race, color, national origin, or neighborhood.<sup>31</sup> 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.<sup>32</sup>

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<sup>25</sup> 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>.

<sup>26</sup> *Factsheet: Surveillance Advertising: What is it?*, Consumer Federation of America, August 2021 available at <https://consumerfed.org/wp-content/uploads/2021/08/2-What-Is-Surveillance-Advertising-margins-General-Format.pdf>.

<sup>27</sup> 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/>.

<sup>28</sup> 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>.

<sup>29</sup> 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/>.

<sup>30</sup> 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](https://www.ftc.gov/system/files/documents/public_comments/2014/08/00015-92370.pdf).

<sup>31</sup> 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.

<sup>32</sup> The FTC recently issued orders to eight companies (including Mastercard and JPMorgan Chase) seeking information about surveillance pricing of products and services that incorporate data about

In the housing context civil rights organizations, lawmakers, and journalists have called out Facebook (now Meta) for both discriminatory ad targeting and ad delivery.<sup>33</sup> 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.<sup>34</sup> 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."<sup>35</sup> In 2019, Facebook settled that case as well as other lawsuits alleging that its advertising platform enabled discrimination, agreeing that it would no longer permit advertisers to target ads based on protected classes or close proxies for protected classes.<sup>36</sup> In 2022, the DOJ entered into a consent decree with Meta; the company agreed to put in place an auditing system to reduce bias in the delivery of ad campaigns.<sup>37</sup>

Civil rights organizations also sued Redfin for alleged digital redlining as the company offered no marketing service for homes in non-white areas at a greater rate than for homes in white areas due to a minimum loan amount policy.<sup>38</sup> The complaint alleged that Redfin digitally redlined communities of color by setting minimum home listing prices in each housing market on its website. The company did not offer services to buyers or sellers under this threshold.

The U.S. Department of Housing and Urban Development (HUD) recently issued guidance to shape the advertisement of housing and credit for real-estate related transactions.<sup>39</sup> The agency noted that the newest technology can be used to target advertising toward some consumers

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consumers' characteristics and behaviors. FTC Press Release, *FTC Issues Orders to Eight Companies Seeking Information on Surveillance Pricing*, available at <https://www.ftc.gov/news-events/news/press-releases/2024/07/ftc-issues-orders-eight-companies-seeking-information-surveillance-pricing>.

<sup>33</sup> 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>.

<sup>34</sup> 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>.

<sup>35</sup> 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).

<sup>36</sup> 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).

<sup>37</sup> DOJ Press Release June 22, 2022, available at <https://www.justice.gov/opa/pr/justice-department-secures-groundbreaking-settlement-agreement-meta-platforms-formerly-known>.

<sup>38</sup> NFHA, *Our Redfin Investigation*, available at <https://nationalfairhousing.org/issue/redfin-investigation/>.

<sup>39</sup> U.S. Department of Housing and Urban Development, *Guidance on Application of the Fair Housing Act to Advertising of Housing, Credit, and Other Real Estate-Related Transactions through Digital Platforms*, April 29, 2024.

and away from others. Whether done deliberately or through the operation of a complex automated system, this ad-delivery system has the potential to cut certain consumers off from housing and credit.<sup>40</sup> This occurs when targeted ads deny consumers information about housing opportunities, target vulnerable consumers for predatory products or services, discourage or deter potential consumers, advertise different prices or conditions to consumers, steer home-seekers to particular neighborhoods, or charge advertisers higher amounts to show ads to some consumers.<sup>41</sup> Such discriminatory advertising practices may violate the Fair Housing Act when aimed at protected classes.

Hyper targeted online marketing of financial products poses many of the same risks identified by HUD, namely steering and digital redlining. Regulatory supervision should involve a fair lending review of online marketing campaigns. Both the ECOA and the Fair Housing Act apply to advertising. Creditors engaging online advertising platforms that use AI/ML 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.

**B. Discriminatory underwriting, pricing, servicing and valuation can lead to inequitable access to mortgages and other credit, or deny homeowners a chance to save their home.**

The use of AI/ML for underwriting, pricing, servicing, and valuation is rapidly evolving. While creditors appear to deploy the technology aggressively in marketing campaigns (including generative AI) it is less clear how creditors use this technology for underwriting and further upstream in the lending cycle. As our understanding of the industry's use of this technology evolves we will highlight the risks consumers may face.

**i. Underwriting and pricing**

The use of algorithmic models in credit underwriting and decision-making is growing. However, although the industry expresses support for the widespread adoption of this technology, the extent to which banks and mortgage companies are currently using AI/ML in underwriting loans is unclear. A 2023 survey by Fannie Mae found that 7% of mortgage executives said they had deployed AI/ML, but 23% were testing it on a trial basis and 29% expected to use it more broadly in the next two years.<sup>42</sup> ScotiaBank<sup>43</sup> claims to do so without providing details. Infosys offers a system that scores mortgages according to predicted default risk but provides little explicit information or guidance on how scores lead to decisions.<sup>44</sup> One primary factor it uses is

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<sup>40</sup> See *id.*

<sup>41</sup> See *id.* at 2.

<sup>42</sup> <https://www.fanniemae.com/research-and-insights/perspectives/lenders-motivation-ai-adoption>

<sup>43</sup> ScotiaBank, *Using Machine Learning to Make Predictions During an Uncertain Time*, <https://web.archive.org/web/20210106204237/https://www.scotiabank.com/ca/en/about/perspectives/articles.digital.2021-01-grm-machine-learning-analytics.html>

<sup>44</sup> *Infosys Mortgage Default Prediction System*, Infosys, <https://www.infosys.com/industries/financial-services/industry-offerings/mortgage-default-prediction-system.html> (last visited June 10, 2024).

the unemployment rate in a borrower's job location and job sector.<sup>45</sup> This raises fair lending concerns. Lenders such as Churchill Mortgage and Movement Mortgage have partnered with Infosys, but it is unclear whether they use their Mortgage Default Prediction System.<sup>46</sup> Another company, Tavant, states that it uses ML and other predictive models to collect and analyze vast amounts of traditional and nontraditional data to assist in underwriting, fraud detection, affordability advising, and marketing.<sup>47</sup> Currently the most common use appears to be to complete time intensive tasks such as document review.

The use of AI models allows creditors to consider additional data points, beyond the traditional credit score, as discussed above, to enable risk-based pricing.<sup>48</sup> Some automated underwriting may reduce denials for protected classes.<sup>49</sup> Consumers are still at risk, however, for discriminatory pricing.

One 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.<sup>50</sup>

Another study found that fintech lenders reduced but did not erase discriminatory lending

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<sup>45</sup> *Id.*

<sup>46</sup> *Churchill Mortgage Partners with Global Digital Leader Infosys to Launch Churchill Next*, Business Wire (Jan. 28, 2020, 9:01 AM), <https://www.businesswire.com/news/home/20200128005482/en/Churchill-Mortgage-Partners-With-Global-Digital-Leader-Infosys-to-Launch-Churchill-Next>; *Movement Mortgage Selects Infosys to Leads Its Digital Transformation, Development Services*, Infosys (Nov. 5, 2019), <https://www.infosys.com/newsroom/press-releases/2019/bank-digital-transformation-development-services.html>; *Infosys Mortgage Default Prediction System*, Infosys, <https://www.infosys.com/industries/financial-services/industry-offerings/mortgage-default-prediction-system.html> (last visited June 10, 2024).

<sup>47</sup> Dr. Atul Varshneya & Abhinav Asthana, *AI-Endgame: Practical Applications of Artificial Intelligence in Lending* (Oct. 2023), <https://tavant.com/wp-content/uploads/2023/10/fintech-artificial-intelligence-ai-ml-whitepaper.pdf>.

<sup>48</sup> See National Consumer Law Center, *Mortgage Lending* § 6.2.2.2.

<sup>49</sup> 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 . . .”).

<sup>50</sup> 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>.

patterns with respect to the pricing of loans.<sup>51</sup> Latino/ Hispanic and Black 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.<sup>52</sup>

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 model's calculation of risk and the credit decision, and may be hard to uncover.<sup>53</sup> 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.<sup>54</sup>

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.<sup>55</sup> Given enough data almost any input can be correlated to a protected characteristic.<sup>56</sup> In other words many inputs, when recycled through powerful and sophisticated models, can become substitutes or proxies for protected classes.

Lack of transparency in these "black box" models allows patterns of discrimination to go unrecognized and unchallenged. Financial institutions should not benefit from this feature. Treasury and other federal regulators 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.

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<sup>51</sup> Robert Bartlett, Adair Morse, et al., *Consumer Lending Discrimination in the Fintech Era*, National Bureau of Economic Research, Working Paper 25943, June 2019.

<sup>52</sup> *Id.*

<sup>53</sup> 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).

<sup>54</sup> See Cary Coglianese et al., *Regulating by Robot, Administrative Decision Making in the Machine Learning Era*, 105 Geo. L.J. 1147, 1159 (2017).

<sup>55</sup> 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).

<sup>56</sup> 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).



## ii. Valuations & AVMs

Real estate finance depends on reliable property valuations, whether done by a traditional appraisal, an automated valuation model (AVM)<sup>57</sup> or some combination. AVMs are based on data from traditional appraisals, public records, and private vendors.<sup>58</sup> Federal law requires lenders to use a state licensed or certified human appraiser,<sup>59</sup> but an exception to that law covers over 80% of home sales by aggregate dollar volume.<sup>60</sup>

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.”<sup>61</sup> 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.<sup>62</sup> Additionally, applicants may be offered a rate that is too high or charged unnecessary private mortgage insurance (PMI) because the lender mistakenly believes the loan will have an LTV over 80%.

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.<sup>63</sup> But that ignores the fact that AVMs are trained on data that has, itself, been shaped by race.<sup>64</sup>

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<sup>57</sup> 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](https://www.iaao.org/media/standards/AVM_STANDARD_2018.pdf).

<sup>58</sup> CoreLogic, AVM FAQs (11-avm-faq-va-0804-00), <https://www.corelogic.com/downloadable-docs/avm-faqs.pdf> (2014).

<sup>59</sup> 12 U.S. Code §§ 3342, 3343.

<sup>60</sup> 83 Fed. Reg. 63119 (Dec. 7, 2018).

<sup>61</sup> 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>.

<sup>62</sup> 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).

<sup>63</sup> 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/>.

<sup>64</sup> Michael Neal, Sarah Stochak, 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.”<sup>65</sup> But few researchers consider the impact of race on AVM results. Treasury should encourage efforts to 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.

Recently regulators issued a final rule to address the integrity of AVMs.<sup>66</sup> However the rule does not create a private right of action. As a result, Treasury and other regulators must vigorously supervise and enforce compliance with the rule.

### **iii. Mortgage Servicing**

In the mortgage servicing space, Treasury should assess how financial institutions are using AI to cut costs and whether those uses may harm borrowers or may involve unforeseen risks. The “robo signing” scandal of the early 2010s shows that automation of seemingly routine tasks may lead to harm to consumers and may weaken the reputation of financial institutions.

Mortgage servicers have reported using AI in their collection and loss mitigation spaces. Through oversight, Treasury should gather details about precisely how AI is used because inaccuracies can have significant consequences. Robo signing has shown that automation of daily tasks without oversight can have significant ramifications for the whole financial system. Treasury should make sure its review of the mortgage industry extends beyond origination and into mortgage servicing.

## **III. Use of AI and automated tools to open and monitor bank accounts for fraud risks cutting off consumers from financial services and their own money.**

Participation in the mainstream U.S. financial system often begins with access to bank accounts. However, financial institutions have aggressively used AI-driven tools to sort potential customers based on risk and deny them access to bank accounts and mainstream financial services. Companies do this by policing the forms of identification they will accept from consumers when reviewing an application for a demand deposit account and taking other action to rank potential account holders.

Existing customers complain about unanticipated account freezes and closures. One of the reasons for the increase in account freezes and closure is the adoption of AI and machine learning technologies to detect and combat payment fraud and detect suspicious activity. While fraud vigilance is critical, new technologies can harm innocent consumers if not utilized properly

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([https://www.urban.org/sites/default/files/publication/103429/how-automated-valuation-models-can-disproportionately-affect-majority-black-neighborhoods\\_1.pdf](https://www.urban.org/sites/default/files/publication/103429/how-automated-valuation-models-can-disproportionately-affect-majority-black-neighborhoods_1.pdf))

<sup>65</sup> 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>)

<sup>66</sup> See CFPB Press Release, *Agencies Issue Final Rule to Help Ensure Credibility and Integrity of Automated Valuation Models*, (July 17, 2024).

and if institutions do not have clear procedures and timelines in place to restore access to funds that are improperly frozen.

**A. Opaque identification requirements which may utilize AI/ML technologies exclude vulnerable consumers from the banking system and allow for discrimination.**

Financial institutions have broad discretion in setting risk tolerances for who they choose to allow as customers. This broad discretion often translates into policies that negatively impact consumers who are seeking entrance into the financial system.

Financial institutions do not generally publicize which forms of identification they will accept from consumers when reviewing an application for a demand deposit account. This uncertainty means underserved consumers have no sense of whether they will be successful in opening an account.

Consumers are not often told why the financial institution denied a request to open a demand deposit account.<sup>67</sup> This generates an impression among consumers that they are not allowed to engage in the banking system because of some intrinsic quality around their situation, when it could ultimately be caused by a consumer report such as ChexSystems, or a regional or national bank policy, or the use of discretion among individual branch employees. Regardless of the reason, being denied access to financial services can be embarrassing, especially when the denial occurs in person. One negative interaction with our financial system can influence the way a consumer will interact with the system for years to come. The industry opacity is unjustified given the stakes.

The excuse most often cited by financial institutions for this lack of transparency— and their unwillingness to accept certain alternative forms of ID for underserved consumers— is that they must comply with the Bank Secrecy Act (BSA).<sup>68</sup> Among other requirements imposed by the BSA, financial institutions must implement a Customer Identification Program (CIP) to verify the identity of an applicant. Some fintech companies even offer products that can help verify potential customers,<sup>69</sup> but whether these products use AI/ML technology is unclear.

Federal regulations implementing the BSA openly permit banks to use a wide range of identification methods to open accounts for their customers and to implement their CIP. At its core, the CIP must explain the bank's procedures for opening an account, including stating what identifying information will be obtained from each customer and how the bank will verify its customers' identities through both documentary and non-documentary methods.<sup>70</sup>

The rules also require financial institutions to employ "risk-based procedures" for verifying the identity of each customer to the extent "reasonable and practicable," and within a reasonable

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<sup>67</sup> Because a demand deposit account does not meet the definition of credit under the Equal Credit Opportunity Act, no adverse notice is required to be provided to the applicant/consumer. However, if a financial institution relied on a consumer report from ChexSystems, for example, it should provide the consumer with an adverse action notice under the Fair Credit Reporting Act.

<sup>68</sup> 31 U.S.C. 5311.

<sup>69</sup> See, for example, <https://plaid.com/products/identity-verification/>.

<sup>70</sup> 31 C.F.R. § 1020.220(a)(2)(ii).

time after the account is opened.<sup>71</sup> These procedures must enable the financial institution to form a reasonable belief that it knows the true identity of each customer, and the procedures must be “based on the bank’s assessment of the relevant risks, including those presented by the various types of accounts maintained by the bank, the various methods of opening accounts provided by the bank, the various types of identifying information available, and the bank’s size, location, and customer base.”<sup>72</sup>

It is the requirement to utilize “risk-based” procedures consistent with the bank’s level of risk tolerance that gives banks broad discretion in choosing with whom they bank. The “risk-based” procedures are often utilized as a shield for obfuscating account-opening policies. Without transparency into these policies, banks may ultimately engage in discriminatory practices, utilizing overly simplistic policies that exclude immigrants, domestic violence survivors, formerly incarcerated people and unhoused individuals who may lack access to various forms of government-issued identification.

More clarity is needed in the guidance federal regulators provide to financial institutions. Treasury should consider implementing more detailed guidelines on how banks should exercise their discretion to ensure that they meet the obligations of the Bank Secrecy Act while also not excluding consumers from our banking system. These guidelines should emphasize the importance of transparency in account opening requirements, particularly for underserved consumers who may experience barriers to obtaining traditional forms of ID; provide guidance for local governments on developing municipal ID programs; and explicitly name forms of ID that may be used as primary and secondary ID for individuals unlikely to have access to state-issued ID.

Additionally, because consumers do not often understand how financial institutions verify their identity and whether discriminatory algorithms or AI/ML tools are being used, Treasury should also undertake oversight of the technology used in these assessments to ensure the systems are not leading to discriminatory outputs which may unfairly cut some consumers off from banking opportunities.

Regulators should also specify that there is likely a corresponding risk of unfair, deceptive, or abusive practices associated with discriminating against consumers on the basis of race or national origin, and that a denial of a bank account that relies, at least in part, on information obtained within a consumer report triggers adverse action notice requirements under the Fair Credit Reporting Act.<sup>73</sup>

### **B. Overly aggressive AI/ML models can shut out innocent consumers from access to their accounts and funds.**

Financial institutions, payment processors, card networks, money service businesses, and fintech companies utilize tools to combat payment fraud, including AI/ML technologies. Financial institutions who hold consumer deposits may also utilize these same kinds of technologies to comply with their BSA/AML obligations. However, these tools may harm innocent consumers if

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<sup>71</sup> 31 C.F.R. § 1020.220(a)(2).

<sup>72</sup> 31 C.F.R. § 1020.220(a)(2)

<sup>73</sup> 15 U.S.C. § 1681m(a).

not utilized properly and if institutions do not have clear procedures and timelines in place to restore access to funds that are improperly frozen.

Recently, many consumers have raised concerns about freezes and bank account closures that seem to occur without any sudden change of behavior by the consumer. Consumers report frustration and uncertainty tied to account closures and freezes— primarily the lack of information as to why the closure or freeze occurred and the inability to access funds in a timely manner.

The number of consumers who have complained about checking and savings account closures to the CFPB more than doubled since 2017,<sup>74</sup> and in 2022 the CFPB ordered Wells Fargo to pay \$160 million to over one million people for improperly freezing or closing bank accounts from 2011 to 2016 when it “believed that a fraudulent deposit had been made into a consumer deposit account based largely on an automated fraud detection system.”<sup>75</sup>

There have been other stories featured in the media detailing the devastating impact sudden account closures and freezes can have on consumers, especially when they are deprived of access to their funds, are not provided any information about the reason for the institution’s actions, and are not provided an opportunity to address any perceived risk.

Being locked out of a bank account can have immediate and profoundly harmful consequences. According to one consumer, “Chime stole my entire unemployment backpay.... I’m a single mom of 4 kids and they stole \$1,400 from me and refuse to give it back and now we are about to be evicted.”<sup>76</sup> A few examples from the New York Times and other publications highlight the distress consumers face after discovering their accounts were either frozen or closed:<sup>77</sup>

- Naafeh Dhillon, 28, from Brooklyn, NY, learned his account had been closed after his debit card and credit card were declined. He was later told by a Chase representative that the “bank’s global security and investigation team had ultimately made the decision. Would the representative transfer him to that department? Nope... Since he wasn’t given

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<sup>74</sup> Consumer Fin. Prot. Bureau, Consumer Complaint Database, trends data for complaints received due to checking or savings account closure, [https://www.consumerfinance.gov/data-research/consumer-complaints/search/?chartType=line&dateInterval=Month&dateRange=All&date\\_received\\_max=2024-01-27&date\\_received\\_min=2011-12-01&has\\_narrative=true&issue=Closing%20an%20account%E2%80%A2Company%20closed%20your%20account&lens=Product&product=Checking%20or%20savings%20account&searchField=all&subLens=su\\_b\\_product&tab=Trends](https://www.consumerfinance.gov/data-research/consumer-complaints/search/?chartType=line&dateInterval=Month&dateRange=All&date_received_max=2024-01-27&date_received_min=2011-12-01&has_narrative=true&issue=Closing%20an%20account%E2%80%A2Company%20closed%20your%20account&lens=Product&product=Checking%20or%20savings%20account&searchField=all&subLens=su_b_product&tab=Trends). (last visited Feb. 20, 2024).

<sup>75</sup> *In re Wells Fargo Bank, N.A.*, CFPB No. 2022-CFPB-0011 (Dec. 20, 2022) (consent order), available at [https://files.consumerfinance.gov/f/documents/cfpb\\_wells-fargo-na-2022\\_consent-order\\_2022-12.pdf](https://files.consumerfinance.gov/f/documents/cfpb_wells-fargo-na-2022_consent-order_2022-12.pdf).

<sup>76</sup> Kessler, Carson, “A Banking App Has Been Suddenly Closing Accounts, Sometimes Not Returning Customers’ Money,” ProPublica (July 6, 2021), available at <https://www.propublica.org/article/chime>.

<sup>77</sup> Barnard, Tara Siegel and Lieber, Ron, “Banks Are Closing Customer Accounts, With Little Explanation,” N.Y. Times (Apr. 8, 2023), [https://www.nytimes.com/2023/04/08/your-money/bank-account-suspicious-activity.html?unlocked\\_article\\_code=1.QU0.szRm.kfoZRQdD7-O6&smid=url-share](https://www.nytimes.com/2023/04/08/your-money/bank-account-suspicious-activity.html?unlocked_article_code=1.QU0.szRm.kfoZRQdD7-O6&smid=url-share).

a specific reason for the closure, he couldn't disprove whatever raised suspicions in the first place."<sup>78</sup>

- Heather Hauri got a text from Bank of America that suggested her debit card may have been compromised too. When she responded that she had not made the transactions in question, she was locked out of her account. "The whole account is frozen," she said. "You can't get your own money."<sup>79</sup>
- Todd Zolecki, 47 of Media, PA, did not have his account closed, but was locked out of access to his account. "They said your account has been suspended for further review," Why? "We can't tell you that. The only thing we can tell you is it can take up to 60 days for this review."<sup>80</sup>

We do not dispute the fact that financial institutions have obligations under the BSA and accompanying anti-money laundering (AML) regulations to ensure that they maintain and follow internal ongoing customer due diligence (CDD) policies. The CDD policies must allow the institution to understand "the nature and purpose of customer relationships for the purpose of developing a customer risk profile; and [c]onducting ongoing monitoring to identify and report suspicious transactions and, on a risk basis, to maintain and update customer information."<sup>81</sup> Because of these obligations, sometimes the appropriate response by an institution that suspects its customer is engaging in fraudulent or other illicit activity is to freeze a transaction or close an account that is being used to receive fraudulent funds before the funds are gone and more consumers can be defrauded. But sometimes banks get it wrong, especially when automated tools are used.

Some impact on innocent individuals may be impossible to avoid, as banks may need to act quickly on imperfect information. But that is why it is imperative to have procedures in place to enable people to dispute account freezes and closures and get their money back as soon as possible.

Bank of America for example froze 350,000 unemployment debit cards in California after extensive fraud reports. But the freezes caught many legitimately unemployed workers, and the bank failed to respond in a timely fashion to their complaints.<sup>82</sup> Months later, after a lawsuit was filed, a judge prohibited the bank from freezing accounts for California unemployment benefits based solely on an automated fraud filter and required it to do a better job of responding when

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<sup>78</sup> Id.

<sup>79</sup> KCAL News, "Bank Of America Freezes EDD Accounts Of Nearly 350,000 Unemployed Californians For Suspected Fraud," (Oct. 29, 2020), available at <https://www.cbsnews.com/losangeles/news/bank-of-america-freezes-edd-accounts-of-nearly-350000-unemployed-californians-for-suspected-fraud/>.

<sup>80</sup> Barnard, Tara Siegel and Lieber, Ron, "Banks Are Closing Customer Accounts, With Little Explanation," N.Y. Times (Apr. 8, 2023), [https://www.nytimes.com/2023/04/08/your-money/bank-account-suspicious-activity.html?unlocked\\_article\\_code=1.QU0.szRm.kfoZRQdD7-O6&smid=url-share](https://www.nytimes.com/2023/04/08/your-money/bank-account-suspicious-activity.html?unlocked_article_code=1.QU0.szRm.kfoZRQdD7-O6&smid=url-share).

<sup>81</sup> 31 C.F.R. § 1020.210(a)(2)(v), (b)(2)(v).

<sup>82</sup> Bank Of America Freezes EDD Accounts Of Nearly 350,000 Unemployed Californians For Suspected Fraud, KCAL News, (Oct. 29, 2020), available at <https://www.cbsnews.com/losangeles/news/bank-of-america-freezes-edd-accounts-of-nearly-350000-unemployed-californians-for-suspected-fraud/>.

jobless people say their benefits were stolen.<sup>83</sup> The CFPB also brought an enforcement action against Bank of America,<sup>84</sup> and also against U.S. Bank,<sup>85</sup> for similar conduct in indiscriminately freezing accounts and leaving them frozen for long periods of time. This conduct harmed the most vulnerable consumers – those who had lost their jobs and were relying on unemployment benefits.

When a consumer complains about an account closure or freeze, the complaint is often not followed by a reasonable investigation by the financial institution that includes a discussion with the consumer or that provides any clear timeline to unfreeze their money. As a step toward combating this problem, Treasury and bank regulators should issue guidance, instructing financial service providers that the error resolution procedures of the Electronic Funds Transfer Act (EFTA) apply to overly aggressive BSA policies. For example, the EFTA has clear error resolution timelines and procedures, and those should be used when consumers cannot access their funds. If a consumer is unable to make an electronic withdrawal or transfer because of an account closure or freeze based on suspected fraud, that action should be viewed as an error – an incorrect transfer of zero instead of the requested amount – triggering the error resolution rights, duties, timelines, and investigation procedures of the EFTA. Alternatively, if a consumer requests information about a declined electronic fund transfer because of a frozen or closed account, then the request should constitute a “request for additional information or clarification concerning an electronic fund transfer”<sup>86</sup> and trigger the error resolution procedures of the EFTA.<sup>87</sup>

FinCEN and bank regulators should also provide guidance to financial institutions about what information they may and should provide to account holders regarding freezes and account closures while still complying with the BSA. For example, regulators could clarify in an FAQ that, while financial institutions are not allowed to disclose that a SAR was filed, they are allowed to disclose that an account was frozen or closed due to potential fraudulent activity and/or describe the specific activities that raised concerns, giving the consumer an opportunity to respond. Consumers should know why their accounts are closed or frozen.

As shown by the CFPB’s recent enforcement actions and considering risks of unfair, deceptive, or abusive practices when consumers’ funds are held indefinitely, the CFPB and bank regulators should provide guidance to financial institutions about the importance of having clear

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<sup>83</sup> McGreevy, Patrick, Bank of America must provide more proof of fraud before freezing EDD accounts, court orders, Los Angeles Times (Jun. 1, 2021), <https://www.latimes.com/california/story/2021-06-01/bankof-america-ordered-to-unfreeze-unemployment-benefit-cards-in-california>.

<sup>84</sup> CFPB, “Federal Regulators Fine Bank of America \$225 Million Over Botched Disbursement of State Unemployment Benefits at Height of Pandemic,” (Press Release) (July 14, 2022), available at <https://www.consumerfinance.gov/about-us/newsroom/federal-regulators-fine-bank-of-america-225-million-overbotched-disbursement-of-state-unemployment-benefits-at-height-of-pandemic/>.

<sup>85</sup> Consumer Fin. Prot. Bureau, CFPB Orders U.S. Bank to Pay \$21 Million for Illegal Conduct During COVID-19 Pandemic, (Press Release) (Dec. 19, 2023), [https://www.consumerfinance.gov/about-us/newsroom/cfpb-orders-us-bankto-pay-21-million-for-illegal-conduct-during-covid-19-pandemic/#:~:text=The%20CFPB%20and%20OCC%20together,411%2DCFPB%20\(2372\)](https://www.consumerfinance.gov/about-us/newsroom/cfpb-orders-us-bankto-pay-21-million-for-illegal-conduct-during-covid-19-pandemic/#:~:text=The%20CFPB%20and%20OCC%20together,411%2DCFPB%20(2372)).

<sup>86</sup> See 15 U.S.C. § 1693f(f)(6).

<sup>87</sup> A [recent bill](#) introduced by the [House and Senate](#) would make clear that an account freeze or closure itself would be an error under the EFTA.

procedures to enable consumers to quickly regain access to their funds when they are frozen due to concerns of suspicious activity. Consumers should have access to human customer service agents, and not merely chatbots or AI interfaces to ensure proper account review and timely resolution. To further this goal, Treasury and regulators should provide guidance as to the timeliness of any investigation regarding flagged account activity and deadlines to return an account holder's funds after account closure.

In addition to guidance, Treasury and other regulators should ensure that supervisory examinations include testing and validation of AI/ML models used to monitor accounts for suspicious activity. Regulators should ensure that banks' reliance on AI/ML technologies to conduct ongoing account monitoring pursuant to the BSA does not have discriminatory and detrimental impacts on innocent consumers.

#### **IV. Widespread adoption of AI in debt collection poses significant risk for already debt-burdened consumers facing financial crisis.**

The adoption of AI by the collection industry puts consumers at heightened risk for aggressive and abusive collection tactics. This section presents general data about the use of artificial intelligence in the debt collection industry. We also highlight some examples of where AI/ML is currently being used by the debt collection industry, and point out potential risks for consumers created by the use of AI/ML.

##### **A. Adoption of AI Generally**

In a 2023 TransUnion survey of debt collection agencies, 11% of respondents reported that they are currently using AI/ML based technology and an additional 48% were developing or considering the use of such technology.<sup>88</sup> That survey also reported that larger companies have adopted AI/ML at a higher rate than smaller ones thus far.<sup>89</sup>

Debt collectors reported that they currently use or plan to use AI/ML-based technology as follows:

- 58% “to predict payment outcomes, e.g., a person’s ability or willingness to pay a debt;”
- 56% “to segment and profile customers for various workflows;”
- 53% “to augment the self-service platform, e.g., virtual negotiators;”
- 47% “to recommend communications methods;”
- 47% “to analyze account life cycle workflows;”
- 46% “to anticipate consumer behavior;”
- 37% “to direct consumers to the right customer support channels;” and

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<sup>88</sup> TransUnion, Seizing the Opportunity in Uncertain Times: The Third-Party Collections Industry in 2023, at 39 (2023), <https://www.transunion.com/lp/seizing-the-opportunity-in-uncertain-times-the-collections-indus>.

<sup>89</sup> *Id.* at 40. “Thirty-six percent of companies with a million or more accounts already use AI/ML-based technology. Adoption by companies servicing less than 100,000 accounts is far lower: Only 4% of these firms actively use it. Fifty-six percent of companies with less than 100,000 accounts have no plans to use AI, versus only 7% of companies with a million accounts or more.”



- 32% “to monitor agent performance/behavior.”<sup>90</sup>

According to one vendor creating AI/ML products for debt collectors:

By harnessing the power of AI and ML, sophisticated models are developed that go beyond prediction of payment behaviors; they delve into a debtor’s financial life, taking into account their payment history, spending patterns, and overall financial status. . . . They empower the industry to proactively address emerging trends and anticipate shifts in debtor behavior. By continuously analyzing vast datasets, these technologies facilitate the ongoing refinement of collection strategies. They adapt in real time to changes in economic conditions and market dynamics, ensuring that the collections and recovery process remains dynamic, agile, and highly effective.<sup>91</sup>

## B. Examples of How AI Is Used in Debt Collection

### i. Portfolio Analytics

Analytics can be used to provide debt collectors with insights into portfolios of debts. Collectors may use analytics to help them make decisions regarding which portfolios of debts to purchase or how much to pay.<sup>92</sup>

Debt collectors may also use analytics to identify which accounts are most likely to pay or to identify accounts for particular collection techniques based on specific criteria.<sup>93</sup> As FICO

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<sup>90</sup> *Id.* at 39 (2023), <https://www.transunion.com/lp/seizing-the-opportunity-in-uncertain-times-the-collections-indus>.

<sup>91</sup> FICO, A new dawn: modernizing collections and recovery in the US, at 6 (2024), <https://www.fico.com/en/latest-thinking/white-paper/new-dawn-modernizing-collections-and-recovery-us>.

<sup>92</sup> See, e.g., Experian, Debt Portfolio Evaluator: A perceptive analysis tool for debt buyers and sellers (2017), <https://www.experian.com/content/dam/marketing/na/business/product-sheets/debt-portfolio-evaluator-product-sheet.pdf> (“combines credit data, credit-based scoring and advanced analytics to provide a 360-degree view of consumers . . . tool provides data on 33 collection-specific attributes”); TransUnion, TruVizion for Managing Customer Portfolios, <https://www.transunion.com/solution/truvizion/credit-risk/manage-customer-portfolio> (last visited July 19, 2024) (“TruVizion Portfolio Valuation: Estimate the total amount recoverable to determine appropriate pricing for portfolios you sell or acquire.”). See also *Capio Funding, L.L.C. v. Rural/Metro Operating Co., L.L.C.*, 35 F.4th 353, 355 (5th Cir. 2022) (describing how the debt buyer used portfolio analytics, in the context of a forward flow deal, to “algorithmically identify accounts that met the agreed-upon criteria [for purchase]”); *Absolute Resolutions Invs., L.L.C. v. Citibank*, No. 22-cv-335 (Jan. 13, 2022, S.D.N.Y.), <https://storage.courtlistener.com/recap/gov.uscourts.nysd.573253/gov.uscourts.nysd.573253.1.0.pdf> (complaint ¶¶ 18–21, discussing how sample of accounts from portfolio are analyzed before purchase); Shane Shifflett & Justin Scheck, Most Big Debt Collectors Backed Off During the Pandemic. One Pressed Ahead., *Wall St. J.*, Apr. 7, 2021 (mentioning Sherman Financial’s use of computer analytics to estimate portfolio profitability), <https://www.wsj.com/articles/most-big-debt-collectors-backed-off-during-the-pandemic-one-pressed-ahead-11617804180>.

<sup>93</sup> Experian, Debt collection analytics and insights (last visited July 19, 2024), <https://www.experian.com/business/solutions/debt-management-collections/debt-collection-analytics> (“An analytically driven collections model will allow you to score and segment customer accounts by exposure,

explains, “[r]ather than treating all debtors the same, businesses can categorize them into distinct groups based on their risk profiles, preferences, and response patterns.”<sup>94</sup> TransUnion’s 2023 survey of collection agencies found that 34% of respondents are using “predictive scoring to prioritize accounts” for debt collection.<sup>95</sup>

The use of analytics to segment accounts for different types of collection raises questions about disparate treatment - such as identifying certain accounts for collection lawsuits rather than other collection methods - based on zip code or demographic data like race, gender, or age.

## ii. Credit Data Monitoring

Consumer reporting agencies have created a variety of products to help debt collectors monitor consumer credit data and notify collectors of changes to indicators of financial health.<sup>96</sup> As Experian explains:

Using direct access to Experian’s consumer credit database, Collection Triggers<sup>SM</sup> passively monitors accounts for changes that often correlate with a consumer’s ability and willingness to pay. These triggering events could be the first indication that it’s time to add an account back on your call list.<sup>97</sup>

Experian explains that there are “nearly 100 triggers available” that can notify debt collectors when there is a new credit inquiry or tradeline, available credit on an existing credit card or home equity loan, changes in contact information, new employment, or evidence of paying off other debts.<sup>98</sup> Data is collected about the increase in collection related to a particular trigger

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risk, behavioral factors, willingness to pay and preferred contact channel. With collection analytics, you can prioritize your collections activity and better allocate your resources.”).

<sup>94</sup> FICO, A new dawn: modernizing collections and recovery in the US, at 5 (2024), <https://www.fico.com/en/latest-thinking/white-paper/new-dawn-modernizing-collections-and-recovery-us>.

<sup>95</sup> TransUnion, Seizing the Opportunity in Uncertain Times: The Third-Party Collections Industry in 2023, at 36 (2023), <https://www.transunion.com/lp/seizing-the-opportunity-in-uncertain-times-the-collections-indus>.

<sup>96</sup> See, e.g., Equifax, Triggers: Enhance your insight into the Equifax Credit File, (last viewed July 19, 2024), <https://www.consumer.equifax.ca/business/triggers>; Experian, Optimizing your recovery strategy with Collection Triggers (2024), <https://www.insidearm.com/whitepapers/optimizing-your-recovery-strategy-collections-triggers/>; FICO, Beyond the Call Center: Emerging Strategies for Collecting Consumer Debt (Mar. 2019) (“another important data point executives track is changes to individual borrowers’ financial health, typically measured by changes either in credit risk scores or individual attributes contained within credit files”); Equifax, Triggers: Enhance your insight into the Equifax Credit File, (last viewed July 19, 2024), <https://www.consumer.equifax.ca/business/triggers> (“An alert is triggered by events such as: credit score changes, credit balance changes, address changes, new credit inquiries”); TransUnion, Collections Prioritization Engine (2020), <https://www.transunion.com/content/dam/transunion/global/business/documents/TU-CPE%20Asset%20Sheet.pdf>.

<sup>97</sup> Experian, Optimizing your recovery strategy with Collection Triggers, at 2 (2024), <https://www.insidearm.com/whitepapers/optimizing-your-recovery-strategy-collections-triggers/>

<sup>98</sup> *Id.* at 3. See also TransUnion, Collections Prioritization Engine (2020), <https://www.transunion.com/content/dam/transunion/global/business/documents/TU->

over time to further optimize the value of specific triggers.<sup>99</sup> TransUnion’s 2023 survey of collection agencies found that 49% of respondents are using “consumer credit data” for debt collection.<sup>100</sup>

Targeting consumers that show even the smallest sign of financial recovery for an additional wave of collection risks destabilizing the consumers’ potentially fragile initial steps toward financial recovery.

### iii. Collection Communications

Spurred, in part, by the Consumer Financial Protection Bureau’s adoption of debt collection regulations addressing the use of electronic communications,<sup>101</sup> collectors have diversified the modes of communication they use with consumers. TransUnion’s 2023 survey of collection agencies found that 69% of debt collectors communicate with consumers by email, 40% via text, and 2% via social media.<sup>102</sup> An additional 17% of respondents planned to add email communication, 31% planned to add text messages, and 8% planned to add social media communication in the next two years.<sup>103</sup>

As debt collectors increasingly use digital communications to attempt to reach consumers, they are also harnessing data from those digital channels to decide how to contact consumers in the future. Digital communication platforms, “generate valuable data on communication preferences, response times, and engagement patterns.”<sup>104</sup> Analytics can be used to personalize the content or tone of a collection communication, the mode of communication, or even the specific debt collector assigned to contact that consumer.<sup>105</sup>

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[CPE%20Asset%20Sheet.pdf](#) (“Identifies your most collectible accounts by choosing from more than 200 pre-defined credit characteristics”).

<sup>99</sup> Experian, Optimizing your recovery strategy with Collection Triggers, at 6 (2024), <https://www.insidearm.com/whitepapers/optimizing-your-recovery-strategy-collections-triggers/>

<sup>100</sup> TransUnion, Seizing the Opportunity in Uncertain Times: The Third-Party Collections Industry in 2023, at 36 (2023), <https://www.transunion.com/lp/seizing-the-opportunity-in-uncertain-times-the-collections-indus>.

<sup>101</sup> See, April Kuehnhoff, Comprehensive New FDCPA Regulation F Takes Effect November 30 (National Consumer Law Center, Sept. 24, 2021), <https://library.nclc.org/article/comprehensive-new-fdcpa-regulation-f-takes-effect-november-30>.

<sup>102</sup> TransUnion, Seizing the Opportunity in Uncertain Times: The Third-Party Collections Industry in 2023, at 33 (2023), <https://www.transunion.com/lp/seizing-the-opportunity-in-uncertain-times-the-collections-indus>.

<sup>103</sup> *Id.* at 35.

<sup>104</sup> FICO, A new dawn: modernizing collections and recovery in the US, at 7 (2024), <https://www.fico.com/en/latest-thinking/white-paper/new-dawn-modernizing-collections-and-recovery-us>.

<sup>105</sup> Robert J. Szczerba, Which Industry Is Next For A.I. Disruption? The Answer Might Surprise You, *Forbes*, Apr. 26, 2017, <https://www.forbes.com/sites/robertszczerba/2017/04/26/which-industry-is-next-for-a-i-disruption-the-answer-might-surprise-you/?sh=7356d3a93f1c>.

Systems can also learn from engagement with prior communications (e.g., did the consumer click on the link in that email or sign up for a payment plan with a particular collector) in order to tailor future messages.<sup>106</sup> Some debt collectors use machine learning to optimize how frequently they communicate, the time of day they communicate, the content and tone of their communications, and the amount of discount and length of payment plan to offer each consumer.<sup>107</sup>

A bipartisan Congressional working group on artificial intelligence described how one debt collector is using AI in its text message communications with consumers:

One panelist described their use of [large language models] to communicate with individuals whose debt is being collected. This panelist uses [Generative AI] produced text prompts, which are then reviewed by a human for legal compliance and sent to customers. These text prompts are refined through engagement analytics and can be tailored to specific collection scenarios. Statistics provided by the panelist indicate a 25 percent increase in payment in full when using AI generated text compared to human generated text. These text prompts are refined through analytics and can be tailored to specific collection scenarios, including if a customer has already accessed their payment portal, how many times they have been communicated with before, and how far along an individual is in the debt collection process.<sup>108</sup>

Communication with consumers through all of these different channels risks adding to consumer stress or even harassing consumers. Using algorithms to generate personal settlement may result in disparate treatment of some groups of consumers, who may be offered more favorable repayment terms than other groups.

#### **iv. Speech Analytics**

Some debt collectors also use analytics software to record and evaluate collection calls. Speech analytics software transcribes speech into text and then analyzes it for business information.<sup>109</sup> It “extracts information from customer conversations” to identify words or phrases and also “analyze[s] the emotional character of the speech (sentiment analysis).”<sup>110</sup> Debt collectors can use speech analytics to monitor calls for mandatory disclosures and some products allow

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<sup>106</sup> Ryan Lawler, Collectly Is Moving Debt Collection Online (TechCrunch, Mar. 28, 2017), <https://techcrunch.com/2017/03/28/collectly-debt-collection/>.

<sup>107</sup> Noelle Robillard, How TrueAccord Embraces Machine Learning to Create Positive Consumer Experiences in Debt Collection (TrueAccord, Dec. 23, 2021), <https://blog.trueaccord.com/2021/12/how-trueaccord-embraces-machine-learning-to-create-positive-consumer-experiences-in-debt-collections/>.

<sup>108</sup> House Committee on Financial Services, AI Innovation Explored: Insights into AI Applications in Financial Services and Housing (July 18, 2024), [https://financialservices.house.gov/uploadedfiles/bipartisan\\_working\\_group\\_on\\_ai\\_staff\\_report.pdf](https://financialservices.house.gov/uploadedfiles/bipartisan_working_group_on_ai_staff_report.pdf).

<sup>109</sup> Qualtrics, What is speech analytics (last viewed on July 19, 2024), <https://www.qualtrics.com/experience-management/customer/speech-analytics/>.

<sup>110</sup> CallMiner, Speech analytics 101: What is speech analytics? (Feb. 23, 2023), <https://callminer.com/blog/speech-analytics-101-speech-analytics>.

supervisors to monitor calls while they are live.<sup>111</sup> TransUnion’s 2023 survey of collection agencies found that 25% of respondents are using speech analytics tools in their collection efforts.<sup>112</sup>

In addition to concerns about privacy related to the recording and analysis of conversations, speech analytics can also raise questions about disparate treatment. For example, if a speech analytics platform has been trained to identify and respond in a certain way if a caller is angry, does the software respond the same way regardless of the race, age, gender, or ethnicity of the consumer?

#### **v. Chatbots**

AI tools in this category include “chatbots, text messages and website portal negotiators that provide real-time customer care and self-service opportunities.”<sup>113</sup> Ten percent of respondents to the 2023 TransUnion survey indicated that they use a “chatbox [sic] or digital assistant” to communicate with consumers regarding a debt and another 29% indicated that they were looking to add such technology in the next two years.<sup>114</sup>

Like online web portals, chatbots can offer 24/7 information to consumers. AI-driven chatbots may be used to augment online debt collection portals that present static information about the consumer’s account.<sup>115</sup>

The use of AI-driven chatbots raises concerns about consumers being unable to get answers to their questions or receiving incorrect information, particularly for complex or unique questions.<sup>116</sup>

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<sup>111</sup> *Id.*

<sup>112</sup> TransUnion, Seizing the Opportunity in Uncertain Times: The Third-Party Collections Industry in 2023, at 36 (2023), <https://www.transunion.com/lp/seizing-the-opportunity-in-uncertain-times-the-collections-indus>. See also CFPB, Study of Third-Party Debt Collection Operations 34 (July 2016), available at <https://www.consumerfinance.gov> (in a survey of third-party collection agencies, seventeen out of fifty-eight respondents used speech analytics).

<sup>113</sup> Experian, A digital debt collection future: Maximizing collections and staying compliant, at 5 (Sept. 30, 2022), <https://www.experian.com/innovation/thought-leadership/digital-debt-collection-future-maximizing-collections.jsp>.

<sup>114</sup> TransUnion, Seizing the Opportunity in Uncertain Times: The Third-Party Collections Industry in 2023, at 33, 35 (2023), <https://www.transunion.com/lp/seizing-the-opportunity-in-uncertain-times-the-collections-indus>.

<sup>115</sup> *Id.* at 36, 39 (36% of respondents are using “24/7 automated self-serve capability” for debt collection).

<sup>116</sup> See Consumer Financial Protection Bureau, Chatbots in consumer finance (Jun. 6, 2023), <https://www.consumerfinance.gov/data-research/research-reports/chatbots-in-consumer-finance/chatbots-in-consumer-finance/>. See also Consumer Financial Protection Bureau, Fair Debt Collection Practices Act: CFPB Annual Report 2023, at 24 (Nov. 2023), [https://files.consumerfinance.gov/f/documents/cfpb\\_fdcpa-annual-report\\_2023-11.pdf](https://files.consumerfinance.gov/f/documents/cfpb_fdcpa-annual-report_2023-11.pdf) (“An emerging area of concern highlighted in consumer complaints about debt collection is the potential use of generative artificial intelligence (AI) in the development of materials designed to assist in the collection of

## vi. Voice AI

Voice AI software can be used to make interactive, live collection calls with consumers. TransUnion's 2022 survey of collection agencies found that 3% of collection agency respondents had added "automated communications using artificial intelligence (AI) to anticipate behavior" in the last 12 months.<sup>117</sup>

As with chatbots, the use of voice AI may lead to consumers receiving incorrect information. Unless they are informed that this is a digital agent, consumers may not know that they are communicating with an AI.<sup>118</sup> Even if consumers know that they are speaking to an AI, they may struggle to connect with human agents to discuss complex questions if the debt collector uses the new technology to reduce its staffing of human agents.

Finally, the use of voice AI may significantly increase outbound calls from debt collectors, who will be able to make more calls at a lower cost. One voice AI vendor promises:

100% Account Penetration: A Voice AI solution can initiate and handle millions of calls within minutes, covering an agency's entire debt portfolio in an impressively short amount of time. This level of automation has never been possible until recently; it's important to note that over a third of an agency's files often remain untouched.<sup>119</sup>

Making it easier and cheaper to call all of the accounts in a debt collector's portfolio has the potential to exponentially increase phone calls to consumers, who may face increased stress and anxiety due to harassment through repeated phone calls.

## vii. AI Collection Agents

At least one company already advertises "fully human-capable AI Agents specializing in healthcare revenue cycle management."<sup>120</sup> The company's current product focuses on collecting from health care insurance companies rather than collecting directly from individual consumers

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debt, the automation of customer service functions in a way that may make it harder to get a clear answer, and other areas.").

<sup>117</sup> TransUnion, Charting the Course and Steering Toward Success: The Collections Industry in 2022, at 29 (Nov. 2022), <https://www.tlo.com/content/dam/tlo/us/documents/dm-22-f108172-3pc-aite-novarica-collections.pdf>.

<sup>118</sup> Compare, Skit.ai recordings without a disclosure ([https://skit.ai/?utm\\_source=ACA\\_digital&utm\\_medium=ACA\\_newsletter&utm\\_campaign=ACA&utm\\_id=ACA&ct=\(EMAIL\\_CAMPAIGN\\_04\\_08\\_2024\\_COPY\\_01\)](https://skit.ai/?utm_source=ACA_digital&utm_medium=ACA_newsletter&utm_campaign=ACA&utm_id=ACA&ct=(EMAIL_CAMPAIGN_04_08_2024_COPY_01))) and with a disclosure (<https://skit.ai/solution-collection/>) (click on embedded videos for call recordings).

<sup>119</sup> Harshad Bajpai, Entering a New Era of Debt Collections with Conversational Voice AI (Feb. 7, 2023), <https://skit.ai/entering-a-new-era-of-debt-collections-with-voice-ai/>.

<sup>120</sup> Courtney Merolle, Thoughtful AI Launches Human-Capable AI Agents, Raises \$20m in New Funding (Thoughtful AI, July 18, 2024), <https://www.businesswire.com/news/home/20240716834123/en/Thoughtful-AI-Launches-Human-Capable-AI-Agents-Raises-20m-in-New-Funding>.

by engaging AI to process insurance claims, verify patient eligibility, and track payment posting.<sup>121</sup>

Replacing human agents with AI agents raises questions about the ability of consumers to get in touch with human agents if they have questions or concerns about an alleged medical debt. Use of AI agents also raises questions about whether human agents are asked to review work by AI agents and empowered to correct mistakes once identified.

More attention should be focused on debt collectors' use of this technology given the real and emerging potential for these companies to use AI/ML to confuse, harass, and discriminate against debtors. Moreover, with interactions as fraught as debt collection conversations, AI/ML technologies should not replace human agents who can quickly deal with errors, clear up confusion, or request more information on the debt.

## **V. Treasury must ensure robust compliance with consumer protection laws.**

### **A. Fair lending and civil rights laws provide a framework for addressing the systemic risks posed to consumers by AI 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 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.<sup>122</sup> 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.<sup>123</sup> 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.<sup>124</sup> Discrimination in advertising regarding the sale or rental of a dwelling, including related to mortgage credit, is also prohibited.<sup>125</sup>

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 ECOA and FHA also prohibit discrimination based upon

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<sup>121</sup> *Id.*

<sup>122</sup> 15 U.S.C. §§ 1691 et seq. See also 12 C.F.R. § 1002.2(z).

<sup>123</sup> See 12 C.F.R. § 1002.4(b).

<sup>124</sup> 42 U.S.C. § 3605.

<sup>125</sup> 42 U.S.C. § 3604(c); 24 C.F.R. 100.75(c)(3).

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; 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, the final step is to determine 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 the disparate impact analysis 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;<sup>126</sup> mortgage lenders whose policies resulted in more expensive loans to protected classes than similarly situated white borrowers;<sup>127</sup> and predatory home financing schemes using contracts that result in consumers being evicted from their homes and losing their investment in the property.<sup>128</sup> Many of these policies and practices had a disparate impact on Black, Latino/ Hispanic, 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.<sup>129</sup> 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.<sup>130</sup> Financial institutions are well aware of fair lending and disparate impact risks with respect to their credit practices, and should expect robust fair lending examinations of their latest technology. Financial institutions should also have their own fair lending testing, compliance and monitoring regimens in place to decrease such risks. Fair

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<sup>126</sup> 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\\_disparities.pdf](https://www.nclc.org/images/pdf/car_sales/ib-auto-dealers-racial_disparities.pdf).

<sup>127</sup> 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).

<sup>128</sup> *Henderson v. Vision Property Management, LLC*, complaint and other material available at <https://www.nclc.org/litigation/nclc-sues-company-over-rationally-targeted-home-scheme.html>.

<sup>129</sup> See *Policy Statement on Discrimination in Lending*, 59 Fed. Reg. 18266, Apr. 15, 1994.

<sup>130</sup> 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](https://files.consumerfinance.gov/f/201404_cfpb_bulletin_lending_discrimination.pdf).



lending evaluation of AI models is a continuation of the assessment of risk undertaken with respect to more traditional models.

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.

Financial institutions should be required 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 regulators to abandon a rigorous fair lending evaluation or water down long-held and workable standards.

**B. Financial institutions that use complex AI/ML models must ensure that their models are explainable to consumers in compliance with the ECOA and Regulation B.**

The ECOA requires that creditors provide applicants with a statement of reasons outlining the reasons for the denial of credit or for taking other adverse action on an application.<sup>131</sup> General statements which simply say that the 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.<sup>132</sup> Rather, the reasons disclosed must relate to and accurately describe those factors actually reviewed, considered, or scored.<sup>133</sup>

**i. Legislative history of the ECOA requires transparency and an explanation related to the applicant's creditworthiness.**

Congress amended ECOA to ensure equity in credit markets and to "prevent the kinds of discrimination which occurred in the past and to anticipate and prevent discriminatory practices in the future."<sup>134</sup> The Act was initially passed in 1974 to combat well documented discrimination on the basis of sex and marital status against women.<sup>135</sup> ECOA was amended in 1976 following hearings before a senate committee which revealed many instances of discriminatory conduct by creditors against the elderly and people of color.<sup>136</sup> The 1976 amendment established a

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<sup>131</sup> 15 U.S.C. § 1691(d)(2).

<sup>132</sup> Reg. B, 12 C.F.R. § 1002.9(b)(2).

<sup>133</sup> Official Interpretations of Reg. B, 12 C.F.R. § 1002.9(b) (2)-4.

<sup>134</sup> S.Rep No. 93-278, at 3 (1973)

<sup>135</sup> *Id.*

<sup>136</sup> *Id.*

“clear national policy that no credit applicant shall be denied credit he or she wants on the basis of characteristics that have nothing to do with his or her creditworthiness.”<sup>137</sup>

Explainability and transparency of creditor decisions have been at the heart of the ECOA since its inception. 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. Yet this requirement fulfills a broader need: rejected credit applicants will now be able to learn where and how their credit status is deficient and this information should have a pervasive and valuable educational benefit. Instead of being told only that they do not meet a particular creditor’s standards, consumers particularly should benefit from knowing, for example, that the reason for the denial is their short residence in the area, or their recent change of employment, or their already over-extended financial situation. In those cases, in which the creditor may have acted on misinformation or inadequate information, the statement of reasons gives the applicant a chance to rectify the mistake.<sup>138</sup>

**ii. Adverse action notices must accurately describe the factors considered in credit decisions**

Specificity and accuracy are the hallmarks of a compliant ECOA adverse action notice. Regulation B, which implements ECOA, includes sample forms listing “specific reasons for adverse action.”<sup>139</sup> However, if the creditor uses the Regulation B sample form, it may not rely solely on the listing of reasons on the sample form and it may not just check the listed reason closest to the creditor’s actual reason. The creditor must adapt the form to state the specific reason for the adverse action.<sup>140</sup> While a creditor may choose to use some other form, the reasons stated there must be specific and indicate the principal reason or reasons for the action taken.<sup>141</sup>

The CFPB has highlighted the importance of ECOA adverse action notices as it relates to AI/ML models. As the CFPB has stated, “creditors who use complex algorithms, including artificial intelligence or machine learning, in any aspect of their credit decisions must still provide a notice that discloses the specific reasons for taking an adverse action. Whether a creditor is using a

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<sup>137</sup> S.Rep. No 94-589 @ 2 ( 1975).

<sup>138</sup> S. Rep. No. 94-589 (1976), *reprinted in* 1976 U.S.C.A.A.N. 403, 406.

<sup>139</sup> See Reg. B, 12 C.F.R. pt. 1002, app. C.

<sup>140</sup> Reg. B, 12 C.F.R. pt. 1002, app. C. See also *Fischl v. Gen. Motors Acceptance Corp.*, 708 F.2d 143 (5th Cir. 1983) (creditor’s “perfunctory reliance” on the sample form was considered “manifestly inappropriate” because the creditor had indicated that credit had been denied due to insufficient credit references, when the actual reasons were brevity of credit history and excessiveness of the amount to be financed). *But see Aikens v. Nw. Dodge, Inc.*, 2006 WL 59408 (N.D. Ill. Jan. 5, 2006) (in finding that notice met ECOA requirements, distinguishing plaintiff’s case from the facts in *Fischl* because the notice in this case did not give rise to more than one interpretation).

<sup>141</sup> Official Interpretations of Reg. B, 12 C.F.R. pt. 1002, supp. I, § 1002.9(b)(2)-1. See *Aikens v. Nw. Dodge, Inc.*, 2006 WL 59408 (N.D. Ill. Jan. 5, 2006) (ECOA does not require the creditor to utilize the exact language in the sample forms).

sophisticated machine learning algorithm or more conventional methods to evaluate an application, the legal requirement is the same: creditors must be able to provide applicants against whom adverse action is taken with an accurate statement of reasons”<sup>142</sup> The bureau also noted that “the statement of reasons must be specific and indicate the principal reasons for the adverse action.”<sup>143</sup>

As further noted by the CFPB, “specificity is particularly important when creditors utilize complex algorithms because consumers may not anticipate that certain data gathered outside of their application or credit file and fed into an algorithmic decision-making model may be a principal reason in a credit decision, particularly if the data are not intuitively related to their finances or financial capacity.”<sup>144</sup> The Bureau affirmed that creditors must disclose the actual reasons for denial of credit even if the relationship of that factor to predicting creditworthiness may not be clear to the applicant, again emphasizing the importance of transparency and explainability in creditor decision making.<sup>145</sup> The Bureau concluded that “a creditor cannot justify noncompliance with ECOA and Regulation B’s requirements based on the mere fact that the technology it employs to evaluate applications is too complicated or opaque to understand.”<sup>146</sup>

### **iii. Complex AI/ML models that are not explainable defeat the ECOA’s anti-discrimination mandate**

Discrimination is hidden. It is difficult for consumers to detect whether they are being treated worse than other similarly situated applicants with different personal features tied to race, sex, or other characteristics protected under the ECOA. The notices play a pivotal role in uncovering whether the creditor’s decision was discriminatory. 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. As highlighted in the Senate report for the ECOA amendments quoted above, a strict notice provision is a deterrent to discriminatory conduct.<sup>147</sup> Failure to provide accurate information about the reasons for an adverse action poses significant risks to protected classes and undermines a core intention of ECOA, that is, “the production of a more informed and competitive marketplace, where credit applicants can be

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<sup>142</sup> Consumer Financial Protection Bureau, Consumer Financial Protection Circular 2022-03 Adverse Action notification requirements in connection with credit decisions based on complex algorithm, <https://www.consumerfinance.gov/compliance/circulars/circular-2022-03-adverse-action-notification-requirements-in-connection-with-credit-decisions-based-on-complex-algorithms/> at 3.

<sup>143</sup> *Id.*

<sup>144</sup> Consumer Financial Protection Bureau, Consumer Financial Protection Circular 2023-03: Adverse action notification requirements and the proper use of the CFPB’s sample forms provided in Regulation B (September 2023) at <https://www.consumerfinance.gov/compliance/circulars/circular-2023-03-adverse-action-notification-requirements-and-the-proper-use-of-the-cfpbs-sample-forms-provided-in-regulation-b/>

<sup>145</sup> See 12 CFR Part 1002 (Supp. I), sec. 1002.9, para. 9(b)(2)-4.

<sup>146</sup> *Id.*

<sup>147</sup> S. Rep. No. 94-589 (1976), *reprinted in* 1976 U.S.C.A.A.N. 403, 406.

assured of even handed treatment in their quest for what has become a virtual necessity of life,<sup>148</sup> the use of credit.

The adverse action notice required by the ECOA highlights key issues regarding the use of complicated AI/ML models—transparency and explainability. The models must be transparent and explainable to be effective. Consumers are entitled to know what information is being used in credit determinations to evaluate their creditworthiness 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/ML models must use approaches which adhere to the ECOA by providing adverse action notices that disclose, with specificity and accuracy, the principle reason or reasons for the action taken.<sup>149</sup> Opaque AI/ML models which fail to meet this standard must be reengineered or discarded.

The ECOA's notice requirement was designed to fulfill the dual goals of protection against discrimination and education.<sup>150</sup> Any technology no matter how complex must comply with the mandates of the ECOA's adverse action notice provisions. Anything less undermines a core intent of ECOA and may lead to discriminatory conduct by creditors.

## **VI. Summary of General Recommendations**

Financial institutions' use of AI/ML models may lead to unlawful discrimination and abusive practices in the credit, banking and financial services markets. Machine learning in particular 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 to consumers, or even regulators. The result is a significant risk that discriminatory credit practices will go unrecognized and unchallenged.

In addition to the pinpoint recommendations outlined in the sections above, to ensure consumers have nondiscriminatory and equitable access to credit Treasury and other federal agencies should abide by the following general principles:

- Embed principles of equity and transparency in guidance related to AI/ML models;
- Examine financial institutions' use of AI models in all credit decisions and develop guidance and other information on the use of this technology;
- Designate AI/ML as a systemic risk to consumers in all guidance issued to financial institutions;
- 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 and in compliance with fair lending and consumer protection laws;
- Use supervisory and enforcement authority to prevent and address harm from financial institutions' use of AI models;

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<sup>148</sup> S. Rep. No. 93-278, at 3 (1973).

<sup>149</sup> Reg B, 12 C.F. R. pt 1002, app C

<sup>150</sup> *Fischl v. Gen. Motors Acceptance Corp.*, 708 F.2d 143, 146 (5th Cir. 1983).

- Conduct research regarding the use of AI/ML in credit, banking and other consumer-facing activities, especially the effect on consumers of color and other protected classes;
- Hire individuals from diverse backgrounds to evaluate the effect of AI/ML on consumers of color and other protected groups; and
- Engage a diverse group of key stakeholders, including civil rights organizations, consumer advocates, and impacted community members to receive ongoing feedback on regulatory actions.

Thank you for the opportunity to submit these comments as Treasury works to understand how AI is being used within the financial services sector and the opportunities and risks presented by AI within the industry, including risks and benefits to consumers. If you have questions about these comments, please contact Odette Williamson at [owilliamson@nclc.org](mailto:owilliamson@nclc.org) or 617-542-8010.

Respectfully submitted,

National Consumers Law Center (on behalf of its low-income clients)